

Jeong-Do
Almas He
Editors

Productivity, Efficiency, and Economic Growth in the Asia-Pacific Region



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Jeong-Dong Lee • Almas Heshmati (Editors)

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Editors

Prof. Jeong-Dong Lee
Seoul National University
Technology Management,
Economics and Policy Program
Seoul 151-742
Republic of Korea
leejd@snu.ac.kr

Prof. Almas Heshmati
University of Kurdistan
Department of Economics and Finance Hawler
30 metri Zanyari
Federal Region of Kurdistan
Iraq
almas.heshmati@ukh.ac

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Seoul National University, Korea
University of Kurdistan Hawler, Iraq

Jeong-Dong Lee
Almas Heshmati

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Contributors

Editors

Jeong-Dong Lee
Technology Management, Economics, and Policy Program, Seoul National
University, Seoul, South Korea
leejd@snu.ac.kr

Almas Heshmati
Department of Economics and Statistics, University of Kurdistan Hawler,
Kurdistan, Iraq
heshmati@snu.ac.kr

Contributors

Kobchai Chinkul
Department of Agricultural Business Administration, King Mongkut's Institute of
Technology, Bangkok, Thailand
kobchai23@yahoo.com

Dong Ook Choi
Technology Management, Economics, and Policy Program, Seoul National
University, Seoul, South Korea
dochoi@snu.ac.kr

Yongrok Choi
School of International Trade, Inha University, Incheon, South Korea
yrchoi@inha.ac.kr

Das Dipika
Department of Statistical Analysis and Computer Services, Reserve Bank of India,
Mumbai, India
ddas@rbi.org.in

Dogan Ergun

School of Business, Monash University, Selangor Darul Ehsan, Malaysia

ergun.dogan@buseco.monash.edu.my

Dietrich K. Fausten

Department of Economics, Monash University, VIC, Australia

Dietrich.Fausten@buseco.monash.edu.au

Tsu-Tan Fu

Institute of Economics, Academia Sinica and National Taiwan University,

Taipei City, Taiwan

tfu@econ.sinica.edu.tw

Battese George

School of Business, Economics and Public Policy, University of New England,
NSW, Australia

gbattese@une.edu.au

Mika Goto

Socio-economic Research Center, Central Research Institute of Electric
Power Industry, Tokyo, Japan

mika@criepi.denken.or.jp

Dudu Hasan

Department of Economics, Middle East Technical University, Ankara, Turkey

dudu@metu.edu.tr

Almas Heshmati

Professor of Economics, Department of Economics and Statistics, University
of Kurdistan Hawler, 30 Metri Street Zanyari, Erbil, Federal Region of Kurdistan,
Kurdistan, Iraq

heshmati@snu.ac.kr

Mei-Ying Huang

Department of Economics, National Taipei University, Taipei, Taiwan

mying@mail.ntpu.edu.tw

Eui Ju Jeon

Agency for Defense Development, Technology Management, Economics,
and Policy Program, Seoul National University, Seoul, Korea

gangzealot@gmail.com

Kyong-Ihn Jeong

Defense Acquisition Program Administration, Seoul, South Korea

Kyongihn@gmail.com

Kihyun Kim

Technology Management, Economics, and Policy Program, Seoul National
University, Seoul, South Korea

kkihyun6@snu.ac.kr

Young-Hoon Kim

Technology Management, Economics, and Policy Program, Seoul National University, Seoul, South Korea
golyong@snu.ac.kr

Wirat Krasachat

Department of Agricultural Business Administration, King Mongkut's Institute of Technology, Bangkok, Thailand
kkwirat@kmitl.ac.th

Mihir Kumar Mahapatra

Goa Institute of Management, Goa, India
mihir@gim.ac.in

Muhd-Zulkhibri Abdul Majid

Monetary and Financial Policy Department, Central Bank of Malaysia, Kuala Lumpur, Malaysia
khibri1974@yahoo.com

Jong Eun Oh

Technology Management, Economics, and Policy Program, Seoul National University, Seoul, South Korea
serapin7@snu.ac.kr

Seethamma Natarajan Rajesh Raj

Centre for Multi-Disciplinary Development Research (CMDR), Dharwad, Karnataka, India
rajeshraj.natarajan@gmail.com

Chang Hui-Shung (Christie)

Australian Institute of Sustainable Communities, University of Canberra, ACT, Australia
hchangcanberra@yahoo.com

Toshiyuki Sueyoshi

Department of Management, New Mexico Institute of Mining and Technology, Socorro, NM, USA
toshi@nmt.edu

Fadzlan Sufian

CIMB Bank Berhad, University of Malaya, Kuala Lumpur, Malaysia
fadzlan.sufian@cimb.com

Su Wu

School of Accounting, Economics and Finance, Deakin University, VIC, Australia
suw@deakin.edu.au

Chaovanapoonphol Yaovarate (Kai)

Department of Agricultural Economics, Chiang Mai University, Chiang Mai,
Thailand

yao_chao@yahoo.com

Kılıçaslan Yılmaz

Department of Economics, Anadolu University, Eskişehir, Turkey

ykilicaslan@anadolu.edu.tr

Introduction Productivity, Efficiency, and Economic Growth in the Asia-Pacific Region

J.-D. Lee and A. Heshmati

Productivity growth enables an individual firm to raise profit and market share at the micro level, and it helps a country to counteract inflation, create jobs, and to force the necessary industrial restructuring at the macro level. There is widespread consensus among academic researchers in the field of growth theory, policy makers, and/or businessmen that productivity growth is indispensable to sustainable economic growth.

There is no one-size-fits-all solution to improve the productivity, since the ways and means critically depend upon the context and the condition under which firms operate. For example, the strategy for productivity growth in 2000s should be different from that in 1990s, since the parameters forming the economic condition are different and changing. Cross-sectionally, the strategy for automobile industry should not be the same as that for financial institutions, mainly because the production process and industry structure are all different from each other. Thus, the decision maker who is in charge of productivity growth should learn the characteristics of the context, and track down the relevant studies and successful policies that tackle similar sector and/or period.

In the field of productivity research, a case study plays an important role in providing benchmarking information for real practice. Another important contribution of a case study is to accommodate methodological development by itself. For example, we can be ascertained the usability of newly developed methodology, only when we apply it to the real situation and evaluate the outcome. In other cases, the empirical application for the real case will raise other issues requiring further methodological development. This volume is a collection of recent empirical applications to the real case studies using various up-to-date methodologies employed in the literature on productivity and efficiency analysis.

The book focuses on Asia-Pacific region, which is leading the growth of the world economy. There are several characteristics in this region: firstly, countries in the

J.-D. Lee

Technology Management, Economics, and Policy Program, Seoul National University,
Seoul, South Korea

A. Heshmati

University of Kurdistan Hawler, Federal Region of Kurdistan, Kurdistan, Iraq

region are heterogeneous in terms of GDP per capita, size of the economy, technology level, specialization and factor endowments. In the region, high income countries such as Japan, Korea, and Taiwan (China), as well as some of the poorest countries by the standard of UN are located. Even with this significant degree of heterogeneity, the countries are sharing many common characteristics and are closely linked with each other forming a large share of global production network. Intra-regional transaction is prevailing in the form of intra- and inter-sectoral trade flows. Sharing historical background and culture is another important characteristic of the region.

All the features tell us that benchmarking is effective in every aspect of strategy for economic development. The recent book by Yusuf and Evenett (2002), which tries to diffuse the success stories of some countries in East Asia to other countries with the key words of innovation and productivity, exemplifies the potential of benchmarking in the region. Ito and Rose (2004) also contain interesting case studies of productivity research in part of the region. This collected volume intends to contribute to the list of benchmarking studies in the Asia-Pacific countries.

This work is the result of Asia-Pacific Productivity Conference (APPC) 2006, which was held in August 17–19, 2006, at Seoul National University, Seoul, Korea (<http://appc.snu.ac.kr>). APPC 2006 hosted more than 300 experts in the field of productivity and efficiency analysis and it covered the issue of methodological development of Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), firm dynamics, macro economic growth, and sectoral applications, to mention a few. The application fields also ranged from traditional sectors of agriculture to more advanced sectors of finance, ICT manufacturing, etc. ICT, innovation, public policy and strategies are examples of the topics discussed in the diverse sessions. After the conference, a revised version of selected excellent studies through legitimate screening process were collected and transformed into this compendium.

Since its inception in 1999 in Taiwan (China), APPC has become an important assemblage in the field of productivity and efficiency research in this region. Previous APPCs produced two compendiums: Fu et al. (1999, 2002), which became popular in this field. The current compendium is the third collection of productivity and efficiency research out of APPC.

The topics contained in this volume are divided into sub-titles of industrial and firm level productivity analysis, performance in financial sector, performance of public sector and the role of public policy, and ICT related issues. In the following discussion, we provide brief summaries of the individual researches.

In part one, four researches contribute to the section on industrial sectors and firm level efficiency and productivity analysis. These are on factor hoarding, concentration, financial performance and organization of industry and their relations to productivity and efficiency.

Das (Chap. 1) in “Factor Hoarding and Productivity – Evidence from Indian Manufacturing” investigates the productivity of Indian manufacturing considering variable input utilization of capital and labor. Total Factor Productivity (TFP) is computed by relaxing the restrictive assumptions of full capacity utilization of capital and labor. By using a partial equilibrium model in which the author allows for factor hoarding, new series of capital stocks and effective labor use indices

which filter out cyclical variations in input utilization rates was constructed to calculate TFP index/Solow residual. The analysis is at the firm level and covers the period 1973–1974 to 1998–1999. The base year capital used in computing the capital stock series is computed such that no assumption of fixed rate of investment and price behavior of the firm is made. Multilateral TFP index is used to compute the growth and the relative levels of productivity of different sectors, and possible convergence in productivity among the sectors examined. Results show low correlation between TFP growth and output growth. Productivity is steadily increasing with periodical variations over time. The performance ranking of sectors differs over time. Adjustment in TFP for capacity utilization seem to reduce biased measure in TFP from the presence of imperfect competition and scale economies, for which consistent and reliable estimates of the markup and the returns to scale parameter are required.

Dudu and Kilicaslan (Chap. 2) presents their research under the title “Concentration, Profitability and (In)Efficiency in Large Scale Firms”. Large enterprises play an important role as they may be both triggering and detrimental in the growth process. From a Schumpeterian perspective, large firms have higher R&D activity which increases their productive efficiency, and hence, are a primary source of growth. On the other hand, a higher market power leads to loss of efficiency by charging prices above the marginal cost, and also by producing output less than the optimal level. The authors investigate the relationship between concentration, profitability and efficiency in 500 largest enterprises in the Turkish manufacturing from 1993 to 2003. Results based on SFA shows that while higher market share in more concentrated sectors hampers efficiency, it consolidates efficiency in more competitive markets. Among others, the authors find that the private and foreign firms are more efficient than the public firms. Profitability of firms is associated with lower inefficiency and export oriented firms are less efficient.

Goto and Sueyoshi (Chap. 3) touches the issue of financial performance of the energy industry under the title “Financial Ratio Analysis: An Application to US Energy Industry”. They use the Discriminant Analysis (DA) method, which is a decision tool used to predict the group membership score. Recently, a new type of non-parametric DA approach was proposed to provide a set of weights of a discriminant function, which yields an evaluation score for the determination of group membership. The method is referred to as “Data Envelopment Analysis-Discriminant Analysis (DEA-DA)” in the literature. The DEA-DA can serve as a new evaluation method in dealing with many financial ratios in performance analysis referred to as “Financial Ratio Analysis (FRA).” In this study, FRA is applied to the US energy industry in order to evaluate the financial performance of default and non-default energy firms in 2003. The results show that there is a significant difference between default firms and non-default firms in terms of financial performances. Business diversification between electricity and gas does not yield a financial prosperity as expected by corporate leaders and individuals who are interested in the US energy industry. Both leverage and profitability are important financial factors distinguishing between firm type and degrees of diversification. The research results and business implications are extendable to energy sector in other industrial nations.

Raj and Mahapatra (Chap. 4) with the title “On Measuring Productivity Growth in Indian Industry: Analysis of Organized and Unorganized Sector in Selected Major States”, attempts to assess the performance of the industrial sector in India and chosen states during the last two and a half decades, especially during the reforms period. In doing so, the growth in productivity has been estimated by adopting growth accounting and DEA methods. Further, TFP growth has been decomposed into technical change and efficiency change components by using Malmquist productivity index. The result of the analysis reveals noticeable changes in performance of Indian manufacturing. There is a decline in the productivity growth in the organized manufacturing sector and in the TFP growth in the unorganized manufacturing sector, which was the main provider of employment opportunities during the reform period. The changes are attributed to allocation of resources and to some extent, to failure of sustaining technical change during the studied period. The drop in productivity growth in the organized sector can be primarily the result of inefficient use of employment in manufacturing sector, which has witnessed improvement in TFP growth during the reforms period. This can be primarily attributed to the substantial improvement in technological change which outweighed decline in efficiency change. The authors indicate that the economy can not afford to ignore the unorganized sector and therefore, propose that effective industrial policies are needed to address the problems confronted by the unorganized sector.

In the second part, four studies deal with the issue of performance in the financial sector. These cover the areas of efficiency of banks, performance of venture capital companies, performance of non-bank financial institutions, and the effects of public policy on the structure of banking industry.

Dogan and Fausten (Chap. 5) in their study entitled “Technical Efficiency of Banks in South East Asia” use DEA and bootstrap methodologies to examine the performance of banks in Indonesia, Malaysia, Philippines, and Thailand. The investigation period is post the 1997 Asian financial crisis, 2000–2004. Using four different models to measure inputs and outputs, they find that in the Indonesian and Malaysian banking sectors, median efficiency has increased over the period while in contrast, the results for the Philippines and Thailand are ambiguous. In some models, median efficiency increases while it decreases in others. Efficiency differences among banks are not statistically different suggesting significant impacts of the reorganization and restructuring of the banking sectors on the efficiency of banking service. A second main finding is that median efficiency in banking has improved in the sampled countries over the observation period. Furthermore, banks in Malaysia and Thailand appear to be less efficient in generating loans than in generating income. This relatively robust finding stands in contrast to the experience of Indonesia and the Philippines. However, the authors are not able to identify a satisfactory reason for this difference without a careful analysis of the regulatory framework, and data limitations does not allow for analyses of the determinants of technical efficiency.

Jeon, Lee and Kim (Chap. 6) examined the performance of venture capital companies under the title “The Effect of Strategy on Venture Capital Firm Efficiency: An Application of Data Envelopment Analysis”. The venture capital firms in Korea,

as a result of 2004 'Venture Again Policy', are slowly gaining their return on equity and stability. However, there remain problems of unknown nature such as whether the venture capital firms are showing high risk and high return characteristics and efficiency enough to survive in the market. The authors estimate the efficiency of the venture capital firms in respect to operational profitability by using DEA and investigate whether asset composition strategies of the firms have significant effect on their performance. The results indicate that firms focusing on early-stage and long-term investment tend to have lower efficiency than the others. This may be caused by the venture capitalists' lacking the professionalism and experience in managing the venture capital assets. However, the lower efficiency is a result of the limitation of the VC investment defined by the laws related to eligibility and duration of various support and tax incentives. These laws limit the industries amount of investment and the target of investment. This limits the range of high-risk and high-return investment alternatives which decreases the opportunities for gaining high-return profits. Several policy implications are suggested to enhance the market conditions for venture firms. More emphasis should be made on flexibility in decisions to involve venture capital firms in investment that show high-risk and high-return characteristics. Changes in the preferences on short investment horizon are required to encourage firms to invest in long-term assets. This will positively affect technology innovation and development of the economy.

Sufian and Abdul-Hamid (Chap. 7) investigate the issue of productivity growth of non-bank institutions under the title "Post-Crisis Non-Bank Financial Institutions Productivity Change: Efficiency Increase or Technological Progress?" by applying the non-parametric Malmquist Productivity Index (MPI). The main motivation of this study is the Malaysia's Financial Sector Master Plan (FSMP), a long-term development plan charting the future direction of the financial services industry in Malaysia to achieve a more competitive, resilient and efficient financial system, through further liberalization of the banking sector. The authors attempt to investigate productivity changes of the Malaysian Non-Bank Financial Institutions (NBFIs), specifically finance companies and merchant banks, during the post-crisis period of 2001–2004. The aim is to highlight the effectiveness of microeconomic reforms introduced to enhance the competitiveness of the financial services industry. The results suggest that the Malaysian NBFIs have exhibited productivity regress during the post-crisis period, mainly attributed to efficiency decline rather than technological regress in the financial market. The results further suggest that while the merchant banks' have exhibited productivity regress mainly due to technological regress, the finance companies on the other hand, have exhibited productivity progress attributed to technological progress. The second-stage regression analysis results suggest that efficiency level is positively associated with size, level of capitalization and the degree of specialization, while productivity level is negatively associated with overhead expenditures, risk, and favorable economic conditions. Various tests showed that it is appropriate to construct a single service production frontier for both the merchant banks and finance companies.

Wu (Chap. 8) focuses on the Australian banking sector under the title "Impact of the Wallis Inquiry on Australian Banking Efficiency Performance". A super-efficiency

DEA model is used to analyze the efficiency performance of the Australian banking industry between 1983 and 2001. In particular, the impact of the Wallis Inquiry in 1996, to which the Australian Federal Government responded by adopting four pillars policy preventing mergers among the four major banks is examined. The objective is to examine whether there should be merger between the existing four major banks, and whether the Wallis Inquiry improves banks of different groups and the banking industry efficiency performance. The empirical results indicate that newly-established banks have better efficiency performance than existing banks; however, the efficiency gap has been diminishing since the conduct of the Inquiry. The results demonstrate that the impacts from increased pressure are as a result of threat of takeovers on the improving efficiency performance of banks. Even without actual M&A, the threat of takeover itself can serve to intensify competition, and it does facilitate the exit of relatively inefficient banks and increase efficiency of the remaining banks. The primary role of the government is to focus on promoting deregulation and competition in the banking industry. Thus, sooner or later, the government will look at the issue of bank mergers again to determine a relaxation or removal of the restrictive banking policy.

In the third part, efficiency in public sector and the role of public policy are the main issues. It consists of five studies related to the analysis of efficiency of higher educational institutions, efficiency of defense-related industry, performance of agricultural cooperatives, effects of credit guarantee policy on small businesses, and the impacts of agricultural loans on rice farmers' performance.

Fu and Huang (Chap. 9) re-examined the efficiency issue of the educational sector, in a study entitled "Performance Ranking and Management Efficiency in Colleges of Business: A Study at the Department Level in Taiwanese Universities". The information is important for decision makers of higher education institutions in their resource allocation. However, for prospective students and recruiters of graduates, the reputation ranking provides more useful information in their selection. Using the DEA technique, Fu and Huang measure performance ranking and resource management at the department level for the colleges of business in Taiwan. The data reveals that the departments at public universities in general have higher performance scores and are the preferred choice of prospective students and business communities. The empirical results further indicate that there exists a positive relationship between the performance ranking and the efficiency of resource management. The two measures of rank correlation coefficient are 0.6. It is also observed that the best performing departments in national universities are characterized by full efficiency, whereas the worst performing departments in private schools are mostly ranked as the least resource-use inefficient departments. Such a finding seems to imply that the efficiency ranking information can still be useful to prospective students in their decisions to select a college to join in Taiwan. It also confirms the hypothesis that good management, good performance and reputation in higher education are interdependent.

Jeong and Heshmati (Chap. 10) analyzed the efficiency of defense-related industry with the title "Efficiency of the Korean Defense Industry: A Stochastic Frontier Approach". They consider the estimation of stochastic frontier function and efficiency in the Korean defense industry using a flexible translog production functional form.

In the empirical part, panel data on 155 defense firms during the period 1990–2005 is used. They compare technical efficiency by the size of the firm, the industry sector, competition policy, ratio of defense part of the firm, rate of operation as well as over time and across sectors. The empirical results show that the mean annual rate of technical change is 2.1% with minor changes over time. The defense ratio, rate of operation, age of firm, specialization, competitive environment change, and R&D investment in defense part are positively related to the level of technical efficiency of firms. Competitive environment change for specialized and serialized firms does not affect the level of technical efficiency. The size of firm does not affect the technical efficiency. Among large firms, the lower defense ratio is positively related with the technical efficiency. The mean technical efficiency is estimated to be around 76.7% and increasing in post-1998 period, but varying across the industrial sectors. Productivity growth was driven mainly by technical progress, followed by allocative efficiency. TFP in the defense industry has grown at an annual rate of 3.9%, while the scale efficiency effect to TFP growth was very low. Tests related to possible differences in efficiency among defense, commercial and mixed parts show little difference not supporting cost shifting hypothesis from defense to commercial parts. Thus, the technical efficiency that can explain the gap of profitability or productivity is inconsistent with cost shifting explanation for the excess profitability of the defense contractor. Other indicators such as ROA, labor productivity, capital efficiency and profitability are among possible factors explaining the cost shifting issue.

Krasachat and Chimkul (Chap. 11) targets the agricultural cooperatives in a study entitled “Performance Measurement of Agricultural Cooperatives in Thailand: An Accounting-Based Data Envelopment Analysis”. The main purpose is to measure and investigate factors affecting inefficiency of agricultural cooperatives in Thailand in 2004 using the input-oriented variable returns to scale DEA approach. In order to examine the effect of cooperative-specific factors on efficiency, a Tobit model is estimated where in the second step, the cooperative levels of inefficiencies are expressed as a function of these specific factors. The empirical results suggest four important findings. First, the efficiency scores of some cooperatives were considerably low implying that there is significant scope to increase efficiency levels in Thai agricultural cooperatives by 28%. Second, in decomposing of the overall efficiency, the results indicate that pure technical inefficiency makes a greater contribution to inefficiency among cooperatives. Third, there are size disadvantages in the larger Thai agricultural cooperatives suggesting smaller size as more optimal size. Fourth, there is confirmation that cooperative locations, the types of agricultural cooperatives, the cooperatives’ age, lending policies, management’s attitudes on financial leverage and asset size influenced the inefficiency of the agricultural cooperatives in Thailand. The authors suggest that development policies in the above areas should be used to increase the technical efficiency of the inefficient agricultural cooperatives.

Choi (Chap. 12) analyzes the effectiveness of public policy with the title “An Empirical Study on the Performance of Credit Guarantee Policy for Small Business in Korea”. The author argues previous evaluation studies on public policy for small business in Korea were inaccurate and biased in terms of the methodology used. The comparative results by regression analysis and logit models showed the reverse

selection by the risky business and the moral hazard by the consultocratic intermediaries were clearly harmful to the regional economy by substituting the potential business with the risky marginal ones. Thus, the paper suggests the issues are not for the system itself, but for the governance in the public intermediaries.

Chaovanapoonphol, Battese and Chang (Chap. 13) presents their research entitled “The Impact of Agricultural Loans on the Technical Efficiency of Rice Farmers in the Upper North of Thailand”. Despite being the main rice-exporting country in the world, Thailand’s rice yields per unit of land are among the lowest in Asia. The Thai government has continued to promote increased use of inputs to increase rice yields. However, using production inputs in greater amounts has resulted in higher amounts of loans being required, particularly for resource-poor farmers. This paper seeks to investigate the impact of agricultural loans from rural financial institutions on the technical efficiency of rice farmers. Translog stochastic frontier production functions are estimated using survey data collected in 2004 from 656 rice farmers in Chiang Mai and Chiang Rai provinces. The empirical analysis indicates that land and labor are the most significant variables explaining the variation in major rice production, and that the amount of loans has a negative impact on technical inefficiencies of the rice farmers. In addition, the average technical efficiencies of rice farmers were estimated to be 81.9 and 73.2% of the potential frontier production levels in Chiang Mai and Chiang Rai provinces, respectively, showing that there is scope for increasing major rice production efficiency. Hence, agricultural policy makers should focus on the factors affecting the efficiency of farmers, especially the financial services in rural areas and the formal education levels of major rice farmers.

The last part of efficiency of ICT firms consists of two researches on digital content industry and cable industry.

Choi and Oh (Chap. 14) in their research on “Efficiency Analysis of Digital Content Industry in Korea: An Application of Order-m Frontier Model” apply performance methodology to the new digital content industry in Korea in 2002 and 2004. The objective is to identify performance enhancing characteristics of the industry. In their analysis, they use a two-stage framework which includes non-parametric frontier estimation of efficiency level and explanation of its determinants by Tobit analysis. In order to detect and exclude outliers in the frontier analysis, order-m frontier model is used. Three distinctive sub-industries of software, game publishing and information provision are selected and compared in the analysis. As a result of the analysis, all three industries showed improvement in efficiency distribution during the study period but the degree of changes is less for the mature software industry. Reduction in the gap in efficiency among the new game and publishing industries suggest fierce and increasing competition in the market. There is evidence of persistency in distribution of inefficient firms. In the second stage analysis, the authors find that firm size and technology factors determine degree of efficiency in the game industry, while firm size and R&D affect firms’ efficiency in the publishing industry. The efficiency level and other explanatory variables shed some light on the effects of various policies in this industry. In the case of information provision, the labor or capital ratio has a significant correlation with the level of efficiency. Investment in education to supply well educated manpower is crucial for the growth

and competitiveness of the industries. Research based on a better quality data will help to shed light on the necessary competitive enhancing incentive factors.

Kim and Heshmati (Chap. 15) conduct a research on the “Analysis on the Technical Efficiency and Productivity Growth of the Korean Cable SOs: A Stochastic Frontier Approach”. After the introduction of Cable TV in 1995, the market performance in the early 5 years is evaluated to be relatively weak. This has been a result of the early stage development of the Cable TV service in Korea, macroeconomic shock from the Asian financial crisis, but mostly due to the competition structure and over-regulation in the industry. The New Broadcasting Act of 2000 had helped to set the stage for early-stage Cable TV consolidation through the deregulation of cross-ownership restrictions to allow ownership of both PPs and SOs and the establishment of the extent of foreign ownership in Cable TV. The authors aim to analyze Cable SOs’ technical efficiency and productivity growth by stochastic distance function approach to investigate the impact of the policy and deregulation such as the licensing sequence, competition environment, internet availability and M&A on service regions of SOs. The results indicate that mean technical efficiency of the Cable SOs is 0.826. Technical efficiency improved over time and is higher in MSOs in densely populated regions, in places with no internet services, and monopolized SO areas. These empirical results show that the deregulation policy such as the permission of M6A has positively affected the industry’s performance. Introduction of competition to the cable television market has not only resulted in the provision of the service at lower fees and more diverse channels, but competition has also reduced the firm performance. Technical efficiency has decreased with the licensing sequence of Cable SOs, and MSOs are more efficient than single SOs considering that Cable SO needs large scale of infrastructure for its services. The share of MSOs is expected to be higher and boosted by foreign investment which enhances the efficiency of the industry.

In sum, the above fifteen studies cover a whole range of aspects of organizations of different sizes and specializations operating in different sectors of several dynamic economies in the Asia Pacific Region. The contributors are experts in the field studied and use several well-known and up-to-date performance measurement methodologies. The studies’ results shed light on the state-of-the-art of productivity and efficiency in the region. The collected volume is expected to be a significant contribution to the literature on firm and sector level studies, and evaluation of public policies to promote economic growth.

Seoul, September, 2007

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Part I
Industrial Sector and Firm Level
Efficiency and Productivity Analysis

Chapter 1

Factor Hoarding and Productivity: Experience from Indian Manufacturing

Dipika Das

1.1 Introduction

Growth in the neoclassical framework stems from two sources: factor accumulation and productivity growth. The growth driven by increased factor accumulation cannot be sustained because of the non-availability of factor inputs in future as well as diminishing returns to factors. Hence, economists have emphasized on productivity growth. Total factor productivity (TFP) growth is important even for developing countries like India with relatively abundant labour, as these economies face an acute shortage of some other productive resources. Many studies have been undertaken to examine the trends in productivity in India. Most of the empirical studies on productivity in India have focused on the TFP growth (TFPG) of the manufacturing sector in the post reform period. Some of these studies include Brahmananda (1982), Ahluwalia (1991), Golder (1986,1990, 2004), Srivastava (1996, 2001), Chand and Sen (2002), Unel (2003), Das (2003), and Topalova (2003). Evidence on TFPG in India as brought out by these studies vary considerably. This is due to the use of different estimation methods of TFPG, as well as the use of different data sets. None of the above studies has considered variation in input utilization rates over business cycles to compute TFP or Solow residual. In this paper, I have considered variable input utilization – variable capital utilization and variable labour efforts derived explicitly from a partial equilibrium model on Indian data. Variability of factor inputs can occur over a business cycle when firms are not able to disinvest capital or lay off workers in a downturn. It is particularly important for Indian industries which have operated till 1991 under a rigid license, permit and quota regime. During an expansion period, capital is fully utilized while in recession period, there is under utilization of capital stocks. Firms were known to hoard capital above their optimal level as they could claim a lower capital requirement for later expansion, and hence strengthen their claim for production license. On the labour

Dipika Das

Department of Statistics and Information Management, Reserve Bank of India,
Mumbai, India

front, labour protection laws have made it virtually impossible for the firms to lay off workers even when they have stopped producing. Also, training new workers is costly and firms encourage workers to work harder in the expansion period. In the typical TFP calculation, labor/capital inputs are measured as higher than ‘real’ in recessions, and as lower than ‘real’ in expansions. Accounting for factor hoarding or surplus can thus have a significant impact on TFPG estimation since the standard computation of the Solow residual fails to filter out cyclical variation in input utilization rate, assigning it to fluctuations in technology.

In this study, I have used firm-level panel data for the period 1973–1974 to 1998–1999 to compute TFP or Solow residual. Further, I have computed the base year (initial year) capital stock which plays a vital role in the computation of capital stock series in a different way. Every method of estimation of the base year capital stock is based on some specific assumptions as data is not available from the date of incorporation up to the base year. Some authors assume fixed rate of investment of capital as well as price of capital for the period the data is not available (from the year of incorporation up to the base year). However, the data set used in this study reveals that, investment and price do not grow steadily over time. In this paper, I have computed the base year capital stock series in a different way.

The organization of this study is as follows. In Sect. 1.2, concepts of productivity are discussed briefly. Section 1.3 presents the model with factor hoarding. Section 1.4 describes the data and the method of computation of different variables – capital, labour and material inputs. Section 1.5 presents results on Tornqvist productivity index at the aggregate manufacturing level and across different sectors. Convergence of productivity across different sectors over time is also examined in this section. Section 1.6 examines the pro-cyclicality of the computed TFP. The final section summarizes and indicates direction for future research.

1.2 Productivity Growth: Concepts and Measurements

Solow (1957) first developed techniques to measure productivity growth which later came to be known as Solow residual. It is essentially growth accounting and decomposes total growth into capital, labour and technology induced components. The key assumptions of the derivation are competition, constant returns to scale and Hicks-neutral technology. Let Y be output, K be capital, L be labour and A be technology. The production function can be written as follows:

$$Y = AK^{1-\alpha}L^{\alpha} \quad (1.1)$$

Taking the total differentiation of (1.1),

$$\frac{dY}{Y} = \frac{dA}{A} + (1-\alpha)\frac{dK}{K} + \alpha\frac{dL}{L} \quad (1.2)$$

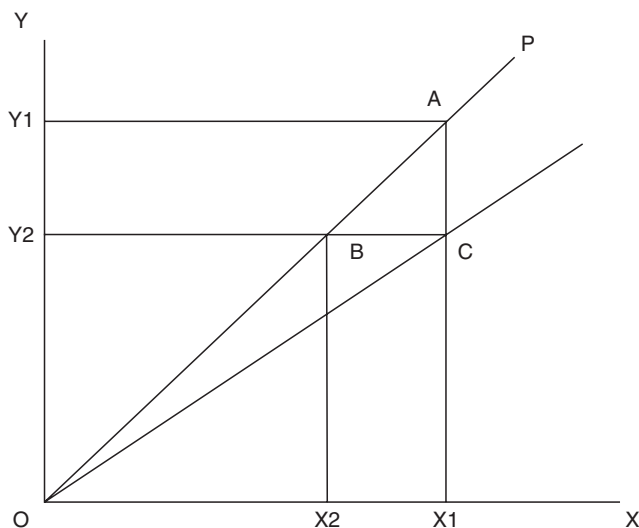


Fig. 1.1 Productivity with factor hoarding-CRS production function

where dA/A is a measure of the changes in output not accounted by changes in inputs, and is called the Solow residual or total factor productivity (TFP). Productivity is shown graphically with respect to a single input production function in Fig. 1.1. The curve OP represents the single input CRS production frontier which represents the maximum output attainable from each input level. The slope of OP measures productivity. At point A , the firm produces Y_1 using X_1 . However, if the factors were mobile in a downturn, it would produce Y_2 using X_2 (at point B), and productivity would be the same at both A and B . But when the factors cannot be unloaded at C , the firm will produce Y_2 using X_1 , and hence showing lower productivity. Similarly, in Fig. 1.2, it is shown that the firm shows increasing returns to scale up to point A , after which there is decreasing returns to scale. The slope of the ray passing through the data point and the origin (Y/X) measures productivity at that particular data point. At point A , the firm produces Y_1 using X_1 . However, if the factors were mobile in a downturn, it would produce Y_2 using X_2 (at point B), and productivity would have been decreased at point B as the slope of the ray would be smaller. This would imply lower productivity at point B . But when factors cannot be unloaded at C , it will produce Y_2 using X_1 showing further decrease in productivity.

The productivity of a firm can change over time as a result of technological advances, which is captured in Total Factor Productivity. This is represented by an upward shift of the production frontier, which produces more output at each level of input.

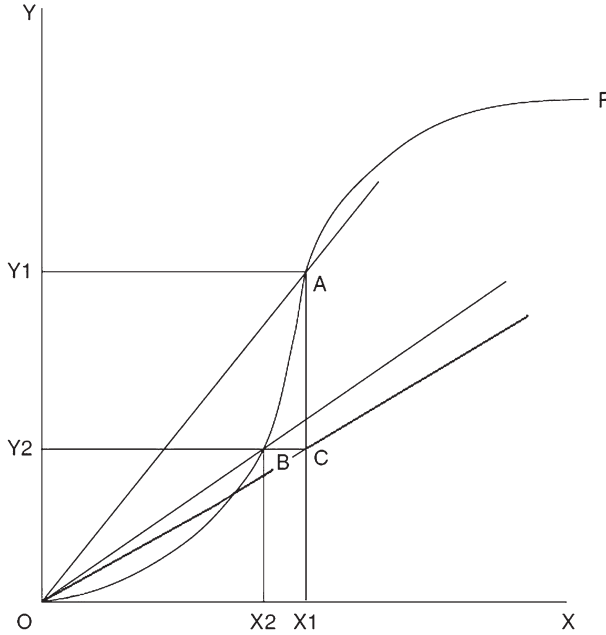


Fig. 1.2 Productivity with factor hoarding-General production function

1.3 The Model with Factor Hoarding

The model with factor hoarding is a partial equilibrium model, which assumes that firms are producing goods using constant returns to scale technology as follows:

$$Y_t = \tilde{A}_t (u_t K_t)^\alpha (e_t N_t)^{1-\alpha} \quad (1.3)$$

where Y_t is output produced, K_t is the capital stock, N_t is the employment, u_t is the utilization rate of capital, e_t is the utilization rate of labour or labour effort and $\tilde{A}_t$ is the total factor productivity corrected for inputs utilization. The firm would maximize profits taking into account the cost of capital and the cost of labour. The cost of capital utilization is modeled as faster depreciation. Following Burnside and Eichenbaum (1996) and Imbs (1999), it is assumed that the rate δ_t at which capital depreciates is a function of capital utilization rate and follows the following equation:

$$\delta_t = \delta u_t^\phi \quad \text{where } \phi > 1 \quad (1.4)$$

$\phi > 1$ ensures that depreciation is a convex function of utilization u_t . It is assumed that $E(\delta_t) = \delta$ or $E(u_t^\phi) = 1$. In this study, it is assumed that firms rent capital

at a rate which is equal to the interest rate r_t plus the depreciation δ_t induced by its use, and rental cost depends on the utilization rate which is observable by the capital owner. As δ_t is a function of the utilization rate u_t , it is assumed that rental cost is not fixed, and hence depends on the utilization rate, which is observable by the capital owner. It is also assumed that it is infinitely more costly to adjust employment, and hence employment is pre-set one period ahead and firms can only adjust the effort of labour instantaneously by offering them a higher wage. Firms choose utilization u_t , capital stock K_t and labour effort e_t in a period. Employment N_t is fixed for the period. Thus the firm's optimization problem can be written as:

$$\max_{u_t, K_t, e_t} \tilde{A}_t (u_t K_t)^\alpha (e_t N_t)^{1-\alpha} - w(e_t) N_t - (r_t + \delta_t) K_t \quad (1.5)$$

where, $w(e_t)$ is the wage schedule.

The first order conditions are given as:

$$\frac{\alpha Y_t}{u_t} = K_t \delta \phi u_t^{\phi-1} \quad (1.6)$$

$$\frac{\alpha Y_t}{K_t} = r_t + \delta_t \quad (1.7)$$

$$\frac{(1-\alpha)Y_t}{e_t} = w'(e_t) N_t \quad (1.8)$$

From (1.6), substituting δ_t for δu_t^ϕ in the R.H.S. we get,

$$\frac{\alpha Y_t}{K_t} = \phi \delta_t \quad (1.9)$$

Taking expectations on both sides of (1.9) and solving for α we get

$$\alpha = \frac{\phi E(\delta_t)}{E(Y_t / K_t)} \quad (1.10)$$

Substituting the value of α in (1.9) we get,

$$\delta_t = E(\delta_t) \frac{(Y_t / K_t)}{E(Y_t / K_t)} \quad (1.11)$$

Also, comparing (1.7) with (1.9) we get,

$$\phi \delta_t = r_t + \delta_t \quad (1.12)$$

Taking expectation on both sides of (1.12) and solving for ϕ we get,

$$\phi = \frac{E(r_t) + E(\delta_t)}{E(\delta_t)} \quad (1.13)$$

Substituting the value of ϕ in the (1.4) and solving for u_t we get,

$$u_t = \left(\frac{(Y_t / K_t)}{E(Y_t / K_t)} \right)^{\frac{E(\delta_t)}{E(\delta_t) + E(\delta_t)}} \quad (1.14)$$

Thus, capital utilization is high when the output-capital ratio is higher than its average value.

Labour effort e_t can be solved from (1.8) for which knowledge of the functional form of $w(e_t)$ is required. Here, it is assumed that the utility of a labour is convex in the product $e_t N_t$ which results to wages being linear in labour effort, i.e.

$$w(e_t) = c e_t \quad (1.15)$$

Assuming the above wage schedule, from (1.8) we get,

$$\frac{(1-\alpha)Y_t}{N_t} = c e_t \quad (1.16)$$

Taking expectations on (1.16) and solving for $(1-\alpha)$ we get

$$(1-\alpha) = \frac{cE(e_t)}{E(Y_t / N_t)} \quad (1.17)$$

Substituting the value of $(1-\alpha)$ in (1.16), we get

$$e_t = E(e_t) \frac{(Y_t / N_t)}{E(Y_t / N_t)} \quad (1.18)$$

Thus, labour effort is high when the output-labour ratio is higher than its average value.

1.4 Data and Computation of Variables

This section describes the data and industry classification used in sectoral analysis, and also explains the methodology for computation of variables.

1.4.1 Data

This study is based on panel data on Public Limited Companies for the period 1973–1974 to 1998–1999 sourced from the Reserve Bank of India. The Reserve Bank of India compiles data from the balance sheet and profit and loss account of Public Limited companies, which are submitted by the companies annually.

The original data set consisted of 49,576 observations and included firms from mining and quarrying, plantation and service sectors. For this study, I have excluded

all the firms which are not from the manufacturing sector, leaving a sample of 37,603 observations. Further, observations were not available for some firms in some years. In such cases, the maximum length of continuous time series data was considered and the other observations excluded. I have also excluded observations which had wrong/unacceptable values in certain data fields. As a result, a data set consisting of 31,652 observations from 3,187 firms was finally considered.

1.4.2 Sectoral Classification

In the original dataset, firms were classified into six major industry groups and 85 sub-groups. The six major groups are: (a) agriculture and allied activities; (b) mining and quarrying; (c) processing & manufacture – foodstuffs, textiles, tobacco, leather and products thereof; (d) processing and manufacture – metals, chemicals and products thereof; (e) processing and manufacture – not elsewhere classified; (f) other industries.

For the sectoral analysis, the National Industrial Classification (NIC) at two-digit level was used. Thus, the company code given in the data set was reclassified into NIC code. The reclassification is described in Table 1.7 in the Appendix 2.

1.4.3 Computation of Variables

For productivity analysis, one needs to define, identify and if necessary compute different variables, namely output, capital, labour, material inputs, and fuel from the observed firm-level data. In this section, I discuss how these variables were computed.

1.4.3.1 Capital

Creation of capital stock series is one of the most difficult tasks in productivity analysis, as it is not directly available from the balance sheet data. The balance sheet data is at historic cost and for calculating capital stock at any time period, it should be converted to replacement cost. The computation of capital stock is explained in the Appendix 1 in details.

1.4.3.2 Output

All variables in this study are from the balance sheets of public limited companies. For real output, I used the field “Value of production” deflated by the index number of wholesale prices. Different deflators were used for different industry sub-groups as classified in the RBI data.

1.4.3.3 Labour

In the data set, wage bill for workers and managers were separately available as “Remuneration to employees” and “Managerial remuneration”. Both were deflated with different deflators calculated from the total wage and employment figures available in Annual Survey of Industries (ASI) at 2-digit level. The ASI has also classified wage for workers and other employees separately. The base year was taken as 1980. Both the real wages (workers and managers) were integrated to compute labour for each firm.

1.4.3.4 Material Inputs

Price indices for the material inputs in different industries were computed using technological coefficients from the input–output table, 1996–1997 constructed by the Planning Commission, and the whole sale price index series (to the base 1980–1981 = 100) for different commodities. There were 65 sectors in the input–output table. Material price indices for various industries were computed as a weighted average of the wholesale price indices of different material used in that industry, where weights are the shares of the price of a particular input in the total input cost.

1.5 Results

TFP indices, which measure the change in productivity in comparison with the initial year or base year, were estimated using Tornqvist index method for the period 1973–1974 to 1998–1999.

1.5.1 *Results on Tornqvist Index at the Aggregate Manufacturing Level*

Results on Tornqvist index at the aggregate manufacturing level are reported in Table 1.1 in the form of output index, output growth rates, normal as well as adjusted TFP index and TFP growth rates. It is observed from Table 1.1 that, in general, whenever there is a drop in output growth, for instance, 1979–1980, 1990–1991, 1993–1994 and 1996–1997, the adjusted TFP for that year is more than the normal TFP index as it accounts for utilized capital and labour instead of the total capital stock and labour available. Although there is a very high correlation (0.98) between normal TFP index and adjusted TFP index showing movement of both series in the same direction, the correlation between output index and TFP index reduces from -0.41 to -0.28 after considering the adjusted TFP.

It is clear from Table 1.1 that, there was a steady rise in productivity in the Indian manufacturing as a whole in the 1970s and early 1980s, with maxima in 1980–1981,

Table 1.1 Output index, TFP index and annual growth rates: All manufacturing industries

Year	Output		TFP		Adjusted TFP	
	Index	Growth	Index	Growth	Index	Growth
1973–1974	100.00		100.00		100.00	
1974–1975	108.66	8.66	98.36	–1.64	98.99	–1.01
1975–1976	116.06	6.81	103.57	5.30	103.59	4.65
1976–1977	124.11	6.94	108.20	4.47	107.71	3.98
1977–1978	131.74	6.15	112.12	3.62	112.03	4.01
1978–1979	144.43	9.63	119.93	6.97	119.21	6.41
1979–1980	141.90	–1.75	117.60	–1.94	118.17	–0.87
1980–1981	148.83	4.88	121.30	3.15	122.13	3.35
1981–1982	173.31	16.45	113.43	–6.49	114.53	–6.22
1982–1983	181.76	4.88	113.39	–0.04	115.03	0.44
1983–1984	187.32	3.06	103.75	–8.50	105.51	–8.28
1984–1985	203.06	8.40	106.05	2.22	107.91	2.27
1985–1986	222.73	9.69	103.88	–2.05	105.71	–2.04
1986–1987	233.98	5.05	103.77	–0.11	105.76	0.05
1987–1988	242.55	3.66	96.82	–6.70	98.92	–6.47
1988–1989	271.76	12.04	100.05	3.34	102.00	3.11
1989–1990	303.76	11.78	106.02	5.97	108.00	5.88
1990–1991	304.75	0.33	104.42	–1.51	106.40	–1.48
1991–1992	330.11	8.32	105.90	1.42	108.72	2.18
1992–1993	339.81	2.94	99.38	–6.16	102.36	–5.85
1993–1994	292.88	–13.81	86.32	–13.14	88.72	–13.33
1994–1995	334.58	14.24	90.87	5.27	93.37	5.24
1995–1996	382.31	14.27	94.47	3.96	96.74	3.61
1996–1997	317.87	–16.86	107.49	13.78	110.27	13.99
1997–1998	375.61	18.16	110.28	2.60	114.69	4.01
1998–1999	384.58	2.39	104.85	–4.92	108.82	–5.12

after which it declined up to 1987–1988, followed by a recovery in 1988–1989. It again showed a decline after the reforms in early 1990s, with minima in 1993–1994 and remained very low (less than 100) for a couple of years, after which a steady rise in productivity is observed since 1994–1995 (see Fig. 1.3). At the manufacturing industry level as a whole, it is observed that, the annual TFP growth was high in the 1970s, followed by a period of very low and negative growth up to 1987–1988, after which it recovered in the late 1980s. There was again a decline in TFP growth just after the reforms in 1990–1991, which has recovered since 1994–1995.

1.5.2 Results on Tornqvist Index at Industry Level

The adjusted TFP indices (with base year 1973–1974 = 100) are computed for the different manufacturing industries separately and the results are presented in Table 1.2. In Table 1.2, I have examined the productivity of a specific industry over the years

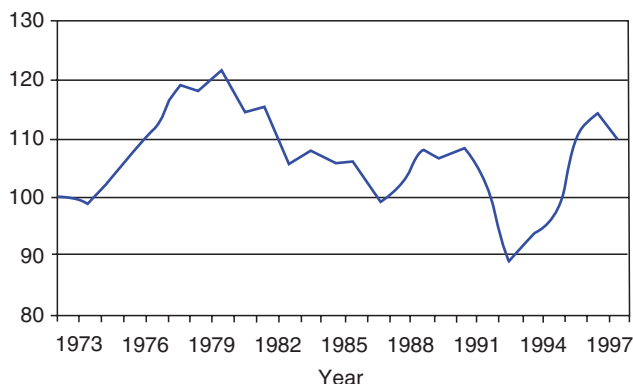


Fig. 1.3 TFP Indices-All Manufacturing Industries

and not the comparison of productivity across the different industries. It is observed that in the 1970s, there was an overall rising trend in productivity in all the industries with an exception of the leather, textile product and rubber/plastic industries. In the 1980s, an overall increase in productivity was observed in the food product, silk/synthetic textile, electrical machinery and transport equipment industries. Most of the other industries showed a rise in productivity in early 1980s and a subsequent fall in the later half of 1980s. In the 1990s, there was an overall decline in productivity in the manufacturing industries. Productivity in the food product, cotton textile, hemp textile, wood product, leather product, rubber/plastic, non-metallic mineral product and metal products was lower in the 1990s compared to the earlier two decades. Hence, the overall conclusion was that during 1990s, the manufacturing industries could not perform well with respect to TFP, which indicates that the input growth has been higher than the output growth.

1.5.3 Sectoral Comparison Using Multilateral Tornqvist Index

In this section, productivity across different sectors is compared using multilateral productivity index proposed by Caves et al. (1982). I have used multilateral Tornqvist index for this purpose. Comparisons between two sectors are obtained by using the TFP of sector 20 (Food Product) in the year 1973–1974 as the basis for making all possible binary comparison, i.e. any two sectors are compared with each other by comparing them with TFP of sector 20 in the year 1973–1974. Relative TFP of different sectors from 1973–1974 to 1998–1999 are presented in Table 1.3 and the annual percentage rate of growth is presented in Table 1.4. It is observed that there is a wide disparity among sectors according to their productivity levels and growth (see Fig. 1.4). The food product, leather industry, chemical and electrical machinery are relatively high productive sectors while cotton textile, silk/synthetic textile,

Table 1.2 Adjusted TFP Index for different sectors

Year	Sector																
	Food product	Beverages	Cotton textile	Silk/synthetic textile	Jute hemp textile	Textile product	Wood product	Paper	Leather	Chemical	Rubber plastic	NMMP	Metal alloys	Metal product	Machine tools	Electrical machinery	Transport equipment
1973–1974	100.00	100.00	100.00	100.00	100.00	100.00		100.00		100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
1974–1975	105.88	97.25	104.30	141.53	97.94	99.47		103.37		101.57	33.09	108.09	107.21	144.22	106.80	97.41	101.67
1975–1976	115.18	97.61	106.46	134.94	115.42	99.31		103.61		107.25	41.07	113.80	100.64	144.93	111.62	97.08	102.28
1976–1977	113.44	101.16	98.40	122.78	112.49	78.86	100.00	95.71	100.00	103.62	80.37	113.44	118.71	104.71	122.65	101.13	108.80
1977–1978	121.17	104.99	96.98	123.37	111.25	83.98	120.27	100.57	101.80	102.84	83.75	119.17	116.11	112.56	127.60	104.83	112.10
1978–1979	141.97	106.97	101.10	132.21	104.72	90.76	125.96	105.87	95.67	122.32	84.22	121.81	123.35	114.56	133.90	108.17	123.48
1979–1980	133.63	109.28	101.06	134.37	93.04	84.39	118.36	102.75	92.16	119.56	87.01	121.12	128.59	117.94	137.13	112.69	120.03
1980–1981	112.74	107.32	105.15	130.53	107.09	80.15	113.41	102.50	92.72	127.99	90.11	121.76	132.67	125.40	145.42	125.55	126.03
1981–1982	120.70	117.79	103.94	189.10	106.24	81.08	104.54	104.74	100.73	101.53	38.84	111.05	137.45	124.02	119.70	129.23	136.35
1982–1983	135.73	126.63	96.86	182.33	102.83	82.40	106.76	102.01	104.57	109.10	38.83	105.66	139.80	115.49	126.25	130.45	138.38
1983–1984	135.30	99.14	100.03	161.93	79.76	78.46	93.61	95.91	105.27	103.81	27.35	92.57	132.69	111.26	115.58	123.84	138.66
1984–1985	136.14	106.91	98.18	168.93	81.03	85.92	105.14	97.47	106.15	112.59	27.44	93.50	145.30	109.87	117.17	129.13	141.28
1985–1986	138.52	109.77	118.94	142.36	78.67	84.96	97.70	93.34	99.90	115.87	23.73	95.59	133.26	100.01	119.42	128.03	138.25
1986–1987	142.38	103.05	101.70	162.28	80.99	84.67	109.95	93.58	101.31	118.44	23.54	102.30	139.24	107.70	127.24	132.01	137.39
1987–1988	112.40	99.63	90.80	163.01	95.67	86.39	112.69	89.95	103.33	107.73	20.00	94.23	137.34	95.08	129.63	130.08	135.27
1988–1989	120.99	101.83	94.57	174.63	94.59	85.93	118.57	97.80	101.40	116.14	19.12	106.38	138.92	102.67	133.31	135.10	143.31
1989–1990	117.05	107.50	95.71	175.38	86.97	89.16	99.11	103.78	98.51	128.01	21.80	110.23	138.83	102.79	143.55	142.44	149.56
1990–1991	75.58	111.30	96.86	190.80	88.08	93.78	122.56	107.26	91.64	124.06	24.58	74.95	131.24	102.33	162.25	132.94	152.16
1991–1992	80.60	118.76	99.53	206.30	79.36	99.86	142.24	107.45	97.45	126.39	25.02	79.48	141.94	110.24	159.92	139.92	150.61
1992–1993	84.45	119.62	94.76	171.80	78.37	98.14	80.50	97.63	99.39	125.63	21.97	76.52	100.51	102.37	147.32	135.29	148.80
1993–1994	75.04	125.26	85.00	140.85	88.82	92.99	56.06	81.25	94.01	115.62	20.48	101.86	90.01	56.98	136.61	100.04	140.50
1994–1995	77.91	132.71	83.95	138.80	82.31	92.26	59.42	92.04	92.13	119.42	22.73	115.39	102.67	55.78	144.72	101.09	158.13
1995–1996	87.48	133.28	79.52	147.69	74.22	87.12	61.79	96.34	90.77	123.88	21.67	116.07	115.00	59.84	154.85	111.29	169.79
1996–1997	87.84	119.84	69.90	274.48	70.08	55.55	75.66	89.99	96.49	113.65	39.58	93.72	108.13	54.98	140.59	93.12	166.10
1997–1998	112.76	120.29	80.91	263.47	82.66	59.91	71.22	101.26	96.34	114.56	43.59	94.78	109.36	61.00	144.44	115.19	143.28
1998–1999	110.86	116.99	80.61	265.88	79.75	63.85	70.77	89.60	101.20	110.77	34.54	101.05	102.28	57.49	135.38	118.58	142.29

Base year 1973–1974 = 100

NMMP = Non-metallic mineral product

Table 1.3 Sectoral comparison: Relative TFP of different industries

Year	Sector																
	Food product	Beverages	Cotton textile	Silk/synthetic textile	Jute hemp textile	Textile product	Wood product	Paper	Leather	Chemical	Rubber plastic	NMMP	Metal alloys	Metal product	Machine tools	Electrical machinery	Transport equipment
1973–1974	100.00	91.07	91.22	53.75	104.40	115.63		75.07		100.00	120.39	73.00	64.47	77.60	71.10	99.81	74.52
1974–1975	106.82	88.91	96.66	74.04	106.65	116.66		78.72		106.99	38.92	78.99	69.77	110.36	76.64	98.59	76.29
1975–1976	117.26	89.92	99.44	70.54	127.80	118.05		78.94		117.50	48.15	82.95	66.01	110.36	80.43	98.92	76.76
1976–1977	115.97	92.94	92.29	66.39	126.11	94.64	82.06	72.82	159.40	115.99	96.87	82.28	76.64	80.45	88.59	103.17	81.65
1977–1978	123.67	96.07	91.29	66.39	124.81	100.83	97.84	76.28	162.03	123.93	101.91	86.23	75.14	86.52	91.97	106.92	84.04
1978–1979	145.61	98.30	95.37	71.03	118.61	108.97	102.59	80.69	153.98	145.96	102.37	87.88	79.94	87.98	96.48	110.51	92.69
1979–1980	136.17	100.35	95.47	71.88	107.16	101.08	96.65	77.94	151.43	136.23	105.82	87.43	83.64	90.58	98.93	115.40	89.93
1980–1981	114.43	98.64	99.06	69.76	122.92	95.88	93.15	77.59	153.69	114.09	109.20	87.91	86.05	96.06	104.93	128.51	94.29
1981–1982	123.84	108.88	97.86	100.33	121.49	97.34	87.03	79.20	166.64	123.50	47.24	80.59	88.69	94.48	86.59	131.97	102.02
1982–1983	139.97	117.33	90.70	96.39	116.66	98.48	89.42	76.69	172.26	139.87	47.18	75.99	89.98	87.13	90.47	132.65	103.09
1983–1984	140.12	91.53	94.01	85.92	88.21	94.15	78.15	72.32	173.86	139.55	33.53	66.35	84.95	83.79	83.23	125.65	103.34
1984–1985	139.19	99.53	92.09	90.93	111.74	102.90	80.70	69.47	169.57	138.24	33.15	71.25	80.86	85.11	83.25	128.47	101.73
1985–1986	143.34	102.19	112.22	77.43	93.49	97.02	81.99	70.25	163.87	141.99	29.07	70.30	82.90	76.51	85.65	129.84	102.33
1986–1987	146.15	96.36	93.82	87.60	94.59	96.65	91.93	70.45	165.52	144.90	29.81	74.59	86.38	81.45	90.73	133.65	101.79
1987–1988	115.83	93.04	85.21	88.35	110.00	99.07	94.00	68.57	167.58	114.27	25.12	69.79	84.97	72.32	92.65	131.42	100.33
1988–1989	123.98	95.01	88.89	94.22	109.39	99.43	98.57	74.41	164.46	122.25	23.61	78.67	85.73	77.91	95.25	136.07	106.19
1989–1990	120.54	100.14	89.83	94.32	101.36	103.46	82.33	79.06	160.64	118.57	27.63	81.41	85.62	78.02	102.68	143.20	110.63
1990–1991	78.90	103.27	90.16	102.53	103.54	112.43	100.47	81.24	149.12	76.90	31.25	56.11	80.62	77.35	115.77	133.83	112.40
1991–1992	83.77	109.35	92.68	108.74	92.40	119.75	115.34	81.07	158.95	81.73	32.00	59.14	86.93	81.85	113.93	140.15	111.29
1992–1993	87.96	109.84	88.23	92.21	90.70	117.92	65.41	73.76	162.10	85.76	28.08	56.91	63.01	76.45	105.28	135.70	110.13
1993–1994	78.70	114.22	79.50	77.41	102.21	111.51	46.91	61.48	154.04	76.47	26.08	74.52	57.50	43.56	97.62	101.39	104.58
1994–1995	82.29	116.45	79.09	76.22	94.81	110.04	50.00	69.07	151.21	79.96	28.62	81.80	65.95	42.73	102.48	102.49	117.40
1995–1996	93.04	117.20	75.22	81.01	85.68	103.77	51.98	72.60	148.77	90.50	27.34	82.80	74.52	46.20	109.89	112.91	125.49
1996–1997	93.98	108.78	66.13	107.56	80.41	67.11	61.55	67.34	157.97	91.21	48.85	68.16	68.54	42.72	100.82	94.21	122.55

1997-1998	119.59	109.39	76.08	116.69	93.40	72.40	58.19	75.20	157.90	116.51	54.24	70.51	69.59	47.20	103.53	110.02	105.35
1998-1999	116.68	106.39	76.22	120.01	90.86	77.18	59.04	67.04	165.93	113.82	43.42	74.89	65.67	44.10	97.28	114.43	105.38
Mean	114.92	102.12	89.57	86.22	104.59	101.24	81.10	74.13	160.47	113.72	51.53	75.40	77.08	76.11	94.85	119.23	100.62
Std Dev	21.82	8.88	9.60	16.76	13.70	13.41	19.08	5.08	7.25	22.42	31.79	9.12	9.51	19.95	11.16	15.35	13.61
% Growth (compounded)																	
Full period	0.62	0.62	-0.72	3.27	-0.55	-1.60	-1.49	-0.45	0.18	0.52	-4.00	0.10	0.07	-2.24	1.26	0.55	1.40
1973-1979	5.28	1.63	0.76	4.96	0.44	-2.22	5.61	0.63	-1.70	5.29	-2.13	3.05	4.43	2.61	5.66	2.45	3.18
1980-1989	0.58	0.17	-1.08	3.41	-2.12	0.85	-1.36	0.21	0.49	0.43	-14.16	-0.85	-0.06	-2.28	-0.24	1.21	1.79
1990-1998	5.01	0.37	-2.08	1.99	-1.62	-4.59	-6.43	-2.37	1.34	5.02	4.20	3.67	-2.53	-6.78	-2.15	-1.94	-0.80

Base = sector 20 in 1973-1974

NMMP = Non-metallic mineral product

Table 1.4 Sectoral comparison of annual TFP Growth rates (Percent)

Sector																		
Year	Food product	Beverages	Cotton textile	Silk/syn- thetic textile	Jute hemp textile	Textile product	Wood product	Paper	Leather	Chemical	Rubber plastic	NMMP	Metal & alloys	Metal product	Machine tools	Electrical machinery	Transport equipment	
1974-1975	6.8	-2.4	6.0	37.7	2.2	0.9		4.9		7.0	-67.7	8.2	8.2	42.2	7.8	-1.2	2.4	
1975-1976	9.8	1.1	2.9	-4.7	19.8	1.2		0.3		9.8	23.7	5.0	-5.4	0.0	4.9	0.3	0.6	
1976-1977	-1.1	3.4	-7.2	-5.9	-1.3	-19.8		-7.8		-1.3	101.2	-0.8	16.1	-27.1	10.1	4.3	6.4	
1977-1978	6.6	3.4	-1.1	0.0	-1.0	6.5	19.2	4.8	1.6	6.8	5.2	4.8	-2.0	7.5	3.8	3.6	2.9	
1978-1979	17.7	2.3	4.5	7.0	-5.0	8.1	4.9	5.8	-5.0	17.8	0.5	1.9	6.4	1.7	4.9	3.4	10.3	
1979-1980	-6.5	2.1	0.1	1.2	-9.7	-7.2	-5.8	-3.4	-1.7	-6.7	3.4	-0.5	4.6	3.0	2.5	4.4	-3.0	
1980-1981	-16.0	-1.7	3.8	-2.9	14.7	-5.1	-3.6	-0.4	1.5	-16.3	3.2	0.5	2.9	6.0	6.1	11.4	4.8	
1981-1982	8.2	10.4	-1.2	43.8	-1.2	1.5	-6.6	2.1	8.4	8.2	-56.7	-8.3	3.1	-1.6	-17.5	2.7	8.2	
1982-1983	13.0	7.8	-7.3	-3.9	-4.0	1.2	2.7	-3.2	3.4	13.3	-0.1	-5.7	1.5	-7.8	4.5	0.5	1.0	
1983-1984	0.1	-22.0	3.6	-10.9	-24.4	-4.4	-12.6	-5.7	0.9	-0.2	-28.9	-12.7	-5.6	-3.8	-8.0	-5.3	0.2	
1984-1985	-0.7	8.7	-2.0	5.8	26.7	9.3	3.3	-3.9	-2.5	-0.9	-1.1	7.4	-4.8	1.6	0.0	2.2	-1.6	
1985-1986	3.0	2.7	21.9	-14.8	-16.3	-5.7	1.6	1.1	-3.4	2.7	-12.3	-1.3	2.5	-10.1	2.9	1.1	0.6	
1986-1987	2.0	-5.7	-16.4	13.1	1.2	-0.4	12.1	0.3	1.0	2.0	2.5	6.1	4.2	6.5	5.9	2.9	-0.5	
1987-1988	-20.7	-3.4	-9.2	0.9	16.3	2.5	2.3	-2.7	1.2	-21.1	-15.7	-6.4	-1.6	-11.2	2.1	-1.7	-1.4	
1988-1989	7.0	2.1	4.3	6.6	-0.6	0.4	4.9	8.5	-1.9	7.0	-6.0	12.7	0.9	7.7	2.8	3.5	5.8	
1989-1990	-2.8	5.4	1.1	0.1	-7.3	4.1	-16.5	6.2	-2.3	-3.0	17.0	3.5	-0.1	0.1	7.8	5.2	4.2	
1990-1991	-34.5	3.1	0.4	8.7	2.2	8.7	22.0	2.8	-7.2	-35.1	13.1	-31.1	-5.8	-0.9	12.7	-6.5	1.6	
1991-1992	6.2	5.9	2.8	6.1	-10.8	6.5	14.8	-0.2	6.6	6.3	2.4	5.4	7.8	5.8	-1.6	4.7	-1.0	
1992-1993	5.0	0.4	-4.8	-15.2	-1.8	-1.5	-43.3	-9.0	2.0	4.9	-12.3	-3.8	-27.5	-6.6	-7.6	-3.2	-1.0	

1993-1994	-10.5	4.0	-9.9	-16.1	12.7	-5.4	-28.3	-16.6	-5.0	-10.8	-7.1	30.9	-8.7	-43.0	-7.3	-25.3	-5.0
1994-1995	4.6	2.0	-0.5	-1.5	-7.2	-1.3	6.6	12.3	-1.8	4.6	9.7	9.8	14.7	-1.9	5.0	1.1	12.3
1995-1996	13.1	0.6	-4.9	6.3	-9.6	-5.7	4.0	5.1	-1.6	13.2	-4.5	1.2	13.0	8.1	7.2	10.2	6.9
1996-1997	1.0	-7.2	-12.1	32.8	-6.2	-35.3	18.4	-7.2	6.2	0.8	78.7	-17.7	-8.0	-7.5	-8.3	-16.6	-2.3
1997-1998	27.3	0.6	15.0	8.5	16.2	7.9	-5.5	11.7	0.0	27.7	11.0	3.4	1.5	10.5	2.7	16.8	-14.0
1998-1999	-2.4	-2.7	0.2	2.8	-2.7	6.6	1.5	-10.9	5.1	-2.3	-19.9	6.2	-5.6	-6.6	-6.0	4.0	0.0
Mean	1.4	0.8	-0.4	4.1	0.1	-1.0	-0.2	-0.2	0.2	1.3	1.5	0.7	0.5	-1.1	1.4	0.9	1.5
Std Dev	12.6	6.3	8.1	15.0	11.9	9.7	15.3	7.0	4.0	12.8	33.8	11.4	9.0	14.7	7.0	8.3	5.4

NMMP = Non-metallic mineral product

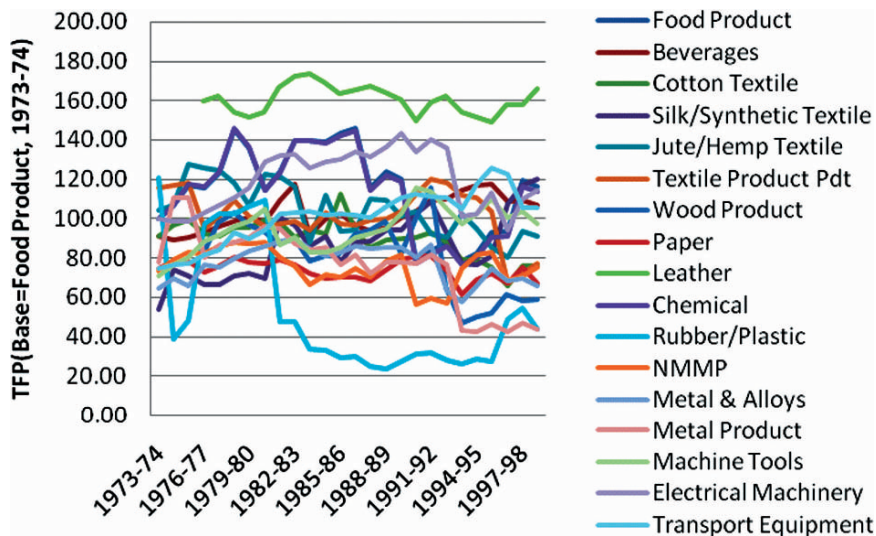


Fig. 1.4 Relative TFP Index for different Industries

wood product, paper industry, rubber/plastic industry, non-metallic mineral products (NNMP), metal and alloys and metal products appear to be relatively the low productive sectors. However, there is a change in the composition of sectors with high productivity in the 1990s.

The food products and chemical sectors shifted from being high productive sectors during the 1970s and the 1980s to being low productive sectors during the 1990s. When TFP growth rates are compared across the three decades, it is observed that with an exception of the textile product, leather and rubber/plastic industries, compounded growth rates were higher in the 1970s compared to the 1980s and the 1990s in all the sectors. TFP growth rates were negative for many sectors in the 1980s and 1990s. However, we can observe a rise in productivity growth in the low productive sectors in the 1990s, viz. food products, chemical, rubber/plastic products and non-metallic mineral products in the later part of the 1990s.

The trends of productivity in different industries (rising or falling) for the last three decades are shown in Table 1.5. It can be observed that, while in the 1970s TFP growth was on a rising trend in most of the industries, there was a falling trend in the 1980s and 1990s. In 1990s, only 7 out of 17 industries showed a rising trend of TFP.

1.5.4 Convergence of Productivity in Different Sectors

Finally, it may be natural to ask whether productivity ranks of the sectors (cross-sectional ranking) differs significantly across the years. In other words, we want to

Table 1.5 Trends of TFP in different industries at two digit level

ASI sector	Name	73–79	80–85	86–90	91–98
20	Food products	R	R	F	R
22	Beverages, tobacco	R	F	R	F
23	Cotton textile	NT	R	F	R
24	Silk, synthetic fibre	R	F	R	R
25	Jute, hemp textile	F	F	F	F
26	Textile product	F	F	R	F
27	Wood & wood pdt	F	F	R	F
28	Paper and paper product	F	F	NT	R
29	Leather & leather pdt	R	R	F	R
30	Chemical & chemical pdt	R	R	R	F
31	Rubber, plastic, petroleum and coal pdt	R	F	NT	NT
32	Non metallic mineral pdt	R	F	F	R
33	Basic metals and alloys	R	R	R	F
34	Metal Pds and parts	F	F	F	F
35	Machinery and machine tools	R	R	R	F
36	Electrical machinery	R	R	R	F
37	Transport equipments and parts	R	R	R	R
	Total number of R's	11	8	9	7

Notes: *R* Rising Trend; *F* Falling Trend; *NT* No Trend

examine whether the sectors having lower productivity level are remaining less productive throughout the years, or whether there has been any change in the cross-sectional ranking. To address this issue, I calculated the Kendall's index of rank concordance along with the co-efficient of variation of TFP. The Multi-Annual Kendall's index of rank concordance takes into account the ranks for intervening years between t and 0 (initial year) by computing the index for a moving sum of years. The value of rank concordance index lies between 0 and 1. The denominator of the index is the maximum sum of ranks, which would be obtained if there were no change in ranking over time. The closer the index value is to zero, the greater the extent of mobility within the distribution. The null hypothesis that there is perfect agreement of ranks across the years was tested and rejected for all the years, indicating that the ranks are changing over the years. Also, the variability of TFP indices has increased over the years as observed from the co-efficient of variation. The results are presented in Table 1.6.

1.6 Pro-Cyclicality of Measured TFP

The growth accounting technique should yield an estimate of Total Factor Productivity Growth that is exogenous to the rate of growth of output. The procyclical behaviour can occur due to the failure of any of the assumptions of constant returns

Table 1.6 Measures of convergence of TFP across sectors

Year	Co-efficient of variation	Multi-annual Kendall	P-value
1975–1976	0.243	–	–
1976–1977	0.241	–	–
1977–1978	0.231	0.3460	0.0153
1978–1979	0.213	0.5009	0.0002
1979–1980	0.197	0.4516	0.0000
1980–1981	0.195	0.3564	0.0001
1981–1982	0.264	0.2433	0.0009
1982–1983	0.285	0.1943	0.0030
1983–1984	0.332	0.2020	0.0011
1984–1985	0.319	0.1884	0.0012
1985–1986	0.327	0.1695	0.0021
1986–1987	0.316	0.1627	0.0020
1987–1988	0.321	0.1579	0.0019
1988–1989	0.305	0.1513	0.0021
1989–1990	0.294	0.1444	0.0025
1990–1991	0.289	0.1293	0.0060
1991–1992	0.295	0.1315	0.0040
1992–1993	0.342	0.1252	0.0053
1993–1994	0.374	0.1378	0.0014
1994–1995	0.352	0.1378	0.0010
1995–1996	0.343	0.358	0.0010
1996–1997	0.341	0.1387	0.0006
1997–1998	0.317	0.1377	0.0005
1998–1999	0.349	0.1375	0.0004

to scale, perfect competition and/or measured errors caused by the failure to capture the variable factor utilization over the business cycle. Analyzing data from 21 manufacturing industries of the US economy, Hall (1990) and Basu and Fernald (1995) showed that the procyclicality of TFP is due to the procyclical measurement error caused by the failure to capture the variable factor utilization over the business cycle in computation of the Solow residual. Srivastava (2000) explored the correlation between TFPG and output growth based on productivity studies on the Indian economy and showed that the co-efficient of correlation between output growth and TFPG for Public Limited Companies was 0.72.

In the typical TFP calculation, labor/capital inputs are measured as higher than ‘real’ in recessions, and lower than ‘real’ in expansions. The standard computation of the Solow residual fails to filter out the cyclical variation in input utilization rate, assigning it to fluctuations in technology. In this paper, I have taken into account the variable input utilization rates over the business cycle to derive a measure of Total Factor Productivity, which effectively provides a more accurate measure of TFP. In this study, I have observed very low correlation (0.156) between TFPG and output growth for the Public Limited Companies. In Fig. 1.5, TFP growth and output growth are plotted to see their pro-cyclical behaviour.

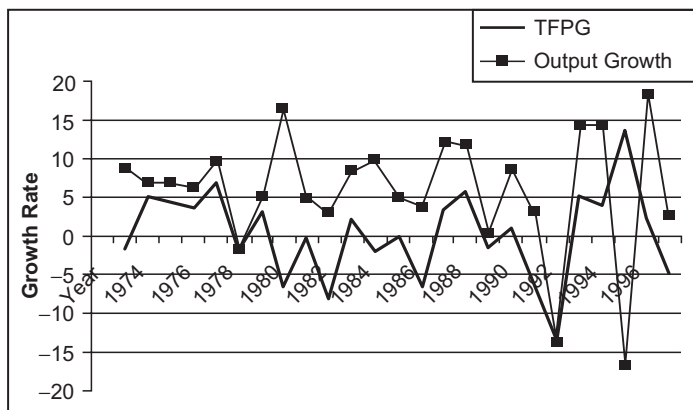


Fig. 1.5 TFPG and output growth

1.7 Concluding Remarks

This article investigates the productivity of the Indian manufacturing over the last three decades based on firm-level panel data for the period 1973–1974 to 1998–1999. Using a partial equilibrium model which allows for factor hoarding, new series of capital stocks and effective labour has been constructed and used for computation of TFP. Further, new techniques have been used to compute the base year capital stock. The measured TFPG is less procyclical and the correlation between TFPG and output growth is 0.156.

Analysing the data using the above model reveals that there was a steady rise in productivity in the Indian manufacturing as a whole in the 1970s and early 1980s, with maxima in 1980–1981, after which it declined up to 1987–1988, followed by a recovery in 1988–1989. It again showed a decline after the reforms in the early 1990s, with minima in 1993–1994, after which there was a steady rise in productivity since 1994–1995.

The multilateral TFP index was used to compute the growth and relative levels of productivity of the different sectors, and examined to determine whether there are productivity convergence among sectors. The null hypothesis of perfect agreement of ranks across the years is rejected for all the years indicating that the ranks are changing over the years. Also, an increase in variability of TFP indices across the sectors over the years was observed from the co-efficient of variation.

TFP is very important for sustainability of growth. Thus, its correct assessment is essential for the formulation of economic policies. In this study, TFP was adjusted for variable factor utilization. To improve upon it, further research can be aimed at eliminating biases resulting from the presence of imperfect competition and scale economies, for which consistent and reliable estimates of the markup and the returns to scale parameter are required.

Appendix 1

Computation of Capital Stock

Un-adjusted Capital Stock Series

In the data set, Gross Fixed Assets (GFA) were available for each year for different kind of assets, namely plant and machinery, building, land, furniture and fixtures, capital work-in progress, etc. Capital was classified into three categories, namely plant and machinery, building and other capital. This other capital consists of furniture, fixtures, land and miscellaneous other capitals. Perpetual Inventory Method (PIM) was used for generating the capital stock. The PIM method requires the estimates of capital stock for a benchmark year and investment in the subsequent years. Investment in time t in capital i (I_t^i) was defined as the difference between Gross Fixed Assets across two years:

$$I_t^i = GFA_t^i - GFA_{t-1}^i \quad i = 1, 3 \quad (1.19)$$

Real investment and capital stock figures were obtained by deflating nominal investments and capital stocks by price of investment in different types of capital stocks. The price of capital (P^i) for total capital formation, capital formation in plant and machinery and construction were obtained from the National Account Statistics, in which separate series are available for these three categories at the current year and the base year 1980–1981 prices. The deflator for other capital was obtained as a weighted average of the price of capital in plant and machinery, and constructed using weights calculated in the study from RBI 1990 bulletin, which shows that plant and machinery, and buildings account for approximately 71.5% and 13.8% of GFA respectively, and other capital account for the remaining 14.7%. The capital stock of type i at time t is generated using PIM as:

$$K_{t+1}^i = K_t^i (1 - \delta^i) + I_{t+1}^i \quad i = 1, 3 \quad (1.20)$$

where K_t^i is the capital stock in the t th year, I_t^i is investment in the t th year and δ^i is the depreciation rate of capital of type i .

This method requires the computation of base year capital stock K_0^i . In this study, it is assumed that the base year capital stock is the replacement cost.

New Capital Stock Series, Capital Utilization Rate and Labour Effort

The steps involved in the computation of the capital utilization rates are as follows. First, from the standard capital stock series K_t , δ_t^i is computed using (1.11), afterwhich the depreciation rates are used to compute alternative capital stock series iteratively as:

$$\tilde{K}_{t+1}^i = \tilde{K}_t^i(1 - \delta_t^i) + I_{t+1}^i \quad i = 1, 3 \quad (1.21)$$

Capital utilization series are computed using (1.14) while labour effort series are computed using (1.18). The data reveals that Y_t/N_t and Y_t/K_t are not stationary but trend stationary. Hence, the expected value is dependent on time, and time trends of Y_t/N_t and Y_t/K_t have been used as the denominator in (1.11), (1.14) and (1.18).

Calculation of the Base Year Capital Stock

The computation of the base year capital stock K_0^i is difficult and needs some assumptions. In some literature related to productivity in India (Srivastava 1996, 2001), the following assumptions were made:

1. The price of capital has changed at a constant rate from the date of incorporation up to the initial year the data is available.
2. Investments for all firms have increased at constant rate from the date of incorporation up to the initial year.

The above assumptions are restrictive and in general not true. In this study, for computation of the base year capital stock, I have made much simpler assumptions,¹ that the capital-output ratio for two consecutive years are the same, i.e.

$$\frac{K_t}{Y_t} = \frac{K_{t+1}}{Y_{t+1}} \quad \text{for all } t \quad (1.22)$$

Where Y_t represents the t th year output and K_t represents the t th year capital stock. Equation (1.22) can be written as:

$$\frac{K_{t+1}}{K_t} = \frac{Y_{t+1}}{Y_t} \quad \text{for all } t \quad (1.23)$$

It should be noted that, Y_t 's are known, and hence the RHS of (1.23) is known. The capital in the current year K_t has two components, namely the depreciated base year capital and the capital based on the investment taken place after the base year (the first year the data is available). In mathematical terms;

$$K_t = K_f(1 - \delta)^{t-f} + K_t(0) \quad \text{for all } t \quad (1.24)$$

where, δ is the depreciation rate and $K_t(0)$ is the capital stock at time t assuming base year capital stock as zero. It should be noted that, $K_t(0)$ is known because investment figures are known. Substituting (1.24) in (1.23) and solving for K_f we get,

¹ Assumption is made only for the computation of the base year capital stocks and not used for the computation of the TFP index.

$$K_f = \frac{(Y_{t+1}/Y_t)K_t(0) - K_{t+1}(0)}{(1-\delta - (Y_{t+1}/Y_t))(1-\delta)^{t-f}} \quad \text{for all } t \quad (1.25)$$

By equating capital-output ratios for every two consecutive years, many estimates of the base year capital stocks were obtained, and the mode value of these estimates was taken as the final estimation of the base year capital stock. The base year capital stocks of different categories were obtained by assuming capital stocks of plant and machinery, construction and others in the proportion of 71.5%, 13.8%, and 14.7% respectively, according to a 1990 study published in RBI bulletin.

TFP Indices

A total factor productivity (TFP) index measures change in total output relative to the change in the usage of all inputs. The TFP index for two time periods s and t is defined as,

$$\ln TFP_{st} = \ln OutputIndex_{st} - \ln InputIndex_{st} \quad \text{for all } s, t \quad (1.26)$$

Suppose the firm produces N outputs $i = 1, \dots, N$ using M inputs $j = 1, \dots, M$. Let Y_{it} , Y_{is} and X_{jt} , X_{js} represent observed quantities of i th output and j th input in time t and s respectively while ω_{it} , ω_{is} and v_{jt} , v_{js} represent value shares for the i th output and j th input in time t and s respectively. The Tornqvist TFP index is defined in its logarithmic form as:

$$\begin{aligned} \ln TFP_{st} = & \sum_i^N \frac{(\omega_{is} + \omega_{it})}{2} (\ln Y_{it} - \ln Y_{is}) \\ & - \sum_j^M \frac{(v_{js} + v_{jt})}{2} (\ln X_{jt} - \ln X_{js}) \quad \text{for all } s, t \end{aligned} \quad (1.27)$$

To compute Tornqvist productivity index, single output and five inputs, namely worker, manager, capital, material and fuel were used.

Multilateral Tornqvist Index

Multilateral Tornqvist index proposed by Caves et al. (1982) was computed as follows:

$$\begin{aligned} \ln TFP_{st} = & 1/2 [(\omega_t + \bar{\omega})(\ln Y_t - \ln \bar{Y}) - (\omega_s + \bar{\omega})(\ln Y_s - \ln \bar{Y})] \\ & - 1/2 [\sum_j (v_{jt} + \bar{v}_j)(\ln X_{jt} - \ln \bar{X}_j) \\ & - \sum_j (v_{js} + \bar{v}_j)(\ln X_{js} - \ln \bar{X}_j)] \quad \text{for all } s, t \end{aligned} \quad (1.28)$$

where TFP_{st} is the transitive TFP index, $\ln Y_t$, $\ln \bar{Y}$, $\ln X_{jt}$, $\ln \bar{X}_j$ represent log output, arithmetic mean of log output, log of j th input and arithmetic mean of log of j th input in time t respectively, and ω_t , $\bar{\omega}$ and v_{jt} , $\bar{v}_j$ represent output shares, arithmetic mean of output shares, input shares of j th input and arithmetic mean of input shares of j th input in time t respectively.

Multi-Annual Kendall's Index

The multi-annual Kendall's index of rank concordance is calculated as follows:

$$KI_T = \frac{\text{Variance} \left\{ \sum_{t=0}^T \text{Rank}(TFP_{st}) \right\}}{\text{Variance}(T+1) \text{Rank}(TFP_{s0})} \quad (1.29)$$

where KI_T is the multi-annual Kendall's index of rank concordance, $\text{Rank}(TFP_{st})$ is the actual rank of TFP in sector s in year t , $\text{Rank}(TFP_{s0})$ is the actual rank of TFP in sector s in the initial year 0 and $(T+1)$ is the number of years for which data are used in constructing the index..

Appendix 2

Table 1.7 Sectoral classification

NIC code	Name of sector in NIC	Name of sector in RBI data	RBI industry code
20	Manufacture of food Products	Sugar	331
		Grains and pulses	310
		Other food products	332
		Edible oils	320
22	Manufacture of beverages, tobacco and tobacco products	Breweries and distilleries	370
		Cigarettes	341
		Other tobacco	342
23	Manufacture of cotton textiles	Cotton textiles-spinning	351
		Cotton textiles-composite	353
		Cotton textiles-others	354
		Cotton textiles weaving	352
24	Manufacture of wool, silk, and synthetic fiber textiles	Silk and Rayon textiles-spinning	356
		Woolen textiles	359
		Silk and Rayon textiles-weaving	357
		Silk and Rayon textiles-composite	358
25	Manufacture of jute, hemp and mesta textiles	Jute textiles	355

(continued)

Table 1.7 (continued)

NIC code	Name of sector in NIC	Name of sector in RBI data	RBI industry code
26	Manufacture of textile products	Ginning, pressing and other textiles products	360
		Miscellaneous Products	390
27	Manufacture of wood and wood products	Wood products, furniture and fixtures	553
28	Manufacture of paper and paper products, printing and publishing	Paper	551
		Printing and publishing and other allied activities	573
		Products of Pulp, paper and board	552
		Printing	571
		Publishing	572
29	Manufacture of leather and leather products	Leather and leather products	380
30	Manufacture of chemical and chemical Products	Medicines and pharmaceutical	466
		Other chemical products	468
		Other basic industrial chemicals	465
		Man-made fibers	463
		Industrial and medical gases	469
		Paints, varnishes and other allied products	467
		Chemical fertilizers	461
		Dyes and dye stuffs	462
		Plastic raw materials	464
		Matches	470
31	Manufacture of rubber, plastic, Petroleum and coal products	Plastic products	580
		Other rubber products	542
		Tires and tubes	541
		Mineral oils	510
32	Manufacture of non- metallic mineral Products	Cement	521
		Structural clay Products	531
		Other glass products	562
		Glass containers	561
		Asbestos and asbestos products	522
		Pottery, china and earthenware	532
		Diversified Products	589
		Miscellaneous Products	590
		Steel tubes and pipes	452
		Steel wire ropes	453
		Aluminium ware	456
33	Basic metals and alloys	Other non-ferrous metals	430
		Aluminium	420
		Iron and Steel	410
		Other ferrous/non-ferrous metal products	457
		Foundries and engineering workshops	455
		Steel forgings	454

(continued)

Table 1.7 (continued)

NIC code	Name of sector in NIC	Name of sector in RBI data	RBI industry code
34	Manufacture of metal products and parts (except machinery and transport equipment)	Miscellaneous machinery	451
		Machine tools	449
		Textiles machinery and accessories	450
35	Manufacture of machinery, machine tools and parts	Miscellaneous Products	490
		Other electrical machinery, apparatus, appliances, etc	448
		Cables	445
		Electric lamps	447
36	Manufacture of electrical machinery, apparatus, appliances	Dry cells	446
		Autos-parts/repairs	442
		Autos-vehicles	441
		Other transport equipment	444
37	Manufacture of Transport equipment and parts	Railway equipments	443

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Chapter 2

Concentration, Profitability and (In)Efficiency in Large Scale Firms

H. Dudu and Y. Kılıçaslan

2.1 Introduction

The relationship between efficiency and market structure has been under investigation in the literature for a long time. According to Hicks (1935), firms with higher market power can survive in the economy even if they have higher costs since they can charge prices above the marginal cost. Although the relationship between firm performance measured by profits and market structure is obvious (Peltzman 1977), the direction of causality remains ambiguous (Clarke et al. 1984). There are different explanations of this relationship. One is to start with market power and relate the higher firm efficiency to the ability of firms with higher market power to charge prices above the cost margin. The second one, originally developed by Demsetz (1973), is based on the efficient structure of production and relates higher market power to the higher profits brought about by higher efficiencies. Although these two approaches try to explain the same relationship from the firm side, the welfare implications would be completely different. The reason for this is that in the first approach, that is, the market share hypothesis, firm performance (efficiency) is measured by the profitability of a firm and the relationship with market structure examined. According to this hypothesis, market power and efficiency are either negatively related, or not related. In the second approach, firm performance is measured by the efficiency of production. According to efficiency hypothesis, market power and efficiency are positively related. Feeny and Rogers (1999), Choi and Weiss (2005), Oustapassidis et al. (2000) and Bhattacharya and Bloch (1997) test both hypotheses for different countries and sectors and report controversial results. Thus, there is no clear evidence supporting any of the two hypotheses.

Large enterprises have a special place in economic modelling since they may be both triggering and detrimental in the growth process. From a Schumpeterian perspective, a large firm has a higher tendency to make product and process innovations which increases

H. Dudu

Department of Economics, Middle East Technical University, Ankara, Turkey

Y. Kılıçaslan

Department of Economics, Anadolu University, Eskişehir, Turkey

productive efficiency, and hence, is one of the primary sources of growth. On the other hand, a higher market power is related to loss of efficiency by charging prices above the marginal cost, and by producing output less than the optimal level (Hicks 1935).

Turkey is one of the most industrialized economies in its region, with a strong manufacturing industry. The share of manufacturing industry in GDP has been historically increasing since the establishment of the country. However, the efficiency structure of Turkish manufacturing firms has not been subjected to any analysis in a general framework. The most extensive study on the efficiency of Turkish manufacturing sector is by Taymaz and Saatçı (1997), where the efficiency structure of medium and small sized Turkish manufacturing firms in cement, textile and motor vehicles industries are analyzed. They use firm specific variables for technological change in production, ownership of firm and inter-firm relations as efficiency explanatory variables. Taymaz (2005) extends the same analysis to the years 1987–1997. However, Taymaz and Saatçı (1997) and Taymaz (2005) did not relate the inefficiency of firms to market structure at all. Another study that focuses on firm level efficiency in the manufacturing industry is Önder et al. (2003) in which the efficiency structure of the Turkish manufacturing firms are analyzed at a regional level. However, Önder et al. (2003) does not relate technical efficiency to any market structure factors, but give a detailed picture of the relationship between efficiency and regional factors as well as ownership structure. Çakmak and Zaim (1992) and Saygılı and Taymaz (2001) measure the change in efficiency of Turkish cement firms under the privatization practices. The former uses a non-parametric method, while the latter follows a parametric method to estimate the efficiency. However, both methods exclude market structure from the analysis.

All the studies on the efficiency of Turkish manufacturing industry are based on either small and medium firms, or few industries of manufacturing. This notwithstanding, 60% of the manufacturing output of Turkey is produced by the 500 largest manufacturing firms. This paper, therefore, aims at investigating the relationship between concentration, profitability and efficiency in large scale enterprises in the manufacturing industry of Turkey. In this paper, Stochastic Frontier Analysis (SFA) is used to estimate the firm level efficiencies and its relationship with market structure and some other firm specific variables by making use of a panel data on the 500 largest industrialist firms of Turkey from 1993 to 2003.

The paper is organized as follows: The next section gives a brief survey of Stochastic Frontier Analysis and presents the specification of the Stochastic Frontier Analysis used as the method of estimation in the paper. The data and variables used in the econometric analysis are introduced in the Section 2.3. Section 2.4 presents the estimation results and discusses their interpretations. Section 2.5 of the paper summarizes the conclusion of the study.

2.2 Theoretical Background and the Model

Attempts to define the sources of efficiency in economic activities are dated back to Smith (1776) who tried to explain the relationship between land tenure and efficiency of crop production. Although a detailed analysis of the efficiency structure of

firms has been ignored by mainstream economists, activity analysis developed by Koopmans (1951) and Debreu (1951) has prepared the scene for efficiency measurement analysis. Farrell (1957) is assumed to be the first systematic contribution in the literature which has developed a systematic approach to measure the firm level efficiency. Analytical tools supplied by Koopmans (1951) and Debreu (1951) were in the core of the analysis of Farrell (1957), although he did not refer to any of these leading authors.

Farrell's (1957) approach was calculating an efficient frontier that envelopes all observations by using linear programming methods. Once an efficient frontier is calculated, the efficiencies of individual firms are measured by their distance to this frontier. Although the idea is simple, the contribution broke down a new ground for deployment of quantitative methods to elaborate the efficiency of individual firms. Farrell's (1957) contribution has been extended by many authors, since late in the 1970s. These include, Førsund and Hjalmarson (1974), Fare (1975), Fare and Grosskopf (1983a, b), Fare, et al. (1983). to mention a few. Kumbhakar and Lovell (2000) and Murillo-Zamorano (2004) give a detailed survey of the literature about theoretical contributions.

Applied work based on these theoretical contributions has followed two different paths. Data Envelopment Analysis (DEA) which is based on Charnes et al. (1978), has deployed linear programming models while Stochastic Frontier Analysis (SFA) which is based on Afriat (1972), has deployed econometric methods. Both approaches used the deterministic model developed in Aigner and Chu (1968). A recent survey and detailed description of DEA is given in Cooper et al. (2004), while a comprehensive review of SFA is given in Kumbhakar and Lovell (2000).

The stochastic frontier approach defines efficiency as deviation from an efficient frontier which is estimated by various econometric methods. The deviation is modeled by a compound error term. The compound error term is the sum of a normally distributed noise term, and an asymmetrically distributed "inefficiency" component, which is always negative. The most general form of the model can be written as

$$Y = F(X; \beta) \exp(v - u) \quad (2.1)$$

where,

$$v \sim N(0, \sigma_v^2)$$

$$u \sim \left| N(0, \sigma_u^2) \right|$$

The random component of composite error term v , and the inefficiency component of the error term u , are distributed identically and independently from each other and regressors. Y is a one by $i \times t$ vector consisting of output level. $F(\cdot)$ is the imposed functional form of the frontier and it takes X which is a $k + 1$ by $i \times t$ matrix consisting of a column of ones and k input variables. β is a one by $k + 1$ vector of parameters. u and v are one by $i \times t$ vectors of inefficiency and random components respectively.

This model can be estimated under both time invariant and time-varying inefficiency by using maximum likelihood estimation methods. Details of the former can be found in Kumbhakar and Lovell (2000) while Batesse and Coelli (1992) describe the latter.

The model in (2.1) is non-linear in this form. Hence, logarithms of output and input variables are used to make a log-log transformation and a functional form appropriate for this transformation is selected. Generally, the Cobb–Douglas or transcendental logarithmic (translog) production functions are assumed in applied work.

Batesse and Coelli (1995) further modify the model in (2.1) to incorporate the firm specific effect variables that explain the inefficiency of firms.¹ They specify the efficiency component of compound error term as a linear function of the factors that affect production process but are not arguments of production frontier. Accordingly, the following model is estimated in one-step by maximum likelihood methods

$$Y = F(X;\beta) \exp(v-u) \quad (2.2)$$

where

$$v \sim N(0, \sigma_v^2)$$

$$u \sim \left| N(G(Z;\delta), \sigma_u^2) \right|$$

and Z is a $l + 1$ by $i \times t$ matrix which consists of a column of ones and l exogenous variables, while δ is a one by $l + 1$ vector of parameters. Here, distributional assumption about w guarantees that $u_{it} \geq 0$ since it assigns a truncated normal distribution to u by truncating w at the point $Z\delta$. Equation (2.2) is also non-linear in this form. Same transformations are also applied to (2.2). $G(\cdot)$ is assumed to be a linear function of Z with coefficients δ in applied work.

In this paper we use a common specification of (2.2) by assuming a translog production and efficiency effects functions.² Our model can be written as

$$\begin{aligned} \ln Y_{it} = & \beta_0 + \sum_{k=1}^K \beta_k \ln x_{kit} + \sum_{k=1}^K \eta_k (\ln x_{kit})^2 \\ & + \frac{1}{2} \sum_{r \neq s} \sum_{r=1}^K \theta_r \ln x_{rit} \ln x_{sit} - u_{it} + w_{it} \end{aligned} \quad (2.3)$$

Where

$$u_{it} = \left(\delta_0 + \sum_{l=1}^L \delta_l z_{lit} + \sum_{s=1}^K \sum_{p=1}^L \alpha_l z_{pit} x_{sit} \right)$$

¹This approach is also known as technical efficiency effects model.

²This model is introduced by Batesse and Broca (1997).

The frontier part of the model in (2.3) consists of inputs, their squares and cross multiplications. This specification allows interaction between inputs and thus it models production in a quite elastic way. The inefficiency effects part consists of inefficiency effect variables and their multiplications with inputs allowing for interaction between these two. This model is quite useful in investigating the reasons of inefficiency and in explaining the relationship between firm efficiency and exogenous factors. Besides, it allows one to see the relationship between input utilization and efficiency effects. Thus, it is used very frequently in the literature. Among others, Fitzpatrick and McQuinn (2005), Kern and Süßmuth (2005), Berg (2005) and Lin (2005) can be given as recent examples.

2.3 Data

The data used in this analysis is obtained from the 500 largest industrial enterprises of Turkey prepared by Istanbul Chamber of Industry (ICI). The ICI announces the top 500 manufacturing firms of Turkey every year, since 1993. The data set consists of output, revenue, profits, employment, export figures, ownership structure, and the location of the 500 largest firms. The ranking is done according to sales from production of the firms. This criterion is related to both efficiency of production and market power of the individual firms.

All variables in the ICI-500 data set are reported in nominal values. The nominal values are converted into real values by using industry-specific deflators separately for public and private firms. The export figures are not transformed into real values, since they have been reported in US Dollars.

The dependent variable used in the analysis is the real gross value-added. The variables that are incorporated in the production function are labour, capital, their square and cross multiplications as well as time trend, its square and its multiplication with input levels. Labour is measured by the number of employees for each firm. However, no economically sound capital data is reported in the ICI database. “Net assets” which is obtained by discounting accumulated depreciation from total assets of the firm is used as a proxy for capital. The time-trend is incorporated to catch the effect of technical change on production over time.

A well-known trick to obtain the elasticities of labour and capital directly from the translog production function is using mean deviation form of input variables in estimations. Thus, the estimated coefficients of labour and capital are corresponding elasticities of output. The coefficients of their cross terms shows the marginal effect of inputs over each other. A positive coefficient implies that employing an additional unit of one of the inputs increases the effect of the other input on output level. On the other hand, the coefficients of the squared terms show the marginal effect of a change in the level of relevant input on the output. A positive coefficient for the squared terms will however show that the effect of a change in the level of input on the output increases as the level of output increases. The coefficients of time trend and its square show the direction of technical change and its “acceleration”

in the sense that the latter captures the marginal effect of technical change on production level. A positive time trend coefficient shows a technical change that increases the level of output, *ceteris paribus*. A positive coefficient for the square of the time trend depicts an increasing positive (or negative if the coefficient of time trend is negative) effect of the relevant input on the output.

The efficiency effect variables used in the analysis are size, export share, profitability, ownership, and market share of a firm together with sectoral concentration and time dummies. The size of each firm is measured by the logarithm of number of employees. Export share is the ratio of exports in domestic currency to the output. Exports, which are reported in US Dollars in the original data set, are converted into domestic currency by using a weighted average of effective exchange rates of Central Bank of Turkey. Profitability is the ratio of accounting profits (or losses if negative) to the output. There are two dummy variables for ownership structure of the firms, one for public firms and the other for foreign firms. These dummies take the value one if the firm is in the appropriate ownership group. Sectoral concentration is measured by the Herfindahl–Hirschman Index.³ This index is not calculated from ICI-500 database but is taken directly from State Institute of Statistics (2002). The market share is used as a proxy for market power. It is calculated as the ratio of output of each firm to the total output of corresponding ISIC-4 level industries. Industry level output is obtained from State Institute of Statistics.⁴ We also incorporate the multiplication of sectoral concentration and market share to account for the effect of interaction of these two factors on efficiency of firms. Time dummies take the value of one if the observation is on the relevant year. A positive coefficient of the efficiency effect variables means that the relevant factor decreases the efficiency.

We have also incorporated cross multiplication of inputs and efficiency effect variables. A positive coefficient for these cross terms will imply a positive relationship between the relevant input and efficiency effect variable. That is, an increase in the input increases the effect of efficiency effect variable on efficiency. Since data for 2001–2003 period is not available from SIS (2002), we have used linearly interpolated series of industry level outputs from the data for 1993–2000 period.

Table 2.1 shows the mean values of the variables used in the estimation. The firms in labour-intensive industries are characterized by lower output and capital as well as lower concentration, larger size and exports and lower average market share. Firms in resource-intensive industries, on the other hand, have a higher output, smaller size, very low exports, higher number of firms, more public and private firms and a significantly less competitive market structure. Firms in resource-intensive industries employ a higher number of employees than the average. The most important properties of the firms in scale-intensive industries are lower average employment, high profitability, and high number of private and foreign firms. The firms in

³Herfindahl–Hirschman Index is calculated by squaring the market share of each firm competing in the ISIC-4 sector and then summing the resulting numbers.

⁴Since data for 2001–2003 period is not available from SIS (2002), we have used linearly interpolated series of industry level outputs from the data for 1993–2000 period.

Table 2.1 Mean values of variables used in estimation

Period	Variable	Unit	RI	LI	SI	SB&SS	ALL
1993– 1996	Output	TRY ^a	702,975	1,425,399	1,332,137	1,248,893	1,197,656
	Capital	TRY	685,162	1,241,866	1,240,494	1,083,526	1,080,891
	Labour	Person	1015	1159	924	928	1,033
	Size		6.6	6.15	6.25	6.46	6.33
	Export share	Percent	34.66	16.16	21	20.72	22.61
	Profitability	Percent	6.6	6.78	8.96	1.23	6.52
	Public firms	#	23	70	67	13	173
	Private firms	#	415	516	326	162	1,419
	Foreign firms	#	15	72	63	77	227
	Concentration		0.06	0.07	0.14	0.12	0.09
	Market share	Percent	10.45	42.11	28.36	24.47	28.33
	Output	TRY	890,015	1,395,782	1,543,871	1,967,224	1,388,115
1997– 2000	Capital	TRY	1,031,794	1,429,031	1,496,808	1,795,323	1,399,629
	Labour	Person	1,189	1,127	909	1,014	1,069
	Size		6.8	6.19	6.35	6.56	6.43
	Export share	Percent	42.18	18.18	26.73	24.51	27
	Profitability	Percent	1.69	4.76	6.22	6.25	4.61
	Public firms	#	10	52	47	8	117
	Private firms	#	417	553	371	146	1,487
	Foreign firms	#	16	76	84	83	259
	Concentration		0.03	0.07	0.11	0.12	0.08
	Market share	Percent	10.34	44.36	30.58	27.19	30.37
	Output	TRY	880,566	1,216,047	1,647,751	2,286,385	1,385,400
	Capital	TRY	960,381	1,221,009	1,497,505	2,377,839	1,377,900
2001– 2003	Labour	Person	1,127	1,010	875	1,038	1,005
	Size		6.75	6.12	6.21	6.52	6.35
	Export share	Percent	51.65	22.03	35.05	35.76	34.66
	Profitability	Percent	1.6	4.39	3.53	6.32	3.7
	Public firms	Number	4	37	24	5	70
	Private firms	Number	316	370	287	99	1,072
	Foreign firms	Number	21	78	69	68	236
	Concentration		0.04	0.06	0.1	0.12	0.08
	Market share	Percent	15.37	60.52	39.77	34.76	40.43

Source: Authors' calculations from ICI (2002, 2003 and 2004). *RI* resource-intensive industry; *LI* labour-intensive industry; *SI* scale-intensive industry; *SS* specialized-supplier industries; *SB* science-based industries

^aTRY is the New Turkish Liras

scale-intensive firms are similar to firms in the resource-intensive industries, but the latter operate in a more competitive market environment. Firms in science-based and specialised-supplier industries are significantly distinguished by a higher number of foreign firms and quite impressive development: doubling output, 11% increase in employment, and 10% increase in export share. However, the market structure for these industries has become significantly less competitive since 1993. Table 2.1

show that the worst performing group has been the firms operating in resource-intensive industries. There is a significant 15% and 13% decline in output and employment, respectively. Besides, the profit rates have also fallen. However, the share of exports in output has increased by 5%. Number of scale-intensive firms in the top 500 has declined nearly by 30%. These figures suggest that firms in the resource-intensive industries have significantly been affected by the 2001 economic crisis. Although there has been a slight decline in the aforementioned figures between 1993 and 1998, the decline after the 2001 economic crisis is drastic.

In spite of the fact that the firms in labour-intensive industries do not seem to be affected from the crisis as seriously as the firms in the resource-intensive industries, they have experienced a significant decline in their output, employment, capital along with an increase in exports. The most likely reason for the labour-intensive firms not to be affected by the crisis is the fact that they could take the advantage of undervalued local currency better than the firms in the resource-intensive industries.

The firms in the scale-intensive industries have gone through a transformation during the era under investigation. They increased their output and capital along a decline in employment, and became less profitable but more export-oriented. Although the sectoral concentration has fallen, average market share of the firms has increased.

The main conclusion of the descriptive analysis can be summarized in two main points: Firstly, it is possible to see the tremendous effects of the 2001 crisis from the descriptive statistics. The firms in resource-intensive industry, which employ more people on the average, are the ones that are most seriously affected by the crisis. Secondly the market structure for the sectors in which there has been a noteworthy privatization effort, became more monopolistic, rather than being more competitive.

2.4 Estimation

The model is estimated for four different groups of industries. The ISIC-4 level industries are classified according to their orientation based on OECD (1992). This classification, in fact, is based on the factor use in production. Therefore, they may as well reflect the differences in production technologies. The classification of the manufacturing industries into five categories is as follows: resource-intensive, labour-intensive, scale-intensive, specialised-supplier and science-based industries. The list of industries in each group is given in Appendix Table 2.7. The production of resource-intensive industries crucially depends on natural resources such as food, paper or cement industries. The labour-intensive industries use labour more intensively compared to the other industries such as textile, furniture and musical instruments. The scale-intensive industries depend on the returns to scale in production such as ship building, chemical industry and iron production. Lastly, the science-based and specialised-supplier industries are those whose production activity is closely related

to scientific (or technological) knowledge, or which supplies special products to specific consumers such as agricultural machinery, aircrafts and medicine.

The estimations are held separately for each group. Making separate estimations for each group makes it impossible to compare the efficiencies across different groups, but it is likely to yield more precise estimations of efficiencies. All estimations are made by FRONTIER 4.1[®] software. The details about FRONTIER 4.1[®] can be found in Coelli (1996).

Table 2.2 gives the results of some statistical tests run on the estimation results. All the tests are likelihood ratio tests except the constant returns to scale test. To test CRS we use a t-test. The first null hypothesis is tested for the validity of Cobb–Douglas production function specification by imposing the restriction $\eta_k = \theta_k = 0$. The null hypothesis is rejected for all orientation groups except the labor intensive

Table 2.2 Test results

Whole sample	RI	LI	SI	SS&SB	Critical value	Degrees of freedom
Cobb–Douglas production function: $\eta_k = \theta_k = 0$						
211.57	185.49	0.51	48.29	39.21	7.81	3
(Reject)	(Reject)	(Accept)	(Reject)	(Reject)		
Constant returns to scale: $\beta_L + \beta_K = 1$						
1.98	0.35	−0.32	−0.06	−0.11	1.96	1
(Reject)	(Fail)	(Fail)	(Fail)	(Fail)		
Returns to scale: $\beta_L + \beta_K$						
1.04	1.02	0.98	0.99	0.99		
(IRS)	(CRS)	(CRS)	(CRS)	(CRS)		
No inefficiency: $\gamma = \delta_i = \alpha_i = 0^a$						
2087.72	1125.27	560.15	910.35	356.91	55.19	56
(Reject)	(Reject)	(Reject)	(Reject)	(Reject)		
No stochastic inefficiency: $\gamma = 0^a$						
75.84	43.46	97.29	114.61	80.53	8.76	4
(Reject)	(Reject)	(Reject)	(Reject)	(Reject)		
No efficiency effects: $\delta_i = \alpha_i = 0^b$						
527.07	580.12	237.11	588.14	200.03	73.31	54
(Reject)	(Reject)	(Reject)	(Reject)	(Reject)		
Neutral model: $\alpha_i = 0$						
716.51	422.03	108.99	142.17	93.30	51.00	36
(Reject)	(Reject)	(Reject)	(Reject)	(Reject)		
Time invariant inefficiency: $\beta_t = 0^c$						
105.36	194.55	10.25	51.12	17.45	43.77	30
(Reject)	(Reject)	(Fail)	(Reject)	(Fail)		

RI resource-intensive industry; *LI* labour-intensive industry; *SI* scale-intensive industry; *SS* specialized-supplier industries; *SB* science-based industries

^aTest statistic has a mixed chi-square distribution

^bFor $i > 0$

^cCoefficients of time variables and their cross products are equal to zero

industries. We continue to use translog production function assumption for labor intensive sectors, to be able to make comparisons among sectors. The second row of Table 2.2 shows the results of the tests for constant returns to scale (CRS). The null hypothesis is that the sum of coefficients of labor and capital equals to one. The test fails to reject CRS for all the groups of sectors. The fourth row of Table 2.2 reports the test statistics for the null hypothesis of “no inefficiency”. This test statistic has a mixed chi-square distribution as noted in Coelli (1996), and the critical values are taken from Kodde and Palm (1986). The test fails to reject the hypothesis of “no inefficiency” in all orientation groups. On the other hand, the fifth row of Table 2.2 reports the test statistics for null hypothesis of “no stochastic inefficiency”. This test statistic also has a mixed chi-square distribution and hypothesis of “no stochastic inefficiency” is also rejected for all the groups.

A test for the significance of inefficiency effects is run by imposing the restriction of $\delta_i = \alpha_i = 0$ for $i > 0$. Also, a separate test is run by imposing only $\alpha_i = 0$ for $i > 0$ to test the neutrality of efficiency effects. Both tests rejected the null hypothesis of “no inefficiency effects” and “neutral model” for all the groups.

Lastly time invariant inefficiency is tested by restricting the coefficients of time variables and their cross products to zero. The test failed to reject time invariant efficiency for the labor-intensive and the science and specialized-supplier-intensive groups. The test statistic rejects the time invariant inefficiency for the resource and the scale-intensive industries.

Table 2.3 gives the coefficients of estimated frontier for different orientation groups. The coefficients of labor and capital show that marginal productivity of capital is higher in all sectors. The output elasticity of capital is higher in the specialized supplier and science based sectors.

Trend and interaction of inputs with trend are incorporated into the analysis to account for the technical change. Coefficients of time and time square variables are insignificant for the labor intensive sectors indicating the fact that there is no

Table 2.3 Coefficients of estimated frontier

Variable	ALL	RI	LI	SI	SS&SB
Constant	13.05***	13.04***	12.86***	13.19***	13.27***
Labour	0.27***	0.23***	0.24***	0.23***	0.07
Capital	0.77***	0.79***	0.74***	0.76***	0.92***
Labour square	-0.01	-0.03	-0.01	0.08**	0.07**
Capital square	0.04***	0.08***	0.01	-0.02	0.03
Labour X capital	0.07***	-0.02	-0.02	0.02	0.02
Time	-0.02	-0.09***	-0.03	-0.04*	-0.01
Time square	0.00	0.01***	0.00	0.00	0.00
Time X labour	-0.01*	-0.05***	-0.01	0.00	0.02*
Time X capital	0.03***	0.07***	0.00	0.00	-0.02

Source: Authors' calculations from ICI (2002, 2003 and 2004). *RI* resource-intensive industry; *LI* labour-intensive industry; *SI* scale-intensive industry; *SS* specialized-supplier industries; *SB* science-based industries.

*Significant at 10%, **Significant at 5%, ***Significant at 1%

technical change in these sectors. The results also show an evidence of decreasing technical change in the scale-intensive and the resource-intensive industries. For the characteristics of technical change, the findings suggest significant labor saving technical change only in resource-intensive industries.

Table 2.4 presents the estimated coefficients of the efficiency effect variables. The results may be summarized as follows: Larger firms turn out to be more efficient in all groups of industries except the resource intensive sectors. The resource intensive sectors turn out to be less concentrated as the Herfindahl–Hirschman index for this sector is the lowest among the sector groups. Hence, it can be concluded that size loses its effect on efficiency as the market become more competitive. In Turkey, there is a prevailing conviction about the fact that exporting firms are more efficient. However, our finding on the relationship between exporting and efficiency

Table 2.4 Effects of efficiency effect variables

Variable	All	RI	LI	SI	SS&SB
Constant	6.44***	2.16**	6.66*	8.46***	10.68***
Size	-0.95***	-0.22	-1.16**	-1.24***	-2.01***
Export	0.77***	0.82***	0.63***	0.64***	1.36***
Profit.	-0.03***	-0.03***	-0.05***	-0.04***	-0.05***
Public	-0.14	0.23	-3.11***	-0.19	
Foreign	-0.56***	-0.40***	-1.94***	-0.24*	0.17
Herf.	-0.95***	-0.92*	1.63	-1.65***	1.98**
Mrk Shr. ^a	-3.82***	-5.90***	0.00	-11.41***	-0.00
Herf. X Mrk. ^a	-0.57***	-1.01***	0.00	-2.29***	0.00
D 1994	0.29**	0.05	0.82**	0.41**	1.38***
D 1995	0.14	-0.06	0.43	0.28	0.91*
D 1996	0.17	-0.06	0.34	0.22	0.58
D 1997	0.01	-0.06	-0.19	-0.15	0.02
D 1998	0.14	-0.04	0.21	0.13	0.31
D 1999	0.39***	0.32**	0.07	0.41*	0.46
D 2000	0.46***	0.65***	0.51	0.15	0.12
D 2001	0.48***	0.71***	0.15	0.21	1.56***
D 2002	0.62***	0.88***	0.83**	0.58***	-0.23
D 2003	0.71***	1.04***	1.09***	0.54**	0.29
Sigma Squared	0.66***	0.44***	1.00***	0.70***	1.19***
Gamma	0.85***	0.86***	0.93***	0.95***	0.91***
Log-like.	-4,358.84	-1,302.49	-877.34	-1,003.80	-480.66
LR 2,087.72	1,125.27	560.15	910.35	356.91	
Iterations	181	240	121	249	66
Firms	926	332	233	238	123
Years	11	11	11	11	11
Total Obs.	4,794	1,720	1,193	1,268	613

Note: $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$. Source: Authors' calculations from ICI (2002, 2003 and 2004). RI resource-intensive industry; LI labour-intensive industry; SI scale-intensive industry; SS specialized-supplier industries; SB science-based industries.

^aBoth variables are multiplied by 1,000 for normalization

*Significant at 10%, **Significant at 5%, ***Significant at 1%

suggest the reverse: higher volume of exports is associated with lower firm efficiency in all industries. This result may be explained by the fact that exporting is not necessarily related with higher firm efficiency in Turkish manufacturing, but related with export promotion policy of Turkey which is based upon persistently devaluated national currency during the last decade.

The estimation results indicate a very strong and significant relationship between profitability of a firm and its efficiency. In fact, the causality between these two variables may run from efficiency to profitability.

When the ownership structure of firms is considered, public firms are found to be more efficient in labor intensive industries. On the other hand, there is no statistically significant difference between public and private firms with respect to efficiency operating in the resource-intensive, science-based and specialized-supplier industries. We also found that foreign firms are more efficient in all the groups with an exception of the science-based and the specialized-supplier industries.

The estimation results suggest a positive relationship between the degree of competition measured by the Herfindahl & Hirschman Index and the efficiency of the firms operating in the resource and the scale intensive industries. However, in the science-based and the specialized-supplier industries, we found a significant association between concentration and lower efficiency. Finally, no significant relation is found between concentration and firm efficiency in the labor intensive industries. Similar results were obtained for the market share-efficiency nexus: Firms having relatively higher shares in the market are more efficient in the resource and scale intensive industries. No significant relationship between market share and efficiency is found in the other two industries.

A negative or insignificant relationship between sectoral concentration and efficiency is postulated by the market share hypothesis, while efficient market structure hypothesis anticipates the inverse. Thus, our findings support the latter for all the industries with an exception of the specialized-supplier and science-based industries. The positive coefficient of Herfindahl–Hirschman index for the specialized-supplier and science-based industries, which are characterized by less competitive market structures supports the market share hypothesis. The scale incentives industries also have high concentration and but are significantly different from the specialized-supplier and science-based industries with respect to firm size and profitability. This difference implies that the market dynamics are as important as the market structure. If larger firms dominate the market, then concentration hampers the efficiency while in a market that is dominated by smaller firms, efficiency and concentration is positive.

The coefficient of the product of market share and the sectoral concentration is negative in all the industry groups, but is significant only in the labor-intensive industries. This implies that the second derivative of efficiency with respect to market share and concentration is negative. That is to say that, the effect of the market share, which was found to be positive, decreases as the concentration in the sector increases. This shows that concentrated market structure hampers efficiency not only by itself but also by impeding the positive effect of market share on efficiency.

This finding also explains the relationship between market share and concentration. However, for relatively more competitive sectors, sectoral concentration decreases the negative effect of market share.

The coefficients of the cross terms of inputs and efficiency effect variables, which are given in Appendix Table 2.6, reveal that input composition of the firms are effective in determining the relationship between monopoly power, market structure and efficiency. The cross terms are more effective in the resource and labor intensive industries.

The positive effect of concentration on efficiency in the resource intensive sectors increases as capital employment increases, while employing more capital decreases the positive effect in the scale-intensive industries. This shows the importance of strong capital structure of firms in more competitive markets, while the scale intensive industries that are characterized by a more monopolistic structure employ excess capital.

Capital decreases the positive effect of the market share in resource intensive markets and increases it in the scale-intensive industries. That is to say that firms employing more capital in more competitive industries are less likely to benefit from the positive relationship between market share and efficiency, while the inverse is true in less competitive industries.

The most significant conclusion that can be derived from the interaction of capital with efficiency effect variables is that capital increases the effect of size regardless of the market structure. Note that size is measured by labor employment. Hence this implies that labor becomes more productive as the capital employment increase.

The significant interactions of labor with efficiency effect variables is mostly negative implying that labor employment decreases the effect of all factors on efficiency in the resource-intensive sectors. The interactions of labor in the other industries are mostly insignificant. The most notable exceptions are the interaction of labor with the market share in the scale intensive sectors and public ownership in the labor intensive sectors. Labor increases the positive effect of the market share on efficiency in the scale intensive sectors and the effect of being a public firm on efficiency in the labor intensive sectors. The latter is an interesting finding in the sense that public firms are criticized for over-employment.

The mean efficiencies are given in Table 2.5. The mean efficiencies of all the industry groups decline overtime. The most significant decline is in the resource intensive sectors with 25%. The scale intensive industries follow with 12%. The decline in the labor and specialized supplier and science based sectors is rather moderate. The effects of the economic crisis of 1994 and 2001 can be observed in the mean efficiencies. The mean efficiency increases in the resource intensive sectors during the crisis. The scale intensive sectors are characterized by a high share of exports in firm revenue. There have been considerable devaluations after the 1994 and 2001 crisis, which turned out to be an advantage for exporting firms. In fact, the most significant decline in the mean efficiency of the scale intensive industries has occurred under the fixed exchange rate regime in 1998 and 2000.

Table 2.5 Mean Efficiencies according to estimations for each group

Year	RI	LI	SI	SS&SB	All
1993	0.56 (0.23)	0.65 (0.21)	0.57 (0.28)	0.71 (0.19)	0.61 (0.24)
1994	0.58 (0.23)	0.61 (0.24)	0.52 (0.24)	0.56 (0.24)	0.57 (0.24)
1995	0.60 (0.23)	0.65 (0.2)	0.56 (0.25)	0.66 (0.21)	0.61 (0.23)
1996	0.56 (0.22)	0.65 (0.22)	0.55 (0.25)	0.66 (0.24)	0.59 (0.24)
1997	0.54 (0.22)	0.68 (0.19)	0.57 (0.24)	0.68 (0.22)	0.60 (0.23)
1998	0.52 (0.24)	0.60 (0.22)	0.54 (0.27)	0.66 (0.22)	0.56 (0.25)
1999	0.42 (0.24)	0.59 (0.23)	0.45 (0.25)	0.57 (0.26)	0.49 (0.25)
2000	0.35 (0.24)	0.57 (0.2)	0.48 (0.25)	0.65 (0.19)	0.48 (0.25)
2001	0.36 (0.26)	0.59 (0.25)	0.45 (0.27)	0.53 (0.25)	0.47 (0.27)
2002	0.35 (0.25)	0.57 (0.23)	0.43 (0.25)	0.66 (0.19)	0.47 (0.26)
2003	0.31 (0.25)	0.52 (0.22)	0.45 (0.24)	0.64 (0.22)	0.44 (0.26)

Standard deviations in parenthesis. Source: Authors' calculations from ICI (2002, 2003 and 2004). *RI* resource-intensive industry; *LI* labour-intensive industry; *SI* scale-intensive industry; *SS* specialized-supplier industries; *SB* science-based industries

The mean efficiencies of the other sectors has severely declined during the crisis years, as expected.

Figure 2.1 shows the average mean efficiencies according to the orientation group over time, when the whole sample is used to estimate the efficient frontier. The efficiency orderings of the groups became more apparent and systematic in this case. The resource-intensive firms are at the bottom while the specialized-supplier and science-based firms are at the top. The movement of the mean efficiencies of the scale and labor-intensive firms are similar.

2.5 Conclusion

The results based on the Stochastic Frontier Analysis may be summarized as follows: (1) Our findings support the efficient market structure hypothesis for all industries except the sectors in the specialized-supplier and the science-based industries, which are characterized by less competitive market structures. (2) Private and foreign firms

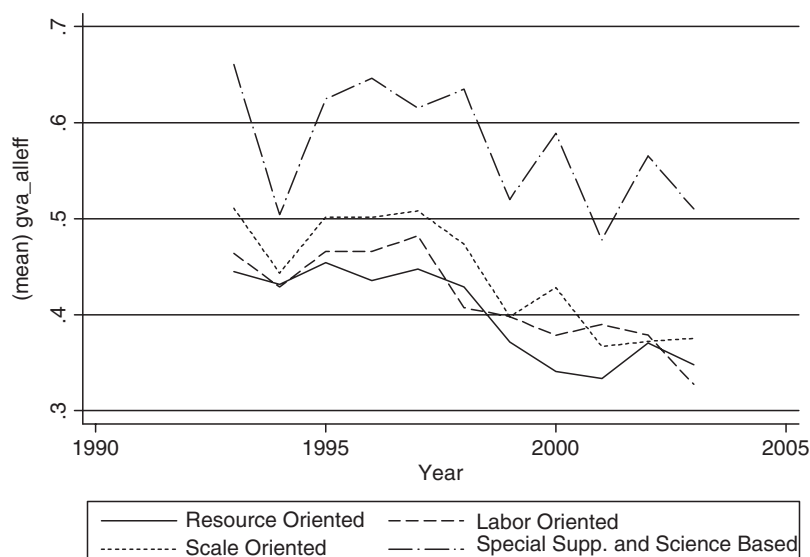


Fig. 2.1 Mean efficiencies for the whole sample over time, Source: Authors' calculations from ICI (2002, 2003 and 2004)

are less efficient in all cases. (3) Profitability of firms is associated with lower inefficiency in Turkish manufacturing industry. (4) Export-oriented firms are less efficient. (5) Higher market share consolidates efficiency in all industries.

Combining all these findings shows the importance of the level of competition in explaining the relationship between market structure, efficiency and profitability. Firm's own monopoly power, which increases the profits, helps to increase the efficiency in relatively competitive sectors. The sectoral concentration reinforces this effect. This suggests that the negative relationship between monopoly power and efficiency is not due to the firm's profits which are thought to hamper firms' incentive in the sectors that are open to more competition. Consequently, for highly competitive firms, the efficient market hypothesis works. On the other hand, market concentration hampers efficiencies for the industries which are less open to competition such as the specialized supplier and science based industries. In those sectors, the market share hypothesis holds.

As a result, it seems that the market share and the efficient market hypotheses explain different dynamics of markets. The former explains the implications of increasing market share and monopoly power of a firm on the efficiency, while latter focuses on the efficiency of monopolist firms. Thus, the firms that increased their monopoly power in a competitive market can be more efficient, but that can not be generalized to all the sectors under all circumstances. The firms that are in the sectors which were initially monopolistic are likely to be less efficient.

Appendix

Table 2.6 Coefficients of cross terms of efficiency effects and inputs

Variable	All	RI	LI	SI	SS&SB
Capital times					
Size	0.14***	0.09***	0.16***	0.13***	0.43***
Export	-0.11	-0.14*	-0.29	-0.40**	-0.10
Profit.	0.00	0.01***	0.01	0.01***	0.00
Public	0.99***	-1.60***	-1.08	1.57***	-0.10
Foreign	-1.30***	1.32**	0.00	-0.80**	0.00
Herf.	-1.21***	-1.74***	0.00	-0.77***	0.00
Mrk Shr ^a	0.03	-0.02	-0.05	0.02	
Herf. X Mrk ^a	0.15*	0.13	0.04	0.44**	-0.30***
D 1994	0.01***	0.00**	0.01**	-0.01**	1.10*
D1995	-1.06***	1.41**	0.62	0.07	0.04***
D 1996	1.79***	0.00	-0.13	3.78***	-2.34**
D 1997	-0.37***	-0.92***	-0.01	0.28***	0.00
D 1998	0.04	0.15	1.48*	0.43*	0.00
D 1999	0.01	-0.22**	0.29	-0.15	-0.29
D 2000	-0.22	0.29**	-0.22	-0.44	-1.82*
D 2001	-0.44***	0.06	0.17	-0.55*	-0.39
D 2002	-0.16	0.36**	0.11	-0.21	-0.81
D 2003	-0.24	0.29*	-0.21	-0.18	0.45
Labor times					
Size	-0.11	0.44***	-0.04	-0.27	-0.90
Export	-0.01	0.54***	0.17	-0.24	0.36
Profit.	-0.25*	0.35**	-0.50	-0.25	-1.09
Public	-0.04	0.54***	0.06	0.08	-1.47*
Foreign	-0.23	0.56***	-0.71	-0.52*	-1.50
Herf.	-0.19	0.58***	-0.54	-0.53*	-1.75*
Mrk Shr ^a	-0.05	-0.30*	-1.09**	-0.41	
Herf. X Mrk ^a	0.00	0.31***	-0.89	0.15	0.05
D 1994	0.25*	-0.24*	0.65	0.58*	2.32**
D1995	0.59***	-0.06	0.58	0.87***	1.11
D 1996	0.26*	-0.29*	-0.06	0.42	0.42
D 1997	0.51***	-0.13	1.08*	0.51*	-0.27
D 1998	0.35***	-0.26	0.53	0.52*	1.17
D 1999	0.20	-0.55***	0.77	0.47*	0.01
D 2000	0.41***	-0.25	0.73	0.34	1.84**
D 2001	0.35**	-0.42**	0.60	0.26	2.43***
D 2002	0.47***	-0.37**	1.02**	0.74***	2.22**
D 2003	0.27*	-0.50***	0.80	0.55*	2.18**

Source: Authors' calculations from ICI (2002, 2003 and 2004)

^aBoth variables are multiplied by 1,000 for normalization

*Significant at 10%, **Significant at 5%, ***Significant at 1%

Table 2.7 Classification of industries according to orientation

Resource intensive industries	
3111	Slaughtering, preparing and preserving meat
3112	Manufacture of dairy products
3113	Canning and preserving of fruits and vegetables
3114	Canning, preserving and processing of fish, crustaceans and similar foods
3115	Manufacture of vegetable and animal oils and fats
3116	Grain mill products
3117	Manufacture of bakery products
3118	Sugar factories and refineries
3119	Manufacture of cocoa, chocolate and sugar confectionery
3121	Manufacture of food products not classified elsewhere
3122	Manufacture of prepared animal feeds
3131	Distilling, rectifying and blending spirits
3132	Wine industries
3133	Malt liquors and malt
3134	Soft drinks and carbonated waters industries
3140	Tobacco manufactures
3411	Manufacture of pulp, paper and paperboard
3412	Manufacture of containers and boxes of paper and paperboard
3419	Manufacture of pulp, paper and paperboard articles not classified elsewhere
3420	Printing, publishing and allied industries
3530	Petroleum refineries
3540	Manufacture of miscellaneous products of petroleum and coal
3610	Manufacture of pottery, china, and earthenware
3620	Manufacture of glass and glass products
3691	Manufacture of structural clay products
3692	Manufacture of cement, lime and plaster
3699	Manufacture of non-metallic mineral products not classified elsewhere
3720	Non-ferrous metal basic industries
Labour Intensive Industries	
3211	Spinning, weaving and finishing textiles
3212	Manufacture of made-up textile goods except wearing apparel
3213	Knitting mills
3214	Manufacture of carpets and rugs
3215	Cordage, rope and twine industries
3219	Manufacture of textiles not classified elsewhere
3220	Manufacture of wearing apparel, except footwear
3231	Tanneries and leather finishing
Labour Intensive Industries (cont.)	
3232	Fur dressing and dyeing industries
3233	Manufacture of products of leather and leather substitutes, except footwear and wearing apparel
3240	Manufacture of footwear, except vulcanized or moulded rubber or plastic footwear
3811	Manufacture of cutlery, hand tools and general hardware
3812	Manufacture of furniture and fixtures primarily of metal
3813	Manufacture of structural metal products
3819	Manufacture of fabricated metal products except machinery and equipment not classified elsewhere
3901	Manufacture of jewellery and related articles
3902	Manufacture of musical instruments
3903	Manufacture of sporting and athletic goods

(continued)

Table 2.7 (continued)

	Resource intensive industries
3909	Manufacturing industries not classified elsewhere
	Scale Intensive Industries
3311	Sawmills, planing and other wood mills
3312	Manufacture of wooden and cane containers and small cane ware
3319	Manufacture of wood and cork products not classified elsewhere
3320	Manufacture of furniture and fixtures, except primarily of metal
3511	Manufacture of basic industrial chemicals except fertilizers
3512	Manufacture of fertilizers and pesticides
3513	Manufacture of synthetic resins, plastic materials and man-made fibres except glass
3521	Manufacture of paints, varnishes and lacquers
3523	Manufacture of soap and cleaning, preparations, perfumes, cosmetics and other toilet preparations
3529	Manufacture of chemical products not classified elsewhere
3551	Tyre and tube industries
3559	Manufacture of rubber products not classified elsewhere
3560	Manufacture of plastic products not classified elsewhere
3710	Iron and steel basic industries
3841	Shipbuilding and repairing
3842	Manufacture of railroad equipment
3843	Manufacture of motor vehicles
3844	Manufacture of motorcycles and bicycles
3849	Manufacture of transport equipment not classified elsewhere
	Science based and specialised supplier industries
3821	Manufacture of engines and turbines
3822	Manufacture of agricultural machinery and equipment
3823	Manufacture of metal and wood-working machinery
3824	Manufacture of special industrial machinery and equipment except metal and wood-working machinery
3829	Machinery and equipment except electrical not classified elsewhere
3831	Manufacture of electrical industrial machinery and apparatus
3832	Manufacture of radio, television and communication equipment and apparatus
3833	Manufacture of electrical appliances and household goods
3839	Manufacture of electrical apparatus and supplier not classified elsewhere
3522	Manufacture of drugs and medicines
3825	Manufacture of office, computing and accounting machinery
3845	Manufacture of aircraft
3851	Manufacture of professional and scientific, and measuring and controlling equipment, not classified elsewhere
3852	Manufacture of photographic and optical goods
3853	Manufacture of watches and clocks

Source: OECD (1992)

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Chapter 3

Financial Ratio Analysis: An Application to US Energy Industry

M. Goto and T. Sueyoshi

3.1 Introduction

Discriminant Analysis (DA) is a decisional tool that can predict group membership of a newly sampled observation. In DA, a group of observations whose memberships are already identified is used for the estimation of weights (or parameters) of a discriminant function by some criteria such as the minimization of misclassifications, or the maximization of correct classifications. A new sample is classified into one of the several groups by DA results.

Recently, Sueyoshi (1999, 2001, 2004, 2005a, b, 2006), Sueyoshi and Kiriara (1998) and Sueyoshi and Hwang (2004) proposed a new type of nonparametric DA approach that provides a set of weights of a linear discriminant function(s), consequently yielding an evaluation score(s) for the determination of group membership. The new nonparametric DA is referred to as “Data Envelopment Analysis-Discriminant Analysis (DEA-DA),” because it maintains discriminant capabilities by incorporating the nonparametric features of DEA into DA.

As an application of DEA-DA, Sueyoshi (2005a) has used the method for financial performance evaluation, not a conventional use of DA. It is widely known that many financial ratios are used in financial analysis. There is no distinction between inputs and outputs in most of the financial data, as required by DEA. The application of DEA-DA can be directed towards financial performance evaluation. In Sueyoshi (2005a), the use of DEA-DA is referred to as “Financial Ratio Analysis (FRA)”, and was applied to the US energy industry in order to evaluate the financial performance of the US energy firms. All the US energy firms were classified by the status of default or non-default in his study.

M. Goto

Central Research Institute of Electric Power Industry, Tokyo, Japan

T. Sueyoshi

New Mexico Institute of Mining & Technology, Department of Management, Socorro, NM, USA and National Cheng Kung University, Tainan, Taiwan

As an extension of Sueyoshi (2004, 2005a, 2006), this study discusses other analytical features of FRA from the perspective of financial performance evaluation, most of which are not investigated in his studies. To achieve the research purpose, this research returns to the mathematical structure of FRA and applies it to the financial performance evaluation of the US electric power firms. The data set used for this study includes financial ratios under different energy services. Thus, there are two types of electric power firms: (a) firms that supply only electricity and (b) diversified firms that supply both gas and electricity. Using the data set, this study examines whether there are any financial differences between the two groups, and discusses how to rank these financial performances. Although this study uses the same financial ratios as those used in Sueyoshi (2005a), the dataset on financial performance under different services is different from the previous study on corporate bankruptcy of the US energy industry. Therefore, it is assumed that the empirical findings obtained in this study will provide new policy implications and suggestions, all of which are not identified in the previous study of Sueyoshi (2005a). Moreover, the two empirical (previous and current) studies are compared in terms of these empirical findings.

The remaining sections of this article are organized as follows: Section 3.2 provides a brief literature review that indicates the position of this research among the existing literature on DA. A review of FRA is methodologically discussed in Sect. 3.3. Section 3.3 also documents the formulation for the multiple group classification and the characteristics of the FRA methodology. The FRA is applied to a data set on the US energy industry in Sect. 3.4. Concluding comments and future extensions are summarized in the last Sect. 3.5.

3.2 Literature Review

The previous research efforts on DA are methodologically classified into the following four groups:

Statistics: This group is interested in the statistical developments of DA. The first contribution may be dating back to Fisher (1936) and Smith (1947). [See, for instance, Maddala (1983), Kendal et al. (1983) and McLachlan (1992) in which previous contributions of statistical DA are compiled.] The conventional statistical DA methods usually assume underlying assumptions on a group distribution. For example, two groups come from normal populations with different means, but the same covariance matrix, all of which should be prescribed. Under these assumptions, the statistical methods provide a theoretical basis for conducting various statistical inferences and tests. Furthermore, an ordinary least squares method (OLS) is usually used to obtain the coefficient estimates of a linear discriminant function. Thus, there is a computational simplicity in the statistical DA methods. Those are methodological strength and contribution, indeed. However, it is also true that many real data sets do not satisfy such underlying assumptions.

Econometrics: If independent variables are normally distributed, the statistical DA estimator is a true maximum-likelihood estimator and therefore asymptotically more

efficient than other DA methods. However, the assumption of normality is not satisfied in many real data sets. To overcome such a shortcoming related to the statistical DA, econometricians have developed other several DA methods that are closely linked to the theory of probabilistic choice discussed by psychologists. The most well known research effort in this area is due to McFadden (1973, 1976, 1980) who has investigated logit and probit models. The two models are usually solved by maximum-likelihood methods. An important feature of logit and probit analyses is that they provide the conditional probability of an observation belonging to a certain class, given independent variables. Both are based on a cumulative probability function and do not require the independent variables to be multivariate normal, or the groups to have equal covariance matrices, unlike the requirements of statistical DA. Furthermore, these approaches have a close linkage with statistical inferences and various tests.

Mathematical Programming: Mathematical Programming (MP) formulations have been proposed for solving various DA problems. These methods consist of the third group. The first contribution of this group was due to Charnes et al. (1955) study, which documented how to formulate L1 metric regression by a goal programming model and how to solve the problem by linear programming algorithm. [See Charnes and Cooper (1977) for a description on goal programming.] A popularity of MP-based DA occurred after the research effort of Freed and Glover (1981a, b). They have presented how a DA problem can be formulated by goal programming. Based upon these optimization techniques, the second group of DA studies is further classified into (a) linear programming methods (e.g., Markowski and Markowski 1987; Glover 1990; Lam and Moy 1997; Mangasarian 1999), (b) nonlinear programming methods (e.g., Cavalier et al. 1989; Stam and Joachimsthaler 1989; Duarte Silva and Stam 1994; Falk and Karlov 2001) and (c) MIP methods (e.g., Bajgier and Hill 1982; Rubin 1990; Abad and Banks 1993; Wilson 1996; Yanev and Balev 1999). A comprehensive review on the MP-based DA is found in Stam (1997), Doumpos et al. (2001) and Zopounidis and Doumpos (2002). A methodological benefit of the third research group is that the MP-based DA methods do not need any assumption on a group distribution. Nevertheless, a shortcoming of the MP-based DA is that statistical inferences and tests have not yet been well established at the level of the statistical and econometric DA approaches. It is clear that this study belongs to the third research group in terms of its methodological features.

Computer Science: The last group of DA research is found in applications of Neural Network (NN), Decision Tree (DT) and other computer science techniques. For example, recently, NN has been successfully applied in classification and pattern recognition problems (e.g., Jain and Nag 1995; Heinz et al. 2001; Tam and Kiang 1992; Markowski and Ragsdale 1995). A methodological strength of the numerical approach is that NN is so flexible such that we do not need any prior specification of a discriminant function. A learning process, incorporated into NN, constantly provides us with an updated discriminant rule. Those are indeed the strengths of NN. A problem related to the NN approach is that it cannot guarantee global optimality of NN solutions. Furthermore, NN produces many weights so that we cannot identify which factor is important or not in terms of group classification. Meanwhile, DT is a heuristic approach that does not generate any classification rule. DT algorithms create

a discriminant tree that properly classifies a training sample (Tam and Kiang 1992). There are several models available to us, such as ID3 (tree induction) proposed by Quinlan (1986) and CART (Classification and Regression Trees) proposed by Breiman et al. (1984) and used by Frydman et al. (1985). Both methods employ a non-backtracking splitting procedure that recursively partitions a set of examples into disjointed subsets. These methods differ in these splitting criteria: the ID3 method intends to maximize the entropy of the split subsets, while the CART technique is designed to minimize the expected cost of misclassifications. An algorithm incorporated in CART is usually structured in a binary classification tree that assigns observations into selected a priori groups. A data space is separated into several rectangular regions on a terminal node. All observations, falling in a given region of data space, are assigned to a sub-group (e.g., G1 or G2). The terminal nodes of a classification tree are assigned to groups in a way that the observed expected cost of misclassification of each assignment is minimized. A new object to be classified descends down the classification tree and is assigned to the group identified with the terminal node into which it falls. Thus, the DT method is very intuitive in terms of group classification. However, it has methodological shortcomings similar to NN (e.g., no theoretical support on optimality).

3.3 Methodology

3.3.1 Formulation

To explain how FRA is applied to the evaluation of the US energy industry, let us consider a decisional case in which there are two groups (G_1 and G_2). The sum of the two groups contains n observations (z_{ij} : $j = 1, \dots, n$) for the i -th financial factor. G_1 is a group of firms, while G_2 is the other group of other firms in the US energy industry. Each observation is characterized by k independent financial factors ($i = 1, \dots, k$). A separation line is expressed by $\sum_{i=1}^k \lambda_i z_{ij}$, where λ_i is a weight for the i -th financial factor.

Following Sueyoshi (2005a, 2006), FRA is mathematically formulated as follows:

$$\begin{aligned}
 & \text{Minimize } \sum_{j \in G_1} y_j + \sum_{j \in G_2} y_j \\
 & \text{subject to } \sum_{i=1}^k \lambda_i z_{ij} - c + M y_j \geq 0, j \in G_1, \\
 & \quad \sum_{i=1}^k \lambda_i z_{ij} - c - M y_j \leq -\varepsilon, j \in G_2, \\
 & \quad \sum_{i=1}^k |\lambda_i| = 1, \\
 & \quad \lambda_j \text{ and } c : \text{unrestricted and } y_j : \text{binary } (0/1)
 \end{aligned} \tag{3.1}$$

Where M is a given large number and ε is a given small number. [A methodological shortcoming of (3.1) is that both M and ε are subjectively determined. The determination of the best combination is still an open question and the research issue will be an important future research task.] The objective function of (3.1) minimizes the total number of incorrectly classified observations by counting y_j . The discriminant score for group classification is expressed by a scalar value “ c ” ($j \in G_1$) and $c - \varepsilon$ ($j \in G_2$), respectively. The small number (ε) is incorporated into (3.1) in order to avoid a case where an observation(s) exists on an estimated discriminant function. All the observed factors (z_{ij}) are connected by $\sum_{i=1}^k \lambda_i z_{ij}$. The equation indicates the discriminant hyperplane for a group classification. These weights are restricted in the manner that the sum of absolute values of λ_i (for all $i = 1, \dots, k$) is unity. A methodological benefit of such an adjustment is that each weight can be expressed by a percentile expression, so that we can easily understand which weight is important or not in terms of group classification.

Equation (3.1) is further reformulated as follows:

$$\begin{aligned}
 & \text{Minimize } \sum_{j \in G_1} y_j + \sum_{j \in G_2} y_j \quad (3.2) \\
 & \text{subject to } \sum_{i=1}^k (\lambda_i^+ - \lambda_i^-) z_{ij} - c + M y_j \geq 0, j \in G_1, \\
 & \sum_{i=1}^k (\lambda_i^+ - \lambda_i^-) z_{ij} - c - M y_j \leq -\varepsilon, j \in G_2, \\
 & \sum_{i=1}^k (\lambda_i^+ + \lambda_i^-) = 1, \\
 & \zeta_i^+ \geq \lambda_i^+ \geq \varepsilon \zeta_i^+ \text{ and } \zeta_i^- \geq \lambda_i^- \geq \varepsilon \zeta_i^- \text{ (} i = 1, \dots, k \text{),} \\
 & \zeta_i^+ + \zeta_i^- \leq 1 \text{ (} i = 1, \dots, k \text{), } \lambda_i^+ + \lambda_i^- \geq \varepsilon \text{ (} i = 1, \dots, k \text{),} \\
 & c : \text{unrestricted, } \zeta_i^+ = 0/1, \zeta_i^- = 0/1, y_j = 0/1, \text{ and all other variables } \geq 0.
 \end{aligned}$$

In transforming λ_i ($i = 1, \dots, k$) into a special ordered set of paired variables ($\lambda_i = \lambda_i^+ - \lambda_i^-$) in (3.1), Sueyoshi (2006) has assumed that these paired variables cannot be simultaneously positive. Mathematically, these variables are defined as

$$\lambda_i^+ = (|\lambda_i| + \lambda_i) / 2 \text{ and } \lambda_i^- = (|\lambda_i| - \lambda_i) / 2, \quad (3.3)$$

each representing a positive or a negative part of λ_i , respectively. These paired variables are transformed into $\lambda_i = \lambda_i^+ - \lambda_i^-$ and $|\lambda_i| = \lambda_i^+ + \lambda_i^-$ and then incorporated into (3.1). Such a transformation needs a Non-Linear Condition (NLC: $\lambda_i^+ \lambda_i^- = 0$) for each $i = 1, \dots, k$ in order to avoid a simultaneous occurrence of $\lambda_i^+ > 0$ and $\lambda_i^- > 0$.

To incorporate NLC ($\lambda_i^+ \lambda_i^- = 0$), this study uses its Mixed-integer Programming (MIP) equivalence. Let $\zeta_i^+ (= 0 \text{ or } 1)$ and $\zeta_i^- (= 0 \text{ or } 1)$ be two binary variables, then, the NLC is expressed by:

$$\zeta_i^+ \geq \lambda_i^+ \geq \varepsilon \zeta_i^+ \text{ and } \zeta_i^- \geq \lambda_i^- \geq \varepsilon \zeta_i^- \quad (i = 1, \dots, k) \quad (3.4)$$

$$\zeta_i^+ + \zeta_i^- \leq 1 \quad (i = 1, \dots, k) \quad (3.5)$$

Where (3.4) indicates the upper and lower bounds of λ_i^+ and λ_i^- respectively. Furthermore, (3.5) implies that the sum of these binary variables is less than or equal to one. It can be easily found that if both $\lambda_i^+ \geq \varepsilon > 0$ and $\lambda_i^- \geq \varepsilon > 0$ occur in (3.4), then $\zeta_i^+ + \zeta_i^- = 2$ is found in (3.5). Hence, the result becomes infeasible and thereby the simultaneous occurrence of $\lambda_i^+ > 0$ and $\lambda_i^- > 0$ is excluded from the computational result of (3.2). All the other λ_i^+ and λ_i^- combinations become feasible in both (3.4) and (3.5), so being feasible in (3.2).

Another possibility, to which we need to pay attention, is a simultaneous occurrence of $\lambda_i^+ = 0$ and $\lambda_i^- = 0$. The occurrence of zeros in the paired variables does not imply a mathematical problem in our computational result. However, in a case where all λ_i estimates are expected to be positive, we need to add the following Non-Zero Condition (NZC):

$$\sum_{i=1}^k (\zeta_i^+ + \zeta_i^-) = k \quad (3.6)$$

in order to avoid a simultaneous occurrence of $\lambda_i^+ = 0$ and $\lambda_i^- = 0$.

Classification of a New Sample: A newly sampled observation, $Z_r = (z_{1r}, \dots, z_{kr})^T$, is classified as follows:

- (a) If $\sum_{i=1}^k \lambda_i^* z_{ir} \geq c^*$, then the observation belongs to G_1 or
- (b) If $\sum_{i=1}^k \lambda_i^* z_{ir} \leq c^* - \varepsilon$, then the observation belongs to G_2

Figure 3.1 depicts the mathematical structure of FRA.

In the figure, we consider two groups of firms. One is a group (G1) of firms and the other is a group (G2) of other firms. All observations in G1 are depicted by “O” and the other observations in G2 are depicted by “X”. Two lines related to c^* and $c^* - \varepsilon$ classify between the two groups. As mentioned previously, the small number (ε) is used to avoid a situation in which some observations are on an estimated discriminant function (a line in Fig. 3.1).

3.3.2 Characteristics of the Methodology

The proposed FRA has the following methodological strengths and shortcomings:

Methodological Strengths: First, FRA can be used for not only DA but also financial performance evaluation. FRA provides us with a financial index and a ranking score of each organization. The criterion is based on how each organization locates above or below the estimated discriminant score that is obtained from the performance of the two groups of observations to be compared. The use of DA is

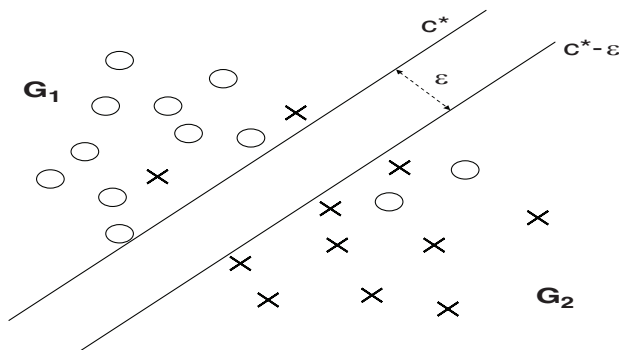


Fig. 3.1 A visual structure of FRA

important. However, this study is more interested in the new use of FRA as a financial evaluation tool, because the application has been insufficiently explored in the previous studies on performance analysis. Second, although DEA-DA (or FRA in this study) originates from DEA, it has a unique feature that is different from DEA. That is, in DEA, each organization (or observation in this study) is evaluated by comparing its performance with those of a part of the whole organization. Thus, the DEA-based efficiency analysis is organization (observation)-specific. In other words, different organizations (observations) have different reference sets, based upon which the efficiency of each organization (observation) is determined. DEA-DA (FRA), meanwhile, is not observation-specific. The approach provides a common weight set upon which all observations are evaluated. Thus, DEA-DA is an industry-wide evaluation. Third, DEA needs to classify a data set into outputs and inputs. In contrast, DEA-DA does not need such a classification. Thus, DEA-DA

fits within the scope of the financial analysis. Finally, The constraint, $\sum_{i=1}^k (\lambda_i^+ + \lambda_i^-) = 1$ restricts the parameter estimates in a manner that these become weights. Of course, the restriction can be eliminated from (3.2). Moreover, we can add the upper and/or the lower bounds to the restriction based on prior information. In these cases, these variables indicate parameter estimates (not weights) for a discriminant function. Thus, FRA (3.2) has flexibility in estimation that cannot be found in the conventional statistical DA approaches.

Methodological Shortcomings: First, the proposed approach needs asymptotic theory upon which we can derive a statistical test(s) related to DA. Many statistical and econometric approaches provide us with various convenient statistical tests in prevalent computer software tools. The software, including such traditional approaches, is usually not expensive. In many cases, we can freely access such DA methods. Such an availability of user-friendly software including many statistical tests really enhances the practicality of FRA. Second, as mentioned previously, the selection of M and ε influences weight estimates. Different selections on such pre-specified numbers often produce different weight estimates. This is a major shortcoming of FRA. Finally, the proposed approach is mathematically formulated

for DA in a cross-sectional data analysis, and not a time-series analysis. Consequently, this study cannot handle a data set in multiple periods. Such a methodological problem needs to be extended by reformulation of (3.2). That is an important future research task.

3.4 An Application to American Energy Industry

Deregulation of the energy industry is a general business trend occurring in many industrial nations such as the United States and Japan. The political purpose of such deregulation can be found in the economic assertion that competition in the energy industry requests managerial effort for efficiency improvement. As a consequence, the financial burden of consumers is reduced and the social welfare and economic prosperity of the industrial nations is increased.

Under such a policy assertion, many industrial nations have deregulated their electric power markets in the last decade. However, the speed and the level of deregulation depends upon the economic and social conditions of each country. For instance, in the US, the enactment of the Energy Policy Act of 1992 opened the wholesale power market to competition, bringing many independent power producers (IPPs) into the wholesale markets. Competition was further encouraged by the Federal Energy Regulatory Commission (FERC) through the issuance of its Orders 888 and 889 in 1996 and Order 2000 in 1999 that approved free access to the transmission network of electricity for all participants. These orders also fostered competitive mechanisms in the wholesale power markets by promoting the wide-scale development of transmission networks under the regional transmission organization (RTO). Indeed, by 2000 nearly half of the states in the US and the District of Columbia had passed legislation adopting competition as expected by the FERC and restructured the electricity industry. All customers in most of those states can buy electricity from other than incumbent utilities. In the US wholesale power markets, electric power producers trade among themselves as well as with power-marketers and power-distribution companies. The US wholesale power market will soon comprise the world's largest commodity market. Meanwhile, Japan has not attained such an advanced level of power deregulation. A wholesale power market was established and started its operation on April 2005, however, the level of trading volume continues to be lower than those of other nations.

Admitting those distinct trends of the deregulation of the energy industry, this research needs to describe that policy makers, corporate leaders and other individuals must acknowledge that business risk is always associated with the managerial discretion under liberalized economic systems. Unfortunately, this important business perspective has not been adequately discussed in previous policy debates. After the deregulation, electric power firms are investor-owned firms that operate under competitive mechanisms of free markets where prices are determined by an economic relationship between supplies and demands. Consequently, under the restructuring circumstances, business opportunities increase for the electric power firms in a manner that they can shift their focus from traditional functions of the industry

including generation and transmission to the new lucrative business of wholesale power trading. Furthermore, they can enter other industries such as gas and telecommunication, simply expecting some synergy effects and higher growth opportunities. However, it simultaneously increases an occurrence of corporate distress and bankruptcy in the worst case, because it is often documented that diversification may not be a profitable option for firms especially if the diversified business is not related to the core business. [See Jandik and Makhija (2005) on the discussion of a diversification trend of the US electric power firms.] A typical example of such bankruptcy in the electric power market was “Enron” that filed for Chap. 11 of Federal Bankruptcy Code in December 2001. The bankruptcy of the Enron was very influential to the energy industry and cast a dark shadow on the progress of the deregulation of the electricity industry. Therefore, examining financial condition becomes more important than before for energy industries to maintain a high level of their operations under competition.

This section indicates results of two application studies of the FRA. The first application is an analysis of corporate bankruptcy that is based on Sueyoshi (2004, 2005a, 2006). The second application evaluates financial performance of the US electric power firms “with” and “without” gas services (electricity and gas firms and electricity-specialized firms). These two applications are interested in different group memberships to be examined. However, they use the same FRA methodology and the same financial ratios for the analysis. Consequently, we conduct a comparative analysis of the two applications to obtain important implications for the energy firms regarding what factors are important in improving their financial performances.

3.4.1 Classification Based Upon Default and Non-Default Firms

3.4.1.1 A Description on the First Data Set

The first data set used in this study consists of 147 existing (non-default) and 24 bankrupt (default) companies. All the firms belong to the US energy industry. See Sueyoshi (2005a) for a list of all the sample firms. The financial factors of the default firm used in his study represent those performances of the last annual period when each firm faced its bankruptcy. The non-default firms were obtained from Mergent Inc Online, Hoover’s Online Database, and US Securities and Exchange Commission Company Filings. On the other hand, the bankrupt companies were sampled from the Bankruptcy Data Site. M is 10,000 and ε is 0.0001 in FRA (3.2). The selection of these firms was based on the availability of these financial data sets. All the data sets on the two groups were treated as cross-sectional in this empirical study. The performance of each firm was measured by the following financial measures:

(a) Current Ratio (current assets divided by current liabilities: a company’s ability to meet short-term debt obligations; the higher the ratio, the more liquid the company is), (b) Working Capital/Total Assets (current assets minus current liabilities divided by total assets), (c) Total Asset Turnover (total revenue divided by total assets), (d) Long-term Debt to Equity (a capitalization ratio comparing loans and obligations

with maturity of longer than one year; usually accompanied by interest payments, to shareholders' equity), (e) Interest Coverage (a calculation of a company's ability to meet its interest payments on outstanding debt. Interest coverage is equal to earnings before interest and taxes for an observed period, usually one year, divided by interest expenses for the same period. The lower the interest coverage, the larger the debt burden on the company), (f) Gross Margin (gross income divided by total revenue), (g) EBITDA Margin (Earnings Before Interest, Taxes, Depreciation and Amortization divided by total revenue), (h) Net Profit Margin (net profit divided by net revenues), (i) Return on Assets (ROA: a measure of a company's profitability equal to a fiscal year's net income divided by its total assets) and (j) Return on Equity (ROE: a measure of how well a company used reinvested earnings to generate additional earnings, equal to a fiscal year's net income divided by stockholder equity).

These measures are categorized into four groups based on what financial characteristics they are closely linked. These are (1) Liquidity: (a) and (b), (2) Activity: (c), (3) Leverage: (d) and (e), and (4) Profitability: (f), (g), (h), (i) and (j). All of them are important factors for examining financial performance of firms and are often used in finance studies.

3.4.1.2 A Mean Test

Table 3.1 lists the mean, standard deviation (SD), maximum and minimum of the two (non-default and default) groups of firms in each financial index.

The bottom of Table 3.1 also lists a t-score of each financial index. The t-score is used to statistically examine whether there is a difference between the averages of the two (non-default and default) groups in terms of each financial factor. The Welch's t-test is used for the examination of the mean test, because a significant difference is statistically identified between the variances of the two groups.

3.4.1.3 Weight Estimates and Classification Rates

Table 3.2 summarizes the resulting weight estimates of FRA, along parameter estimates of logit and probit models.

The two models are well-known econometric models for classification and are used as a methodological alternative to the proposed approach. Furthermore, to avoid a situation where a large observation(s) dominates the other small ones, a data set on each financial factor is divided by its average.

The bottom of Table 3.2 summarizes a classification rate expressed in percentage. Here, the classification rate indicates the number of correctly classified observations in the data set.

Finding 1: The classification rate (97.66%) of FRA slightly outperforms the other two econometric (logit and probit) approaches (96.49% and 95.32%), respectively. This indicates that the proposed FRA performs at least as well as the other well-known methods.

Table 3.1 Characteristics of financial indexes

		Working		Total asset turnover	LT debt to equity	Interest coverage	Gross margin (%)	EBITDA of revenue (%)	Net profit margin (%)	Return on assets (%)	Return on equity (%)
		Current ratio	capital/assets								
Non-default firms	Mean	0.88	-0.05	0.61	2.76	3.09	32.08	24.49	6.90	3.21	40.67
	SD	0.56	0.10	0.45	16.74	2.14	21.65	17.10	6.96	2.44	344.91
	Max	4.27	0.23	3.38	203.29	17.45	102.35	102.19	32.66	12.44	4,192.10
	Min	0.02	-0.51	0.04	-3.22	-1.01	-4.83	-33.15	-31.87	-6.59	-30.16
Default Firms	Mean	1.00	-0.10	0.96	12.43	-6.15	18.75	-30.27	-218.19	-21.88	-230.40
	SD	0.77	0.34	1.58	52.56	20.42	78.17	155.96	802.95	29.13	743.51
	Max	3.00	0.45	7.82	256.40	3.62	84.46	72.59	7.72	3.16	5.01
	Min	0.05	-1.10	0.00	-6.84	-99.80	-318.45	-725.91	-3960.67	-121.15	-3,699.98
t-score		-0.73	0.68	-1.08	-0.89	2.21*	0.83	1.72	1.37	4.22**	1.76

Source: Sueyoshi (2005a). Note: The superscripts * and ** stand for the 5% and 1% level of significance, respectively, of the t-test

Table 3.2 Estimates of three approaches and classification rates

Index	FRA	Logit	Probit
Current ratio	0.16859	0.29851	-0.05865
Working capital/total assets	-0.06464	-0.46989	-0.29401
Total asset turnover	0.00368	-0.03518	-0.15761
Long-term debt to equity	0.29349	1.66861	0.83189
Interest coverage	0.05248	4.17646	1.80510
Gross margin	0.06175	-0.88891	-0.72320
EBITDA of revenue	0.00516	1.30183	0.99070
Net profit margin	0.02059	-0.41521	-0.83196
Return on assets	0.00050	0.29787	1.44097
Return on equity	0.32911	4.92486	1.20944
Discriminant score (constant)	0.28124	-1.05433	-0.25197
Classification rate	97.66%	96.49%	95.32%

Source: Sueyoshi (2005a)

Finding 2: The three different approaches have different signs in the four financial indexes: Current Ratio, Total Asset Turnover, Gross Margin and Net Profit Margin

Finding 3: Long-term Debt to Equity, Current Ratio and Return on Equity have a large magnitude in these weight estimates. This result implies that the leverage, the liquidity and the profitability are all important in predicting the corporate bankruptcy of the US energy firms.

A highly profitable electric power firm with high leverage (large debt) may remain viable as a going concern in the competitive energy market. If a firm has a high leverage in its capital structure, the firm may face a high level of bankruptcy. However, such a case depends upon the profitability of each firm. Many electric power firms often use risky debt, preferred stock and all the other forms of risky securities to operate their business. The financial strategy is acceptable in the regulated electricity industry. However, the deregulation on the energy industry drastically changes the financial structure of each firm. To be a non-default concern, corporate managers need to pay attention to the profitability in a level that each firm can produce a monetary benefit to equity holders.

3.4.1.4 Ranking of American Energy Firms

To rank all the non-default and default firms belonging to the US energy industry, we measure their evaluation scores obtained by $\sum_{i=1}^k \lambda_i z_{ij}$ ($j = 1, \dots, n$). Where λ_i^* is the i -th weight estimate obtained from the proposed FRA. Tables 3.3 and 3.4 documents the ranking results of all the firms.

In the two tables, each firm has an evaluation score along with its rank. The ranking position, expressed by an ascending order, reflects the financial strength of each energy firm, where the financial strength is considered as a managerial capability to avoid different types of corporate distress and bankruptcy in the worst case.

Table 3.3 Result of non-default firms

CN	Evaluation score (rank)	CN	Evaluation score (rank)	CN	Evaluation score (rank)
1	0.68679 (23)	50	0.53855 (55)	99	0.44570 (115)
2	0.57250 (41)	51	0.44571 (114)	100	0.28124 (151)
3	0.79269 (13)	52	0.50805 (67)	101	0.56853 (42)
4	0.53822 (56)	53	0.42289 (129)	102	0.39626 (136)
5	0.50527 (69)	54	0.44976 (113)	103	0.73145 (18)
6	0.43211 (122)	55	0.38422 (139)	104	0.51575 (64)
7	0.46370 (102)	56	2.42340 (2)	105	0.49381 (77)
8	0.46202 (103)	57	0.58717 (35)	106	0.34462 (142)
9	0.54255 (53)	58	0.48485 (88)	107	0.46724 (99)
10	0.50477 (70)	59	0.45415 (109)	108	0.67480 (24)
11	0.46378 (101)	60	0.55118 (49)	109	0.53914 (54)
12	0.50702 (68)	61	0.54859 (51)	110	0.49226 (79)
13	0.41099 (133)	62	0.50196 (71)	111	0.47960 (93)
14	0.44436 (117)	63	54.69930 (1)	112	0.54885 (50)
15	0.46858 (98)	64	0.42880 (126)	113	0.49858 (74)
16	1.06071 (7)	65	0.48916 (84)	114	0.47036 (96)
17	0.59719 (31)	66	0.43393 (121)	115	0.49111 (81)
18	0.91260 (10)	67	0.82700 (12)	116	0.52125 (63)
19	0.49377 (78)	68	0.66541 (26)	117	0.44560 (116)
20	0.38921 (138)	69	0.49522 (75)	118	0.50141 (72)
21	0.42818 (127)	70	0.45548 (106)	119	0.59197 (33)
22	0.47772 (94)	71	1.12975 (6)	120	0.42211 (130)
23	0.45095 (112)	72	0.28124 (149)	121	0.43667 (120)
24	0.45265 (111)	73	0.46697 (100)	122	1.05107 (8)
25	0.52726 (59)	74	0.28427 (147)	123	0.50863 (66)
26	0.71538 (20)	75	0.45523 (107)	124	0.47073 (95)
27	0.53436 (57)	76	0.45919 (104)	125	0.61482 (29)
28	0.51123 (65)	77	0.56663 (43)	126	0.48952 (82)
29	0.58074 (36)	78	0.56625 (45)	127	0.42359 (128)
30	0.48495 (87)	79	0.42957 (125)	128	0.53025 (58)
31	1.78622 (3)	80	0.29347 (146)	129	0.73141 (19)
32	0.59478 (32)	81	0.49482 (76)	130	0.45325 (110)
33	0.70692 (22)	82	0.57480 (39)	131	0.54464 (52)
34	0.50121 (73)	83	0.46906 (97)	132	0.41900 (131)
35	0.45588 (105)	84	0.60427 (30)	133	0.65740 (27)
36	0.39608 (137)	85	0.45439 (108)	134	0.49199 (80)
37	0.43753 (119)	86	0.43085 (124)	135	0.55932 (47)
38	0.61942 (28)	87	0.66926 (25)	136	0.78984 (14)
39	0.48483 (89)	88	0.48168 (92)	137	0.43180 (123)
40	0.84960 (11)	89	0.73826 (17)	138	0.48440 (90)
41	0.28124 (149)	90	0.57731 (38)	139	0.76444 (16)
42	0.48870 (85)	91	0.57446 (40)	140	0.38354 (140)
43	0.52338 (61)	92	0.44232 (118)	141	0.41849 (132)
44	0.92326 (9)	93	0.56647 (44)	142	0.48563 (86)
45	1.27329 (4)	94	0.71301 (21)	143	0.48401 (91)
46	0.78349 (15)	95	0.35217 (141)	144	0.52148 (62)
47	0.57933 (37)	96	0.48918 (83)	145	0.58845 (34)
48	0.40174 (135)	97	0.52503 (60)	146	0.41014 (134)
49	0.56081 (46)	98	0.28124 (149)	147	0.55385 (48)

CN: Company number, Source: Sueyoshi (2005a)

Table 3.4 Result of default firms

Company number	Evaluation score (rank)	Company number	Evaluation score (rank)
1	0.18638 (158)	13	-0.15982 (169)
2	1.22932 (5)	14	0.11145 (160)
3	-0.02884 (165)	15	-0.10403 (167)
4	0.24755 (157)	16	-0.09161 (166)
5	0.07420 (163)	17	0.31462 (144)
6	0.28074 (153.5)	18	0.32715 (143)
7	-0.15616 (168)	19	-0.70705 (171)
8	0.28074 (153.5)	20	-0.16556 (170)
9	0.07741 (162)	21	0.09334 (161)
10	0.28074 (153.5)	22	0.28074 (153.5)
11	0.29632 (145)	23	0.03939 (164)
12	0.11301 (159)	24	0.28074 (156)

Source: Sueyoshi (2005a)

The findings in Tables 3.3 and 3.4 are summarized as follows:

Finding 4: The best performer is Georgia Power (63) and the next to the best is Environmental Power (56) as found in Table 3.3. The worst performer is Struthers Industries (bankrupted on March 9, 1998), as found in Table 3.4. The correct classification rate is 97.66%, as documented at the bottom of Table 3.2. Since there is an overlap between the two groups, FRA has a misclassification (2.34%). For instance, such a misclassified firm is identified as Coho Energy Inc (2) in Table 3.4, which was bankrupted on February 6, 2002. However, the firm is the fifth performer in rating. Admitting the shortcoming, this study uses the evaluation score as a basis of the financial performance analysis of all the energy firms since such a misclassification is only 2.34% in FRA.

3.4.1.5 A Rank-Sum Test

To examine statistically whether there is a difference between the non-default and default firms, we use a rank-sum test whose formulations are as follows:

$$U_A = (n_A \times n_B) + \frac{n_A(n_A + 1)}{2} - \sum R_A \quad (3.7)$$

$$U_B = (n_A \times n_B) + \frac{n_B(n_B + 1)}{2} - \sum R_B \quad (3.8)$$

Where n_A and n_B represent the number of observations in A (a group of non-default firms) and B (a group of default firms) respectively. $\sum R_A$ and $\sum R_B$ represent the sum of the ranks of each group, respectively. Each group can be considered to follow a normal distribution that has a mean $[=n_A n_B / 2 = (U_A + U_B) / 2]$ and a variance $[=n_A n_B (n_A + n_B + 1) / 12]$. See Mann and Whitney (1947). The statistic:

$$Z = [U - n_A n_B / 2] / \sqrt{n_A n_B (n_A + n_B + 1) / 12} \quad (3.9)$$

can be considered to follow a standard normal distribution $N(0,1)$, where U stands for either U_A or U_B . Both produce the same result on Z .

Finding 5: Based on the ranks in Tables 3.3 and 3.4, the rank sum test has $U_A = 3367$ and $U_B = 161$, so $Z = 2.90 (> 1.96)$; hence rejecting that the two groups of firms are sampled from a same population distribution at the 5% level of significance.

3.4.2 Classification Based Upon Electricity-Specialized Firms and Electricity and Gas Firms

3.4.2.1 A Description on the Second Data Set

The second data set (2003) used in this study consists of 74 electricity-specialized firms and 37 electricity and gas firms. The selection of these firms was based on the availability of the financial data sets. The data source is FERC Form 1 and S&P Compustat.

3.4.2.2 A Mean Test

Table 3.5 lists the mean, standard deviation (SD), maximum and minimum of the two (Electricity-specialized and Electricity and Gas) groups of firms in each financial index. The bottom of Table 3.5 lists a t-score of each financial index. The t-score is used to statistically examine whether there is a difference between the averages of the two groups in terms of each financial factor. The Welch's t-test is used to examine the mean test, because a significant difference is statistically identified between the variances of the two groups.

Finding 6: Table 3.5 indicates that the four financial indexes (Total asset turnover, Gross margin, EBITDA, Net profit margin) have different means at the 1% level of significance.

3.4.2.3 Weight Estimates and Classification Rates

Table 3.6 summarizes the resulting weight estimates of FRA, along with parameter estimates of logit and probit models.

The bottom of Table 3.6 summarizes a classification rate. Here, the classification rate indicates the number of correctly classified observations in the data set.

Finding 7: The classification rate of FRA (75.68%) slightly outperforms the other two econometric approaches of logit and probit (71.17%). This indicates that the proposed FRA performs at least as well as the other well-known methods.

Finding 8: The three different approaches have different signs in the two financial indexes: Long-term Debt to Equity and Gross Margin.

Table 3.5 Characteristics of financial indexes

	Current ratio	Working capital/total assets	Total asset turnover	LT debt to equity	Interest coverage	Gross margin (%)	EBITDA of revenue (%)	Net profit margin (%)	Return on assets (%)	Return on equity (%)
Electricity-specialized firms	Mean	1.29	1.24	0.66	1.28	3.71	28.75	21.27	8.85	3.35
	SD	0.77	1.96	0.25	0.67	1.15	12.37	9.88	5.07	1.61
	Max	4.96	10.25	1.30	4.99	8.25	88.10	71.19	29.53	7.55
	Min	0.15	0.00	0.13	0.41	2.30	11.27	6.73	1.00	0.24
Electricity and gas firms	Mean	1.40	1.03	0.77	1.31	3.93	22.00	17.57	5.94	2.97
	SD	1.48	2.18	0.20	0.89	1.86	7.40	4.57	5.57	2.22
	Max	9.39	10.87	1.49	6.02	13.57	35.61	26.58	14.71	6.69
	Min	0.30	-0.10	0.39	0.45	2.27	0.60	7.13	-20.94	-6.75
t-Score	-0.42	1.14	-2.54**	-0.13	-0.70	3.52**	2.70**	2.77**	0.43	-0.13

Note: The superscripts * and ** stand for the 5% and 1% level of significance, respectively, of the t-test

Table 3.6 Estimates of three approaches and classification rates

Index	FRA	Logit	Probit
Current ratio	-0.04287	-0.23594	-0.41722
Working capital/total assets	0.02186	0.11990	0.21711
Total asset turnover	-0.14792	-0.19920	-0.27503
Long-term debt to equity	-0.00001	0.88156	1.62373
Interest coverage	-0.00001	-0.69991	-1.46559
Gross margin	-0.00001	1.58163	2.71234
EBITDA of revenue	-0.33496	-1.64624	-2.74384
Net profit margin	0.31466	1.21341	2.08880
Return on assets	-0.13079	-0.01496	-0.05343
Return on equity	-0.00692	-0.77933	-1.31533
Discriminant score (constant)	-0.37990	0.32985	0.53979
Classification rate	75.68%	71.17%	71.17%

Finding 9: EBITDA of Revenue, Net Profit Margin, Total Asset Turnover and Return on Assets have a large magnitude in the weight estimates. This result implies that the profitability (EBITDA of Revenue, Net Profit Margin and Return on Assets) and the activity (Total Asset Turnover) are important financial factors in predicting the service type (electricity-specialized or electricity and gas) of the US electric power firms.

3.4.2.4 Ranking of American Electric Power Firms

Tables 3.7 and 3.8 document the evaluation scores and ranks of all the firms. In the two tables, each firm has an evaluation score along with its rank. Findings in Table 3.7 and Table 3.8 are summarized as follows:

Finding 10: The best performer is New England Power Co. (45) in Table 3.7, which provides electricity, followed by Cincinnati Gas and Electric Co. (15) in Table 3.7, which also provides electricity. The worst performer is Aquila Inc. (1) in Table 3.8 that provides electricity and gas.

Finding 11: Based on the ranks in Tables 3.7 and 3.8, the rank sum test has $U_A = 3605$ and $U_B = 2611$, which results in $Z = 1.03$ (< 1.96). Hence, at the 5% level of significance, we cannot reject that the two groups of firms are sampled from the same population.

3.5 Conclusion and Future Extensions

The Financial Ratio Analysis (FRA) is utilized for examining the financial performance of the American energy industry. The approach is a new type of nonparametric DA that provides a weight set of a linear discriminant function, consequently

Table 3.7 Result of electric-specialized firms

CN	Evaluation score (rank)	CN	Evaluation score (rank)	CN	Evaluation score (rank)
1	-0.339 (59)	31	-0.237 (17)	61	-0.241 (18)
2	-0.292 (33)	32	-0.431 (103)	62	-0.353 (64)
3	-0.334 (55)	33	-0.393 (91)	63	-0.4 (93)
4	-0.318 (45)	34	-0.409 (96)	64	-0.327 (51)
5	-0.19 (10)	35	-0.292 (34)	65	-0.299 (35)
6	-0.363 (68)	36	-0.374 (76)	66	-0.425 (101)
7	-0.186 (8)	37	-0.366 (72)	67	-0.333 (54)
8	-0.515 (109)	38	-0.303 (37)	68	-0.29 (31)
9	-0.353 (65)	39	-0.322 (47)	69	-0.397 (92)
10	-0.289 (30)	40	-0.261 (22)	70	-0.187 (9)
11	-0.331 (53)	41	-0.267 (25)	71	-0.28 (28)
12	-0.177 (7)	42	-0.231 (14)	72	-0.255 (21)
13	-0.22 (11)	43	-0.308 (43)	73	-0.29 (32)
14	-0.28 (27)	44	-0.38 (79)	74	-0.315 (44)
15	0.002 (2)	45	0.171 (1)		
16	-0.254 (20)	46	-0.334 (57)		
17	-0.175 (6)	47	-0.409 (95)		
18	-0.375 (77)	48	-0.365 (71)		
19	-0.319 (46)	49	-0.576 (110)		
20	-0.365 (70)	50	-0.247 (19)		
21	-0.089 (4)	51	-0.34 (60)		
22	-0.38 (78)	52	-0.38 (80)		
23	-0.331 (52)	53	-0.369 (74)		
24	-0.322 (48)	54	-0.304 (39)		
25	-0.367 (73)	55	-0.364 (69)		
26	-0.303 (38)	56	-0.423 (99)		
27	-0.27 (26)	57	-0.233 (15)		
28	-0.263 (24)	58	-0.345 (63)		
29	-0.334 (56)	59	-0.38 (81)		
30	-0.305 (40)	60	-0.012 (3)		

CN: Company number

yielding an evaluation score for group membership. Such weight estimates and a discriminant score provide a total financial evaluation measure, upon which we can determine the financial performance of each firm. The FRA compares the financial performances of 147 non-default firms with those of 24 default firms in the US energy industry. In addition, the FRA also compares the financial performances of 74 electricity-specialized firms with those of 37 electricity and gas firms in the US energy industry. Eleven empirical findings are identified and summarized in this study.

The comparison between the two groups of empirical results leads to the following business implications on the US energy industry: First, Findings 5 and 11 indicate that there is a significant difference between default firms and non-default firms in

Table 3.8 Result of electricity and gas firms

CN	Evaluation score (rank)	CN	Evaluation score (rank)	CN	Evaluation score (rank)
1	-0.786 (111)	16	-0.383 (85)	31	-0.224 (12)
2	-0.384 (86)	17	-0.358 (66)	32	-0.306 (41)
3	-0.408 (94)	18	-0.38 (82)	33	-0.429 (102)
4	-0.302 (36)	19	-0.359 (67)	34	-0.326 (50)
5	-0.478 (107)	20	-0.387 (87)	35	-0.308 (42)
6	-0.389 (88)	21	-0.34 (61)	36	-0.38 (84)
7	-0.326 (49)	22	-0.153 (5)	37	-0.371 (75)
8	-0.413 (98)	23	-0.38 (83)		
9	-0.338 (58)	24	-0.237 (16)		
10	-0.459 (104)	25	-0.391 (90)		
11	-0.511 (108)	26	-0.413 (97)		
12	-0.261 (23)	27	-0.391 (89)		
13	-0.282 (29)	28	-0.461 (105)		
14	-0.345 (62)	29	-0.229 (13)		
15	-0.424 (100)	30	-0.465 (106)		

CN: Company number

terms of the financial performances. However, there is no significant difference between electricity-specialized firms and electricity and gas diversified firms in terms of these financial performances. The two evidences may imply that business diversification between electricity and gas does not yield a financial prosperity as expected by corporate leaders and the individuals who are interested in the US energy industry. [We admit that this study examines only the financial performance of the US electric power firms in 2003 and therefore, its implication is limited in a scope of scientific evidence. However, the implication implies an important business suggestion on a future direction of the energy industry. A further investigation is an important future research extension.]

Second, Findings 3 and 9 indicate that the profitability (Return on Equity), the leverage (Long-term Debt to Equity) and the liquidity (Current Ratio) are important financial factors for distinguishing between default and non-default firms, while the profitability (EBITDA of Revenue, Net Profit Margin and Return on Assets) and the activity (Total Asset Turnover) are important in distinguishing between electricity-specialized firms and electricity and gas diversified firms. It is clear in this study that the profitability is important for the two types of FRA-based financial evaluation: (a) default and non-default firms and (b) electricity-specialized firms and diversified firms that provide both electricity and gas.

The research results and business implications for the US energy industry are further extendable to other major industrial nations including Asia and European nations. The applications of FRA will be an important future extension of this study. Finally, we look forward to seeing further research extensions as discussed in this study.

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Chapter 4

On Measuring Productivity Growth in Indian Industry: Analysis of Organized and Unorganized Sector in Selected Major States

Rajesh Raj S N and Mihir K. Mahapatra

4.1 Introduction

The Indian industrial sector has gone through various phases since independence. During the late 1970s and 1980s, there was a stagnation in the Indian industrial production. The slowdown in industrial production observed during the 1980s was primarily on account of low productivity. There was persistence of high costs on account of adoption of obsolete technology and low quality of production. However, progress in the process of deregulation was initiated during the 1980s.

The major reforms in Indian Industrial sector were witnessed during the 1990s. For instance, in 1991, there was a gradual dismantling of industrial licensing, removal of import licensing from nearly all manufactured intermediate and capital goods, tariff reduction and relaxation of rules for foreign investment.¹ The reforms in respect of the industrial sector were intended to free the sector from barriers to entry and from other restrictions to expansion, diversification and modification so as to improve the efficiency, productivity, and international competitiveness of the Indian industry. Against this backdrop, the paper makes an attempt to examine the impact of reforms on Industrial sector (both organized and unorganized sector) in India during the reforms period by adopting both partial factor productivity and total factor productivity approach.² Further, to identify the role of technical efficiency and technical change, attempt has been made to decompose total factor productivity growth (henceforth, TFPG) into technical change and efficiency change by using Malmquist index.

Rajesh Raj S N,

Centre for Multi-Disciplinary Development Research (CMDR), Dharwad, Karnataka, India

Mihir K. Mahapatra

Goa Institute of Management, Goa, India

¹For a detailed review on the industrial policy reforms, see Srinivasan (2000).

²A distinction is often made in the Indian manufacturing sector between organized and unorganized sectors. Unorganized manufacturing sector consists of units with less than ten employees using power and those units with 10–19 employees not using electric power. All other manufacturing activities are classified under the organized manufacturing sector.

The level of industrial development is determined by several factors including resource endowment, policy prescription of the state governments and so on. This indicates that mere introduction of economic reforms cannot necessarily improve the level of industrial development. Therefore, it necessitates the performance analysis of the selected major states from various levels of industrial development.³ The rationale of choosing three major states, namely Maharashtra, Karnataka and Orissa is as follows. In percentage share of gross value-added by the factory sector, Maharashtra, occupied the first position among the major Indian states while Orissa remained at the bottom level and Karnataka occupied one of middle positions. Again, these said three states are from the high income, middle income and low-income categories (Raj and Mahapatra 2006). Overall, the study is different from other studies in two respects: (a) it brings together both organized and unorganized sectors into the analytical spectrum and (b) the study also investigates the relationship between level of development and productivity by analyzing the performance of the sector in three states drawn from different levels of development.

The paper is organized as follows: Sect. 4.2 deals with data base and methodology adopted while in Sect. 4.3, the growth performance of the Indian manufacturing sector has been discussed. In Sect. 4.4 an attempt is made to examine the productivity performance of the organized and unorganized manufacturing sectors while Sect. 4.5 deals with policy issues followed by summary and conclusion in Sect. 4.6.

4.2 Data Base and Methodology Adopted

4.2.1 Data Base

The study is based exclusively on secondary data collected for both the organized and unorganized sectors. A detail description about the sources of data is as follows.

4.2.1.1 Unorganized Manufacturing Sector

The richness of the statistical database of the unorganized sector available through published official statistics needs close scrutiny (Singh 1991; Das 2000). In spite of a rich theoretical understanding on the informal sector, there exists a somber mismatch between the issues discussed in the literature and the official data available in India (Das 2000). The enterprise surveys of the Central Statistical Organization (popularly known as Economic Census), and the National Sample Survey Organization (NSSO) are the major sources that provide information on the unorganized sector. The Central Statistical Organization (CSO) conducts Economic

³There are 15 major states in India. About 90% of the total population lives in those states.

Census, which provides data on the number of enterprises and workers in the Own Account Enterprises and Establishments at two-digit industry level. This also provides information separately for the rural and urban areas.⁴ Nevertheless, one of the drawbacks of the CSO dataset is that it does not provide any production related information. The NSSO surveys, conducted as follow-up surveys to the Economic censuses, provide information on several production related factors such as output or value-added, employment, fixed assets, and emoluments for the unorganized manufacturing sector; both at the state level and industry level. Enterprise formed the basic ultimate unit for all these surveys.

The NSSO survey data are widely used by the studies on unorganized manufacturing sector in India. It should be noted that the unorganized manufacturing sector is comprised of three types of enterprises, namely, Own Account Manufacturing Enterprises (OAMEs), Non-Directory Manufacturing Enterprises (NDMEs), and Directory Manufacturing Enterprises (DMEs).⁵ The NSSO provides information about the OAMEs, NDMEs and more recently for DMEs. It also provides information for rural and urban areas. Since its inception up to date, the NSSO has conducted surveys for the unorganized manufacturing sector for five times, namely 33rd (1978–1979), 40th (1984–1985), 45th (1989–1990), 51st (1994–1995) and 56th (2000–2001) rounds. These large-scale surveys covered all the states and Union Territories (UTs).⁶

Data for the present study are obtained from these five rounds of surveys on the unorganized manufacturing sector by NSSO. In order to obtain the figures for the unorganized sector as a whole, data for each enterprise type (OAMEs, NDMEs and DMEs) and by location (rural and urban) have been added. A similar approach has been adopted in the selected states too. In order to examine the impact of the reforms, the entire time period (1978–2001) has been sub-divided into pre-reforms period (1978–1979 to 1989–1990) and reforms period (1994–1995 to 2000–2001).⁷

⁴Own account enterprises employ only family labour. Units employing hired labour in addition to family labour are classified as establishments.

⁵OAMEs employ only family labour while NDMEs and DMEs employ both family and hired labour. NDMEs employ less than six workers while DMEs employ more than or equal to six workers.

⁶For instance, the recent survey conducted in 2000–2001 covered the whole of the Indian Union except (a) Leh and Kargil districts of Jammu and Kashmir, (b) villages situated beyond 5 km. of bus route in the state of Nagaland and (c) inaccessible villages of Andaman and Nicobar. A stratified sampling design was adopted for selection of the sample first stage units (FSUs). The FSUs were villages in rural areas and UFS blocks in urban areas. A total of 14,528 first stage units consisting of 5,586 villages and 8,942 urban blocks were surveyed. The Ultimate Stage Units (USUs) for the survey were enterprises. The method of circular sampling has been employed for selecting the USUs from the corresponding frame in the FSU. A total of 152,494 enterprises (Rural: 60,770 and Urban: 91,724) were surveyed all over India. A detailed note on sample design and estimation procedure followed in the 56th survey is given in Appendix B of the survey report.

⁷Major economic reforms in India were introduced in July 1991. But it is not feasible to gather information about the unorganized sector during 1991–1993 as NSSO conducts survey for unorganized sector periodically. Therefore, the reforms period for unorganized sector (1994–2001) is not the same as observed in the organized manufacturing sector (1991 onwards). Further, it is difficult to update the figures for the unorganized sector beyond 2001 as NSSO has not come out with any publication on unorganized sector after 56th round.

4.2.1.2 Organized Manufacturing Sector

As regards the organized manufacturing sector, the study has relied on Central Statistical Organization's Annual Survey of Industries (ASI) for the factory sector as a whole. The period of study for the organized sector covers 23 years since 1981. Subsequently, the entire period (1981–2003) has been subdivided into two sub-periods: Pre-Reforms (1981–1991) and Reforms Period (1992–2003). However, this study failed to capture the performance of various groups of industries at two-digit level.

4.2.2 Definition of Output and Inputs

The basic variables used in the study for estimating productivity growth in the organized and unorganized industrial sector are output, capital, labour and emoluments. To make the values of output, fixed capital stock and emoluments comparable over time and across states, suitable deflators have been used:

- (a) *Output*: Gross value-added is used as the measure of output in this study. The Wholesale Price Index (WPI) for manufactured products has been used to deflate the nominal values of gross value-added in the organized industrial sector. For the present study, 1981–1982 base year is chosen instead of 1993–1994 as some price deflators for some of the variables are not available at 1993–1994 prices. Since WPI during the study period was expressed in three different base years (1970–1971, 1981–1982 and 1993–1994), a common base year (1981–1982) was chosen through splicing method.

The gross value-added for the unorganized manufacturing sector was deflated by the Net State Domestic Product (NSDP) at factor cost pertaining to the unregistered manufacturing sector at 1993–1994 prices.

- (b) *Capital (K)*: The capital input has been represented by gross fixed capital stock expressed in 1981–1982 prices. ASI reports the gross fixed assets and its various components on historical cost. For constructing the capital stock, CSO's data on fixed capital stock for 1981–1982 has been considered as the benchmark year of the capital stock. Gross fixed capital series is then constructed by perpetual inventory accumulation method.⁸

Due to the non-availability of time series data, similar method is not applied to deflate capital stock for the unorganized manufacturing sector. Therefore, the figures for gross fixed assets available in NSSO reports have been used to measure capital input in the unorganized manufacturing sector. This includes land, buildings

⁸The details on the construction of capital stock are given in the Appendix.

and other construction, plant and machinery, transport equipment, tools and other fixed assets that have a normal economic life of more than one year from the date of acquisition. These values have been expressed in 1993–1994 prices.⁹

- (c) *Labour*: Total number of persons engaged is used as the measure of labour input. Since both workers, working proprietors and supervisory/managerial staff can affect productivity, the number of persons engaged was used rather than the total number of workers.
- (d) *Emoluments*: Total emoluments primarily constitute wages to workers, contribution to provident fund (PF) and other benefits and so on. To estimate real emoluments, the nominal value has been deflated by Consumer Price Index.

4.2.3 Methodology

In view of the importance of measuring partial factor productivity ratios especially labor productivity (Balakrishnan 2004) in the Indian context, an attempt is made in this paper to capture the levels and trends in both partial and total factor productivity in the Indian industrial sector. As regards the partial factor productivity ratios, the study has considered labour productivity and capital productivity. The definition of the said indicators is as follows:

1. *Labour Productivity*: Gross real value added/Total number of persons engaged
2. *Capital Productivity*: Gross real value added/Real fixed assets, (excluding working capital)

In the empirical section, the total factor productivity growth (TFPG) has been estimated by using Growth Accounting method (GA) in the organized manufacturing sector. The results obtained are then compared with TFPG rates estimated by using Data Envelopment Analysis (DEA). Due to the non-availability of data on emoluments, a similar exercise could not be carried out in the unorganized manufacturing sector. Hence, the TFPG in the unorganized manufacturing sector is estimated by using only DEA.

⁹Following Salim and Kalirajan (1999) and Hossain and Karunaratne (2004), we argue that the use of gross figures to represent the capital stock can be justified in the case of developing countries such as India in general and unorganized manufacturing sector in particular on the ground that capital stocks are more often used at approximately constant levels of efficiency for a period far beyond the accounting life measured by normal depreciation until it is eventually discarded or sold for scrap. Thus even though the value of old machine declines, it need not lead to any decline in the current services of the capital equipment. In addition, we believe that if there were any distortion in the capital input, it would be distorted uniformly in all the states. Therefore, the relative performance of states should not be seriously affected by this shortcoming.

4.2.3.1 Growth Accounting Method

The root of the growth accounting approach (GAA) is the severance of change in output due to change in the quantity of factor inputs from residual effects such as technological change, learning by doing, managerial efficiency and so on. TFP growth substitutes these influences. In this paper, a two-input framework has been used for estimating the TFP growth rates, as done earlier by Ahluwalia (1991) and Balakrishnan and Pushpangadan (1994). Following Balakrishnan and Pushpangadan (1994), the Divisia–Törnquist (D–T) approximation has been used for the calculation of TFPG. The TFPG under the D–T approximation is given by the following equation:

$$TFPG = (\ln Q_t - \ln Q_{t-1}) - \sum_{i=1}^n 1/2 (s_{i,t} - s_{i,t-1}) (\ln X_{i,t} - \ln X_{i,t-1}) \quad (4.1)$$

where Q denotes output, X_i factors of production and s_i share of the i th factor in total output

In the growth accounting framework, information about the share of each primary factor (s_i) in total value added is required. In the present study, the share of emoluments in total value added is taken as proxy for the share of labour. Assuming constant returns to scale, the share of capital is one minus the share of labour.

4.2.3.2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) was first introduced by Charnes, Cooper and Rhodes (1978) and further generalized by Banker, Charnes and Cooper (1984). The advantage of this non-parametric method is that it is parameter free, and it does not assume a parametric functional form. A production frontier is empirically constructed using linear programming methods from observed input–output data of the sampled firms. The efficiency of firms is then measured in terms of how far they are from the frontier.

DEA can be either input-orientated or output-orientated. In the input-orientated case, the DEA method defines the frontier by seeking the maximum possible proportional reduction in input usage, with output levels held constant for each state while in the output-orientated case, the DEA method seeks the maximum proportional increase in output production with input levels held fixed. The output- and input-oriented measures provide equivalent measures of technical efficiency when constant returns to scale exist (Fare and Lovell 1978). The present study adopted the output oriented measure.

Malmquist index is used to measure TFPG, which is estimated using DEA. Malmquist productivity indexes were first introduced into the literature by Caves, Christensen, and Diewert (1982) and were empirically applied by Fare, Grosskopf, Norris and Zhang (FGNZ) (1994). FGNZ developed a non-parametric approach for estimating the Malmquist indexes, and showed that the component distance

function could be derived using a DEA-like linear program method. They also decomposed total factor productivity indexes into efficiency change and technical change components. According to them, the total factor productivity may grow by more efficient utilization of resources or by technical change. Nishimizu and Page (1982) in their paper argued that it is very important to study the distinction between technical change and efficiency change particularly in the context of developing countries. Following FGNZ, the output-oriented Malmquist TFP change index between period s (the base period) and period t (the terminal period) is given by

$$m_0(y_s, x_s, y_t, x_t) = \frac{d_0^s(y_t, x_t)}{d_0^s(y_s, x_s)} \left[\frac{d_0^s(y_t, x_t)}{d_0^t(y_t, x_t)} \frac{d_0^s(y_s, x_s)}{d_0^t(y_s, x_s)} \right]^{1/2} \quad (4.2)$$

where the notation $d_0^s(y_t, x_t)$ represents the distance from the period t observation to the period s technology. A value of m_0 greater than one indicates positive TFP growth from period s to period t while a value less than one indicates a TFP growth decline. In (4.2), the term outside the square bracket measures the output-oriented measure of Farrell technical efficiency between period s and period t and the term inside measures technical change, which is the geometric mean of the shift in the technology between the two periods. In other words, TFP growth can be decomposed as

TFP Growth = Technical Efficiency Change (Catch-up Effect) $\times$ Technical Change (Frontier Effect)

This study assumes a constant returns-to-scale (CRS) technology to estimate the above distance functions so as to obtain accurate measure of TFP index (Grifell-Tatje and Lovell 1995). In any case, the assumption of CRS seems to be appropriate when applying the Malmquist index at state level, while in the case of plants such an assumption could be more problematic. This paper employed linear programming (LP) technique to calculate the distance functions. This requires solving of four LPs for each DMU. The four LPs to be solved for each DMU are:

$$\begin{aligned} \left[d_0^t(y_t, x_t) \right]^{-1} &= \max_{\phi, \lambda} \phi, \\ st \quad & -\phi y_{it} + Y_t \lambda \geq 0, \\ & x_{it} - X_t \lambda \geq 0, \\ & \lambda \geq 0, \end{aligned}$$

$$\begin{aligned} \left[d_0^s(y_s, x_s) \right]^{-1} &= \max_{\phi, \lambda} \phi, \\ st \quad & -\phi y_{is} + Y_s \lambda \geq 0, \\ & x_{is} - X_s \lambda \geq 0, \\ & \lambda \geq 0, \end{aligned}$$

$$\begin{aligned}
 \left[d'_0(y_s, x_s) \right]^{-1} &= \max_{\phi \lambda} \phi, \\
 st \quad & -\phi y_{is} + Y_s \lambda \geq 0, \\
 & x_{is} - X_s \lambda \geq 0, \\
 & \lambda \geq 0,
 \end{aligned}$$

and

$$\begin{aligned}
 \left[d^s_0(y_t, x_t) \right]^{-1} &= \max_{\phi \lambda} \phi, \\
 st \quad & -\phi y_{it} + Y_t \lambda \geq 0, \\
 & x_{it} - X_t \lambda \geq 0, \\
 & \lambda \geq 0,
 \end{aligned}$$

where y_{it} is a $M \times I$ vector of output quantities for the i th state in the t th year:

- x_{it} is a $K \times I$ vector of input quantities for the i th state in the t th year
- Y_t is a $N \times M$ matrix of output quantities for all N (15) states in the t th year
- X_t is a $N \times K$ matrix of input quantities for all N states in the t th year
- λ is a $N \times I$ vector of weights and ϕ is a scalar

It should be noted that the performance of the organized and unorganized sector cannot be strictly compared partly due to absence of uniformity in time series data. In other words, figures for the unorganized sector are available at different years based on various rounds of survey while the study has resorted to time series data for the organized sector. Second, the organized sector analysis concentrates on the entire industrial sector comprising manufacturing sector, gas, electricity and water supply whereas the unorganized sector data covers exclusively the manufacturing sector. Third, due to non-availability of data on emoluments for the unorganized sector, the growth accounting method was not adopted. In other words, DEA has been employed to measure productivity in the unorganized sector while for the organized sector, the growth accounting method has also been considered besides the DEA method.

4.3 Growth Performance of the Indian Manufacturing Sector

The industrial sector in India comprises of three broad subsectors: (a) Manufacturing, (b) Mining and Quarrying and (c) Electricity, Gas and Water Supply. The manufacturing sub-sector constitutes about 80% of the industrial sector's gross value-added and this can be further subdivided into (a) factory sector (organized/registered manufacturing sector) and (b) Non-factory sector (unorganized or unregistered manufacturing sector). Factory sector covers all the manufacturing enterprises registered under the Indian Factories Act of 1948. Unregistered/Unorganized manufacturing

sector covers all manufacturing units employing less than ten workers, if using power, or less than 20 workers if not using power.

At the outset, the present study presents a comparative analysis of relative position of the organized sector vis-à-vis the unorganized sector in the industrial sector in terms of some selected variables. The comparative analysis reveals that the unorganized sector contributes 80–85% of total employment in the manufacturing sector (Table 4.1). In contrast, the organized sector generates around 70% of gross-value added in the manufacturing sector. This indicates low productivity in the unorganized manufacturing sector, which explains its low contribution to national income.

The comparative analysis of the growth performance of key industrial indicators reveals that the performance of various indicators does not seem to be quite encouraging during the reforms period in both the sectors (Table 4.2). During the reforms period, the gross value-added grew at a very low rate especially in a backward state like Orissa. The decline in the growth of gross value-added in India and the selected states could be primarily as a result of the decline in the growth of factors of production. However, there has been an improvement in fixed capital stock and employment during the reforms period in India and in few states in the organized manufacturing sector. On the other hand, the growth of employment and fixed capital stock declined in the unorganized manufacturing sector during the reforms period as compared to the pre-reforms period. Overall, the analysis shows that

Table 4.1 Share in manufacturing employment and gross value-added in India: Organized Vs Unorganized

Year	Employment		Gross value added	
	Organized sector	Unorganized sector	Organized sector	Unorganized sector
1984–1985	15.7	84.3	67.7	32.3
1989–1990	16.6	83.4	70.5	29.5
1994–1995	19.4	80.6	76.6	23.4
2000–2001	17.6	82.4	70.5	29.5

Source: ASI and NSSO Reports, Government of India

Table 4.2 Growth of key industrial indicators: India vis-à-vis selected states

Period	Variables	India		Karnataka		Orissa		Maharashtra	
		Org	Unorg	Org	Unorg	Org	Unorg	Org	Unorg
Pre-Reforms Period	GVA	7.3	11.1	7.6	13.8	16.0	1.3	7.8	8.3
	FK	0.9	6.3	0.9	7.4	1.7	11.0	1.0	5.0
	EMPT	0.2	12.8	1.1	5.1	1.6	10.6	0.8	7.9
Reforms period	GVA	4.2	6.2	6.2	7.6	0.4	0.6	3.5	5.0
	FK	1.3	1.9	2.8	1.6	1.0	–5.5	1.5	3.4
	EMPT	1.2	6.7	1.0	7.3	4.9	–1.5	1.1	–2.3

Source: NSSO Reports and ASI Bulletins. *GVA* Gross value added; *FK* Fixed capital; *EMPT* Employment; *Org* Organized sector; *Unorg* Unorganized sector

Note: Annual average compound growth has been estimated

despite the growth in employment and fixed capital stock, the growth of value-added has declined in the organized manufacturing sector. In contrast, it can be said that decline in growth of value-added in the unorganized manufacturing sector is primarily due to the decline in growth of employment and fixed capital stock. Due to the divergence in the growth performance of the organized and unorganized sectors especially in employment and fixed investment, it is important to probe the impact of this diverse performance on the productivity of the sectors.

4.4 Productivity Growth in Indian Manufacturing Sector

Productivity is defined as the ratio of output (or real value-added) to input(s). Productivity growth has long been recognized as an important factor that drives economic growth and it has been the subject of intense research interest. According to Krugman (1994), a higher growth in output due to growth in total factor productivity is preferred to an input driven growth, as the inputs are subjected to diminishing returns. The two commonly used measures of productivity are single factor productivity (SFP) or partial factor productivity and total factor productivity (TFP).

The comparison of partial factor productivity approach vis-à-vis total factor productivity approach reveals that the former considers only one factor of production at a time in assuming the contribution of the other factors of production as constant, while the latter measures the contribution of all the inputs used in the production process on output. Based on this, total factor productivity method is preferred over partial factor productivity method. However, Balakrishnan (2004) argues that partial factor productivity measure such as labour productivity is a measure of potential consumption; and a steady rise in the productivity of labour is necessary for a sustained increase in the standard of living of a population. Thus, there is a strong case for measuring labour productivity particularly in the Indian context (Balakrishnan 2004). Taking cognizance of it, an attempt is made in this paper to capture the levels and trends in both partial and total factor productivity in the Indian industrial sector.

4.4.1 *Organized Manufacturing Sector*

4.4.1.1 Movements in Labour and Capital Productivity

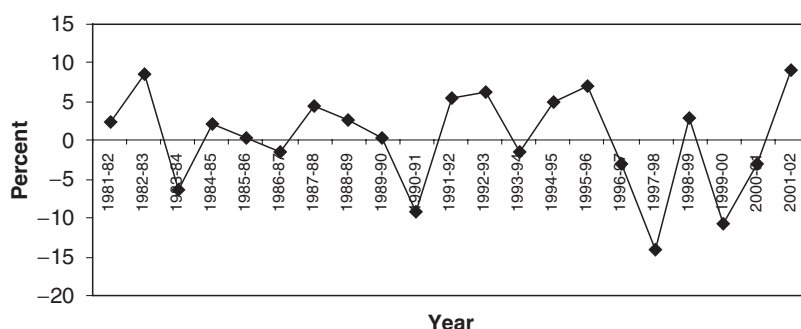
The productivity of the factor inputs determines growth of output to a large extent. In this context, the rate of growth of labour productivity and capital productivity during the pre-reforms (1981–1991) and reforms (1992–2003) period have been estimated (Table 4.3).

From Table 4.3, it is evident that both labour productivity and capital productivity declined during the reforms period but the extent of the decline is pronounced

Table 4.3 Growth of factor ratios in India and selected states (in percent)

Ratios	Pre-reforms period				Reforms period			
	India	Karnataka	Orissa	Maharashtra	India	Karnataka	Orissa	Maharashtra
Labour productivity	7.08	6.45	14.08	8.58	5.45	5.14	5.30	4.62
Capital productivity	6.39	6.55	14.04	6.68	2.83	3.32	0.61	1.89

Source: CSO's Annual Survey of Industries, various issues

**Fig. 4.1** Total factor productivity growth in Indian industry

in capital productivity. Again, erosion in partial factor productivity is quite severe in a backward state like Orissa.

4.4.1.2 Total Factor Productivity Growth

In this paper, annual rate of TFPG in the organized manufacturing sector has been measured using the growth accounting method (GA) and the Data Envelopment Analysis (DEA). The TFPG rates measured using GA in India and the selected states reflect wide fluctuation over the years. The extent of fluctuation is pronounced in India during the reforms period (Fig. 4.1). While comparing the TFPG in India and the selected states during pre-reforms and reforms period, it is observed that productivity growth declined during the reforms period compared to the period prior to the initiation of reforms, especially during the latter part of the 1990s (Table 4.4 and Figs. 4.1–4.4). For instance, the average TFPG in India during 1981–1991 was 1.40% while it became negative and declined to 0.52% during the reforms period (Table 4.4). Among the states, the extent of decline is significant in Orissa followed by Karnataka and Maharashtra.

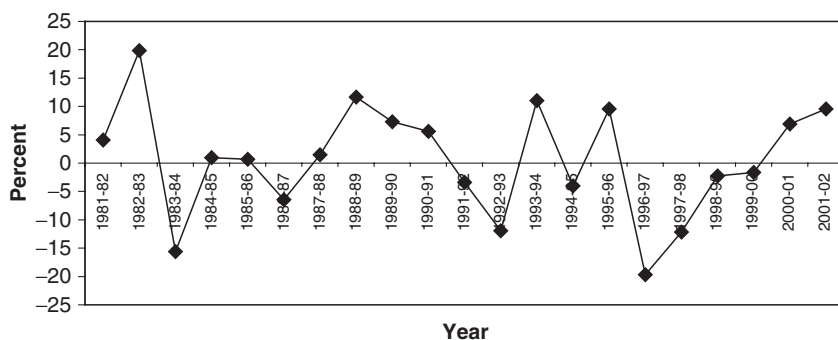


Fig. 4.2 Total factor productivity growth in industrial sector: Karnataka

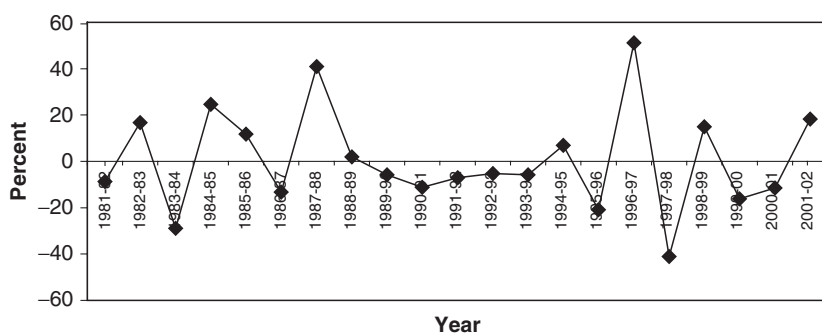


Fig. 4.3 Total factor productivity growth in industrial sector: Orissa

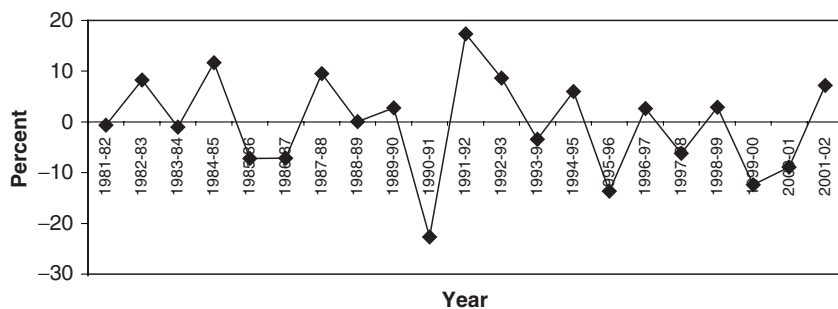


Fig. 4.4 Total factor productivity growth in industrial sector: Maharashtra. Source: Estimated from various Reports of Annual Survey of Industries

Table 4.4 Total factor productivity growth (in percent)

States	Pre-reforms period	Reforms period
Maharashtra	1.81	(-)1.89
Karnataka	2.65	(-)1.03
Orissa	4.38	(-)2.30
India	1.40	(-)0.52

Source: Estimated from CSO's Annual Survey of Industries, Various issues

A review of studies on the organized manufacturing sector shows that the question of 'turnaround' dominated the analysis of productivity growth performance in the 1980s, and the issue of whether there was an improvement in the early 1980s is still far from being resolved (Ahluwalia 1991; Balakrishnan and Pushpangadan 1994; Dholakia and Dholakia 1994; Rao 1996; Pradhan and Barik 1998; Trivedi et al. 2000). The evidence on the TFP growth for the 1990s however confirms that there has been a fall in TFP growth rate relative to the 1980s (Trivedi et al. 2000; Goldar 2006), and this has been endorsed by the findings of this study.

4.4.1.3 Sources of Total Factor Productivity Growth: DEA Approach

The decline in productivity growth is also confirmed by the Malmquist productivity growth estimates. According to the DEA measure, the productivity growth remained positive but declined during the reforms period (Fig. 4.5). The decline in growth is more pronounced in the manufacturing sector in Orissa. In general, the results from the two methods reflect a similar trend. However, the differences could be attributed to the DEA methodology whereby each state is compared in relation to a common framework that can be viewed as the frontier for the whole sector. In contrast, in the traditional TFP measure computed as a weighted sum of the factor productivities with constant weights, each country is compared in relation to itself in the previous periods. The differences could be also attributed to the low discriminating power emerging from less number of DMUs used in the DEA procedure.

An important factor contributing to productivity growth (decline) is an improvement (decrease) in the level of technical efficiency. If a firm becomes more efficient over time, its average productivity rises. Table 4.5 reports year-wise technical efficiency for the selected states and India as a whole for the period 1981–1982 to 2002–2003.

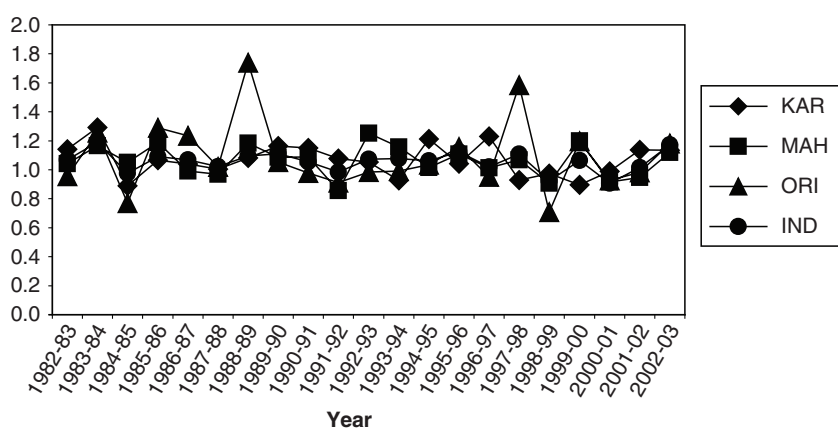


Fig. 4.5 Total factor productivity growth in organised manufacturing sector: India vis-a-vis selected states. Source: Estimated from various Reports of Annual Survey of Industries

Table 4.5 Mean technical efficiency in organized manufacturing sector of selected states in India

Year	Maharashtra	Karnataka	Orissa	India
1981–1982	1.000	0.849	0.672	0.839
1982–1983	1.000	0.912	0.597	0.831
1983–1984	1.000	0.957	0.610	0.812
1984–1985	1.000	0.793	0.489	0.756
1985–1986	1.000	0.707	0.520	0.690
1986–1987	1.000	0.723	0.654	0.727
1987–1988	1.000	0.754	0.685	0.770
1988–1989	1.000	0.822	0.996	0.804
1989–1990	1.000	0.764	0.963	0.747
1990–1991	1.000	0.853	0.858	0.749
1991–1992	1.000	1.000	0.916	0.829
1992–1993	1.000	0.998	0.729	0.790
1993–1994	1.000	0.816	0.616	0.740
1994–1995	1.000	0.963	0.631	0.777
1995–1996	1.000	0.841	0.703	0.778
1996–1997	0.987	1.000	0.647	0.772
1997–1998	1.000	1.000	0.916	0.831
1998–1999	0.902	0.994	0.655	0.788
1999–2000	1.000	0.852	0.733	0.802
2000–2001	1.000	0.944	0.745	0.804
2001–2002	0.900	0.987	0.700	0.772
2002–2003	0.828	0.882	0.668	0.725
Average	0.983	0.882	0.714	0.779
Standard deviation	0.045	0.098	0.137	0.039
Pre-reforms period	1.000	0.813	0.704	0.773
Reforms period	0.968	0.940	0.722	0.784

Source: Calculated by authors. Note: DEA is employed on data for 15 Indian states

A comparative analysis of the average efficiency scores reveals that Maharashtra recorded the highest average level of technical efficiency followed by Karnataka and Orissa. Evidently, Maharashtra remained the state defining the frontier in the pre-reforms period, but there was erosion in its efficiency in the closing years of the 1990s and onwards. Compared to the pre-reforms period, the level of efficiency has improved during the reforms period in India and the selected states with an exception of Maharashtra. Considering the movement of these figures over the period, one may be tempted to conclude that the reform process has positively contributed to enhancing level of technical efficiency in the sector. However, a closer look at the efficiency scores reveals erosion of efficiency in the post 1997–1998 period. This perhaps would have contributed to the observed decline in productivity growth in the sector. This aspect is examined in the following section.

The total factor productivity may grow by more efficient utilization of resources and/or by technical change (Fare et al. 1994). Therefore, it is important to examine which of the components has contributed to the TFPG decline during the reforms period in the organized manufacturing sector. Using the DEA approach, the TFPG has been decomposed into technical change and efficiency change.

Table 4.6 Decomposition of total factor productivity growth in the organized manufacturing sector: India vis-à-vis major states

States	Pre-reforms period			Reforms period			Total period		
	EFF	TECH	MALM	EFF	TECH	MALM	EFF	TECH	MALM
Karnataka	0.1	8.6	8.7	-1.2	5.4	4.2	0.2	6.1	6.3
Maharashtra	0.0	8.2	8.2	-1.8	7.8	5.8	-1.0	6.8	5.8
Orissa	2.8	8.5	11.6	-2.8	7.4	4.4	0.0	6.8	6.7
India	-1.3	8.9	7.4	-1.5	6.3	4.7	-0.8	6.5	5.6

Source: Estimated from NSSO surveys, various issues. *EFF* Efficiency change; *TECH* Technical change; *MALM* Malmquist total factor productivity change

Note: DEA is employed on the data for 15 states. The figures for India represent the average for all the states

Pre-reforms period corresponds to 1981–1991 and reforms period corresponds to 1992–2003

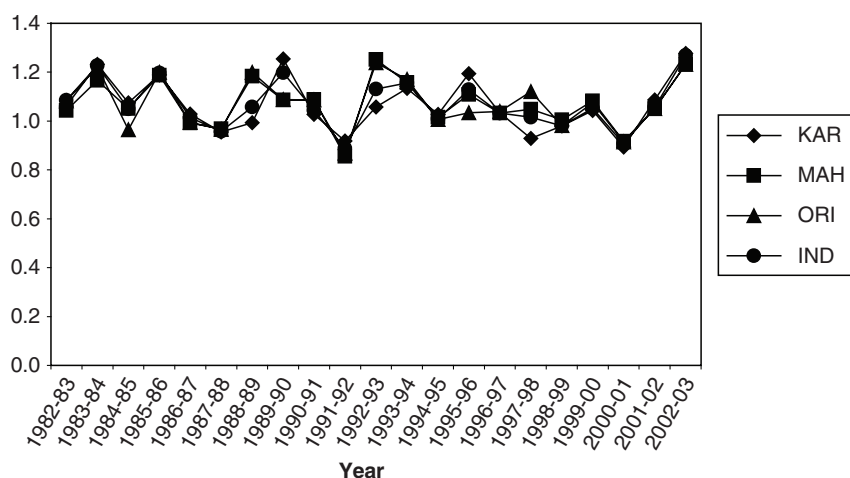


Fig. 4.6 Technical change in organised manufacturing sector: India vis-a-vis selected states.
Source: Estimated from various Reports of Annual Survey of Industries

From Table 4.6, it is found that both efficiency decline and low technology progress have contributed to the decline in TFP growth in the organized manufacturing sector. No doubt, the organized manufacturing sector experienced technological progress but its growth slowed down during the reforms period. A sharp deterioration in technical efficiency has resulted in low and declining TFP growth for the sector. As mentioned above, technical efficiency levels have witnessed considerable erosion in the second half of the 1990s. With limits to acquire and have access to better and newer technology, technological progress can no longer sustain long-term growth (Figs. 4.6 and 4.7). Therefore, more emphasis should be given to raising technical efficiency levels in the sector.

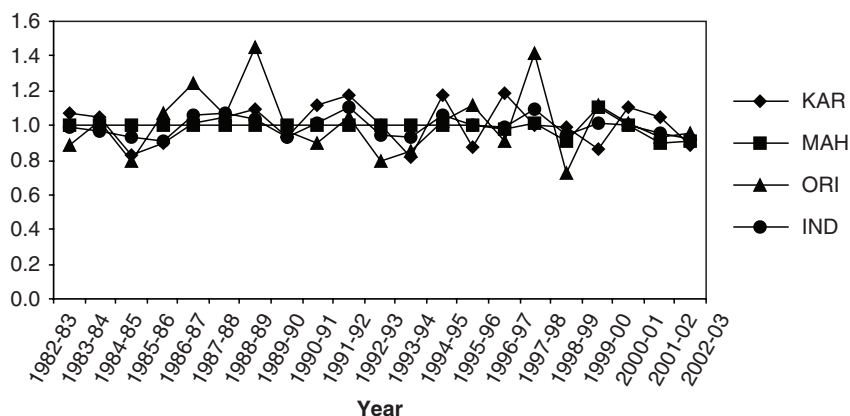


Fig. 4.7 Efficiency Change during 1981–1982 to 2002–2003: India vis-à-vis Selected States
Source: Estimated from various Reports of Annual Survey of Industries.

4.4.2 Unorganized Manufacturing Sector

4.4.2.1 Growth Trends of Labor and Capital Productivity

The productivity of labour and capital during the pre-reforms and reforms periods in the unorganized manufacturing sector reveals that labor productivity declined marginally in India and the selected states barring Orissa during the reforms period.

Considering capital productivity, the sector in Maharashtra and Orissa recorded the highest growth during the reforms period. In contrast, negative growth is observed during the reforms period in the Indian economy as a whole (Table 4.7). Though capital productivity registered positive growth in both the pre-reforms and reforms period in Karnataka, the growth momentum was not sustained during the latter period. The partial factor productivity analysis thus shows that reform process has had a mixed impact on productivity in the unorganized manufacturing sector in India and the selected states (Table 4.7).

4.4.2.2 Total Factor Productivity Growth

In the unorganized manufacturing sector, TFPG estimates have been obtained by using DEA. Based on the DEA results, it is found that total factor productivity grew at a rate of 0.1% in the unorganized manufacturing sector during the entire period under consideration, i.e., 1978–2001 (Table 4.8). The unorganized sector in India and Orissa witnessed a turnaround from decline in total factor productivity in the pre-reforms period to growth in total factor productivity in the reforms period. In

Table 4.7 Growth of partial factor productivity in unorganized manufacturing sector across states

States	Labour productivity		Capital productivity	
	Pre-reforms period (1978–1990)	Reforms period (1994–2001)	Pre-reforms period (1978–1990)	Reforms period (1994–2001)
Maharashtra	3.19	1.50	0.38	7.44
Karnataka	6.00	5.95	8.25	0.28
Orissa	–8.70	6.48	–8.36	2.13
India	4.52	4.21	–1.52	–0.49

Source: Estimated from NSSO Surveys, various issues

Table 4.8 Decomposition of total factor productivity growth in the unorganized manufacturing sector: India vis-à-vis major states

States	Pre-reforms period			Reforms period			Total period		
	EFC	TECH	MALM	EFC	TECH	MALM	EFC	TECH	MALM
Karnataka	6.7	–1.3	4.4	0.2	1.6	1.8	1.2	–0.5	0.6
Maharashtra	2.9	–0.9	1.6	0.9	1.4	2.4	0.6	–0.2	0.3
Orissa	–2.0	–1.7	–3.4	2.5	–1.0	1.2	0.4	–0.7	–0.4
India	1.1	–1.8	–0.3	–0.5	1.1	0.6	0.6	–0.4	0.1

Source: Estimated from NSSO surveys, various issues. *EFF* Efficiency change; *TECH* Technical change; *MALM* Malmquist total factor productivity change

Note: DEA is employed on the data for 15 states. The figures for India represent the average for all the states

Pre-reforms period corresponds to 1978–1979 to 1989–1990; reforms period corresponds to 1994–1995 to 2000–2001; and total period corresponds to 1978–2001

contrast, TFPG declined in Karnataka during the reforms period. The sector in Maharashtra experienced continued productivity growth at an accelerated rate. In general, the analysis shows that productivity growth has improved during the reforms period in India and the selected states despite the decline in value-added, employment and investment.

Before proceeding further to identify the sources of productivity growth, it is essential to examine the performance of the sector in ‘technical efficiency’ both in the chosen states and the country as a whole. A consistently increasing level of technical efficiency is noticed in the country as a whole during 1978–1979 to 1994–1995. However, the sector witnessed erosion in technical efficiency level during the reforms period (Table 4.9). A state specific comparison reveals that Karnataka exhibited higher average level of technical efficiency closely followed by Maharashtra. On the other hand, the sector in Orissa is the least efficient implying that there is considerable scope for improving efficiency in the sector in Orissa. A comparison between pre-reforms and reforms period reflects an improvement in efficiency level in the latter as compared to the former in the selected states. However, it is important to examine whether the change in efficiency has significantly contributed to productivity growth in the sector.

Table 4.9 Mean technical efficiency in unorganized manufacturing sector of selected states in India

Year	Maharashtra	Karnataka	Orissa	India
1978–1979	0.301	0.578	0.542	0.562
1984–1985	1.000	0.550	0.327	0.608
1989–1990	0.906	0.999	0.426	0.694
1994–1995	0.731	0.862	0.606	0.863
2000–2001	0.749	0.946	0.772	0.820
Mean	0.737	0.787	0.535	0.709
Standard deviation	0.268	0.210	0.171	0.130
Pre-reforms period	0.736	0.709	0.432	0.621
Reforms period	0.740	0.904	0.689	0.842

Source: Calculated by authors. Note: DEA is employed on data for 15 Indian states

4.4.2.3 Sources of Total Factor Productivity Growth: DEA Approach

The component measures of TFPG, efficiency change and technical change, show that TFP growth in the Indian unorganized manufacturing sector during the reforms period was aided by technological progress (Table 4.8). On the other hand, technical efficiency progressed at a slow rate in India and the selected states with an exception of Orissa. Despite the technical regress observed by its sector, Orissa recorded a positive growth performance in TFP due to the improvement in technical efficiency. In contrast, the TFP growth in Maharashtra during the reforms period was achieved through faster technological progress.

As far as the unorganized manufacturing sector is concerned, the technical efficiency change component representing output growth caused by greater experience and skill of workers, improved resource utilization, better organization by the entrepreneurs, and so on is more important. It is evident from the literature that the majority of units in the sector depend on indigenous resources and adaptive technology, and the workers acquire their skill mostly ‘on-the-job’. As a result, the firms keep on experimenting until they attain the best possible mix of technology, resource, skill and organization. In brief, diffusion of technology is more important to the firms rather than ‘modernity’ of technology. Therefore, attempts should be made towards enhancing the level of technical efficiency in the sector. This can perhaps be achieved by improvement in managerial input, organization and skill of the workforce. Consolidation of tiny firms may also help in raising the efficiency level of the sector as a whole.

With regards to the unorganized manufacturing sector, very few studies have analyzed its productivity performance using TFP approach. Findings of these studies have confirmed a decline in TFP growth in the reforms period (Unni et al. 2000; Bhalla 2001). In contrast, the present study reflects improvement in productivity growth during the reforms period. The difference can be partly attributed to variation in the time period considered in different studies.¹⁰

¹⁰ Attempts made by various authors have considered 1989–1990 to 1994–1995 as the reforms period where as in the present study 1994–1995 to 2000–2001 represents the reforms period. It may be noted here that reforms initiated in 1991–1992 gained momentum from mid-1990s.

4.5 Socio-Economic Factors and Growth Performance

The performance of the Industrial sector in India is determined by several factors. For instance, Nagaraj (2003) stressed on size and growth of domestic market and this, in turn, is determined by the growth of agriculture. In this context, it should be noted that there has been a slow down in the growth of agriculture during the Ninth Five Year Plan (1997–2002) as compared to the Eighth Five Year Plan (1992–1997). For instance, the annual average growth of agriculture and allied sector (at constant prices) declined from 4.7% witnessed during the Eighth Five Year Plan to 2.1% during the Ninth Five Year Plan. In this context, slow growth in institutional credit, erosion in Credit-Deposit ratio, decline in the growth of public investment and global recession can be taken into consideration.

The state specific analysis reflects a different picture altogether. For instance, using ASI data for 1966–1989, Vyasulu and Kumar (1997) argue that there has been limited growth of dominant industrial groups in Orissa and a few of the large units have contributed a major part of the total. There has also been the absence of diversification in the industrial structure during the said period. It is during the 1990s when the economy witnessed a substantial decline in the share of agriculture in Gross State Domestic Product (GSDP) and a slow down in the growth of agriculture and therefore, affected growth of industry through backward and forward linkages. The poor agricultural base has also affected the emergence of active local entrepreneurial class (Vyasulu and Kumar 1997). There is also the absence of a proper integration between the industry and the agricultural sector, lack of adequate infrastructure and people's movements against setting up of new industries. Some of the major people's movement was noticed in Baliapal (against the missile testing range), the Gandhamardhan movement (in protest to the Balco Alumina project), Chilika movement against the Tata-Orissa (government) shrimp project, Gopalpur movement (against Tata's proposed Steel Plant), Kashipur movement (in protest to the Utkal Alumina project), and the Malkanagiri movement against wooden-log businessmen (Nayak 1996). The unwanted outcome of people's movement has been reflected by death of 12 Tribals in the different parts of the state (Mishra 2006).

The middle income state (Karnataka) has been dominated by the growth of IT industries especially in the state capital Bangalore-popularly known as Silicon Valley of India. No doubt, among the selected states, the performance of Karnataka is relatively better but there is enough scope for further improvement. Apart from the global recession, the non-availability of power supply, huge unsold stocks and underutilization of capacity of Public Sector Units have contributed to some extent in its failure to achieve the desired growth during the reforms period. Therefore, it necessitates improvement in infrastructure including road and rail connectivity, provision of uninterrupted power supply and the availability of institutional credit to the concerned industrial units so as to improve the performance of the industrial sector in the state.

In the developed state Maharashtra, inadequate infrastructure, widespread industrial disputes, relatively high power tariff, persistence of aggressive competition

among the developed states which attract more industries might have affected the industrial scenario during the reforms period.

4.5.1 Performance of Unorganized Sector and Policy Issues

In the recent past, the performance of various types of activities that encompass the unorganized sector has been assigned due importance by the planners partly due to the structural changes taking place in the Indian economy. The significance of the unorganized sector activities in the process of India's development has been emphasized due to the following reasons: (a) there has been a decline in employment growth in the 1970s, 1980s and 1990s in the economy and the growth in employment was lower than the growth of labour force (Planning Commission 2001); (b) reforms introduced in the 1990s have led to reduction in public sector spending on certain crucial sectors. As a result, decline in the growth of organized sector employment was noticed during the 1990s especially in the later part of the 1990s. This was more evident in large scale organized manufacturing sector (Nagaraj 2004); (c) the labour market is widely believed to be suffering from excessive intervention leading to substituting of capital for labour, and thereby creating a downward effect on employment growth in the organized sector. In addition to this, the labour market reforms such as reduction of the extent of protection and repealing of the job security clause might have accentuated the employment problem in the organized sector (Nagaraj 2004). Moreover, with increasing deregulation and delicensing of economic activities, the process of casualisation and feminisation of labour is on the rise (Mitra 2001). 'Flexible specialization' methods of production have encouraged the development of modern small-scale industries with flexible labour regimes. These possibilities have renewed the interest in the informal sector and its role in the economy during this era of liberalization.

The importance of unorganized sector is also determined by the performance of the organized sector. It is often argued that in the backdrop of decline in growth of employment in the organized manufacturing sector, the unorganized manufacturing sector can act as a shock absorber so as to improve the growth of employment. Based on the findings of the present study, it can be concluded that the economic policies introduced during the 1990s have affected the manufacturing sector to a large extent. During the reforms period, there has been a fall in productivity in the organized manufacturing sector. On the other hand, the unorganized manufacturing sector employed its resources more productively as compared to its organized counterpart during the reforms period. It is possible that the steadily increasing labour force and declining employment elasticity in the organized industrial sector especially after the introduction of reforms might have generated more interest on the informal sector activities. Another suggestion is that the increased growth of the unorganized sector in recent years was an outcome of a substantial increase in outsourcing by the organized sector (Ramaswamy 1999). Kalirajan and Bhide (2005) argued that increase in outsourcing during the reforms period was a response

to the rigid labour policies prevalent in the country, which restricts a firm's ability to downsize the workforce as to increased demand.

4.6 Summary and Conclusions

The performance of the industrial sector in India and the selected states from various levels of development has undergone noticeable changes during the reforms period. There has been a decline in productivity growth in the organized manufacturing sector in India and the selected states during the said period, indicating reforms and productivity growth did not move in tandem. Erosion in productivity growth in the organized sector can be primarily attributed to inefficient allocation of resources and to some extent due to failure of sustaining technical change during the said period. In contrast, the unorganized manufacturing sector that provides employment to about 80% of the total employment in the manufacturing sector has witnessed improvement in TFPG during the reforms period compared to pre-reforms period. This can be primarily attributed to a substantial improvement in technological change which outweighed the decline in efficiency change. With limits to acquire and have access to better and newer technology, the study points to the need of raising technical efficiency levels in the sector, both organized and unorganized. The overall analysis indicates that the economy can not afford to ignore the unorganized sector and therefore, industrial policy needs to address the problems confronted by the unorganized sector.

Appendix

The measurement of capital input is the most complex of all input measurements. The conceptual problems involved in the measurement of capital input have been widely discussed by writers on productivity study. Given the theoretical reservations, there are also wide differences in the actual methodology used to build the estimates of capital stock. In other words, there is no universally accepted method for its measurement, and as a result, several methods have been employed to estimate capital stock. Among the methods used, the most widely used procedure in the Indian context is that of the 'perpetual inventory accumulation method (PIAM)' (Ahluwalia 1991; Balakrishnan and Pushpangadan 1994; Trivedi et al. 2000; Trivedi 2004). This study also used the PIAM for generating the series on capital stock.

The relationship between gross fixed capital stock in year T , denoted by K_T , the benchmark capital stock, K_0 , and the gross investment series, (I_t) , can be written as:

$$K_T = K_0 + \sum_{t=1}^T I_t \quad (4.3)$$

the gross investment in year t is obtained using the following equation:

$$I_t = (B_t - B_{t-1} + D_t) / R_t \quad (4.4)$$

where 'B' denotes the book value of fixed capital, 'D' is the depreciation, and 'R' is an appropriate deflator for fixed capital. The study used the wholesale price index of machines and machine tools published by the CSO to deflate fixed capital. The base of this index series has been converted to 1981–1982 year to retain the consistency of single base year for all the price indices.

To provide further details of the capital stock measurement, the net fixed capital stock for the registered manufacturing sector for 1981–1982 taken from the National Account Statistics (CSO 1991) is considered as the benchmark capital stock. This is multiplied by a gross-net factor ratio to get an estimate of gross fixed capital stock for the year 1981–1982. We have calculated the ratio of gross to net fixed capital stock from the ASI for the year 1981–1982 and the same is applied in the CSO net fixed capital stock estimate. To arrive at the fixed capital stock for the selected states, the proportion of capital stock for each state obtained from the ASI fixed capital has been applied to the CSO data on the fixed capital stock. Though we recognize that the assumption of proportionality that has been assumed in the present context is not easy to compare with the reality, any other method of constructing capital stock series for the states would have also involved some rules of thumb in the absence of suitable data.

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Part II

Performance in Financial Sector

Chapter 5

Technical Efficiency of Banks in Southeast Asia

E. Dogan and D.K. Fausten

5.1 Introduction

National financial systems, and banking sectors in particular, assume increasing importance and fluidity with the progress of economic development and the increase in economic openness. This notwithstanding, attempts to measure and formally monitor the performance of the banking sector have largely been confined to western developed economies. As a result, little concrete empirical information and evidence is available about banking productivity and efficiency in non-western countries. Accordingly, the aim of the present investigation is to start filling the gap left by non-industrialized countries in the empirical literature of efficiency studies of banking.

The paper examines the evolution and the contemporary state of bank efficiency in major developing economies of Southeast Asia – Indonesia, Malaysia, Philippines, and Thailand – over the period 2001–2005. During this period, the banking sectors of the sampled countries were involved in a process of restructuring that was often guided or even mandated by the respective governments. For example, the Indonesian government pursued a policy of consolidation, reducing the number of licensed banks by more than 40% (from 238 in 1997 to 134 by the end of 2004) during the sampled period. In Malaysia, the number of banks was reduced by 31%, from 36 in 1997 to 25 in 2004. In the Philippines, consolidation reduced the number of banks from 52 to 44, and in Thailand, from 16 to 12 during the period 1997–2004 (Gosh 2006, pp. 63–65). At the same time, an increase in cross-border mergers, i.e., mergers involving foreign firms, exposed the domestic banking sectors to greater competition from abroad (Deloitte-Touche 2005).

Consolidation does not necessarily improve efficiency in banking. For industrialised countries, there is no robust evidence of large value or efficiency gains from bank M&As (Pilloff and Santomero 1998; Dymksi 2002). Most cost X-efficiency

E. Dogan
School of Business, Monash University, Malaysia

D.K. Fausten
Department of Economics, Monash University, VIC, Australia

studies of M&As completed by US banks during the 1980s find little or no improvement (Berger et al. 1999). This assessment is reinforced by more recent investigations (Peristiani 1997, DeYoung 1997, Rhoades 1998). However, Houston et al. (2001) find evidence of improvement in operating performance of banks, while Akhavein et al. (1997) observe gains in profit X-efficiency, which they attribute to enhanced opportunities for risk diversification. Evidence from Europe (Amel et al. 2004; Lang and Welzel 1999) and Australia (Ralston et al. 2001) is consistent with these US findings.

Consolidation of banks, *ceteris paribus*, inevitably changes the competitive structure of the banking sector with potential consequences on the efficiency of operation. As banks combine, the number of players diminishes and concentration increases. One consequence of such consolidation is that the managers of the newly enlarged companies operate in a less competitive environment. This environment weakens the incentives to reduce costs and increase efficiency compared to more competitive conditions (Williams and Nguyen 2005). On the other hand, consolidation may introduce greater foreign competition into the domestic market since it involves cross-border institutions.

Changes in the governance structure of banks may also affect efficiency by increasing or reducing agency problems. For instance, changes in ownership structure resulting, for instance, from moving family-owned banks into public ownership will create different sets of agency problems that may change the overall efficiency of operation. By the same token, different forms of public ownership may affect efficiency. For example, foreign banks may be more efficient than domestic banks which, in turn, may be more efficient than state-owned banks.

The present study measures bank performance by employing Data Envelopment Analysis (DEA). The nature and robustness of the DEA results are evaluated with bootstrapping methods. To our knowledge, these methods have not been applied in the context of developing countries in Asia. Our methodology of estimating efficiency and bootstrapping is explained in the following section. Data issues are discussed in Sect. 5.3, results are presented in Sect. 5.4, and policy implications in Sect. 5.5. Section 5.6 concludes the paper.

5.2 Methodology

We follow Simar and Wilson (1998 2000a, b) in using DEA together with the bootstrapping methodology. The methodology is demonstrated by Shephard output distance functions that compare actual performance to best practice in the industry (Shephard 1970). Industry best-practice is the empirical approximation of potential optimum output to which the individual firm performance can be compared. Specifically, we estimate an efficiency indicator for each bank by measuring the distance of its location in input–output space from the best practice position. This distance can be measured as the actual relative to the optimum position (in Fig. 5.1, this distance is equal to ab/ad assuming the true technology is known).

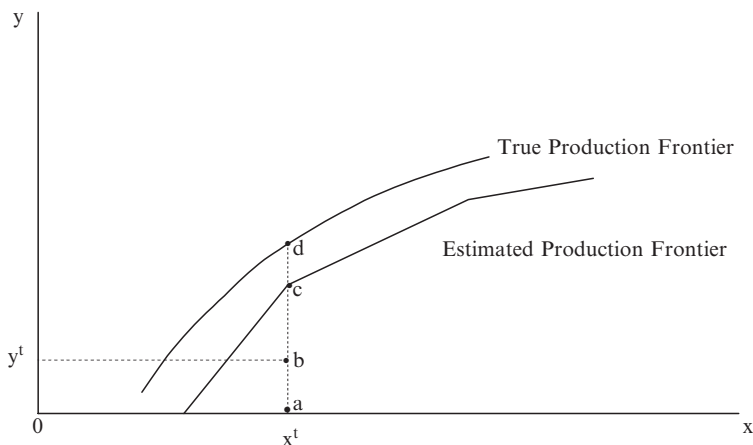


Fig. 5.1 Production frontiers

The best practice technology is represented by the frontier that envelops all current production points. This frontier is constructed by connecting the input–output combinations achieved by the best performing banks. These are most efficient in the sense of achieving the highest level of output from given quantities of inputs. With constant returns to scale (CRS), the position of the linear frontier is fixed by the highest point in the input–output space, irrespective of the bank size as measured by the quantity of inputs used. Conversely, if the returns are variable (VRS), then the frontier is constructed from the set of points representing the banks that are most efficient at different levels of operation. Banks situated below or inside the frontier are considered inefficient in the sense that they produce less than the maximum potential (best-practice) output from a given quantity of inputs indicated by the frontier. Changes in the best practice performance are attributed to technical progress that shifts the frontier outward.

To formalize these concepts¹, consider S banks producing m outputs using n inputs. Let $\mathbf{x}^{i,t} = (x_1^{i,t}, \dots, x_n^{i,t}) \in \mathfrak{R}_+^n$ and $\mathbf{y}^{i,t} = (y_1^{i,t}, \dots, y_m^{i,t}) \in \mathfrak{R}_+^m$ denote input and output vectors respectively of bank $i = 1, \dots, S$ in time period $t = 1, \dots, T$. The production possibilities set at time t is given by:

$$P = \{(\mathbf{x}, \mathbf{y}) | \mathbf{x} \text{ can produce } \mathbf{y}\}$$

The production possibilities set is assumed to be convex and closed. Output sets can also be used to describe the production possibilities set, which are defined as:

$$Y = \{\mathbf{y} | \mathbf{x} \text{ can produce } \mathbf{y}\}$$

¹ The discussion follows Coelli et al. (1998) and Bhattacharya et al. (1997).

We assume that output sets satisfy the following axioms:

1. Y is convex, closed and bounded for all $\mathbf{x} \in \mathfrak{R}^n$
2. Some inputs must be used to produce non-zero output levels
3. Both inputs and output are strongly disposable, that is, a bank can dispose its unwanted inputs or outputs without incurring any cost
4. Zero output levels are possible

The Shephard output distance function for bank i at time t can be defined as

$$D(x^{i,t}, y^{i,t}) = \inf \{ \delta^{i,t} > 0 \mid y^{i,t} / \delta^{i,t} \in Y(x^{i,t}) \}$$

Since it is not possible to observe distance functions directly, we must use approximations. Distance functions can be estimated by using Data Envelopment Analysis (DEA). We construct an intertemporal frontier for the entire observation period, instead of annual frontiers (a separate frontier for each year), which is the more common practice in the literature. The frontiers are country-specific and are constructed separately for each country. The main advantage of pooling data and constructing a single frontier for the entire period is the increase in degrees of freedom associated with the increase in the number of observations (Bhattacharya et al. 1997). Having a large number of observations is especially important since DEA estimators have slow convergence rates (Wheelock and Wilson 2003). Distance functions for bank k under the variable returns to scale (VRS) assumption can be calculated as follows:

$$\begin{aligned} [D(x^{k,t}, y^{k,t})]^{-1} &= \max_{\theta, \lambda} \theta \\ \text{s.t.} \\ \theta y_m^{k,t} &\leq \sum_{i=1}^S \sum_{t=1}^T \lambda^{i,t} y_m^{i,t}, \quad m = 1 \dots M \\ \sum_{i=1}^{S_t} \sum_{t=1}^T \lambda^{i,t} x_n^{i,t} &\leq x_n^{k,t}, \quad n = 1 \dots N \\ \lambda^{i,t} &\geq 0, \quad i = 1 \dots S, \quad t = 1 \dots T \\ \sum_{i=1}^S \sum_{t=1}^T \lambda^{i,t} &= 1 \end{aligned} \tag{5.1}$$

where t indexes the time period and λ is a column vector of intensity variables ($\lambda \in \mathfrak{R}_+^s$).

DEA is a non-parametric technique that does not require the imposition of any specific structure on the production technology (Grifell-Tatje and Lovell 1997, p. 366). At the same time, its usefulness hinges on the strong assumption that there is no random error in the data since all observed deviations from the frontier are attributed to inefficiency. Specifically, DEA does not allow for measurement errors or chance factors that could bias the calculation of efficiency indicators. Conversely, econometric methods of estimating the production frontier, such as the Stochastic

Frontier Approach (SFA), have their own structural shortcomings that potentially bias the results. They require a specific functional form (e.g. translog) and impose restrictive distributional assumptions on the joint error terms that are estimates of inefficiency and stochastic variation around the estimated frontier. These joint-distribution assumptions may not be sustained by the data.

We use the bootstrapping methods developed in Simar and Wilson (1998, 2000a, b). These methods make it possible to approximate the asymptotic distribution of DEA estimators and to construct confidence intervals. In order to use this methodology, additional assumptions must be made. These include: Observations come from “independent draws from a probability density function with bounded support over the production set...This density is strictly positive for all points along the frontier...Starting from any point along the frontier the density is continuous in any direction toward the interior of the production set” (Gilbert et al. 2004, p.2179). These assumptions together with the assumptions about the production set given earlier define the data generating process. The bootstrap algorithm can be summarized as follows (Simar and Wilson 1998; Ray and Desli 2004):

1. Estimate the output oriented efficiency for each bank, $\hat{D}(x^{i,t}, y^{i,t})$, by using the linear programming problem given in (5.1).
2. Generate a random sample of the original size from $\hat{D}(x^{i,t}, y^{i,t})$ by using the smooth bootstrap. Denote these by $D^*(x^{i,t}, y^{i,t})$.
3. Construct a pseudo-dataset by using the original efficiency estimates, $\hat{D}(x^{i,t}, y^{i,t})$ and the resampled ones, $D^*(x^{i,t}, y^{i,t})$. In the pseudo-dataset, input levels should be the same as the original ones; output levels can be calculated by $\hat{y}^{*,i,t} = D^*(x^{i,t}, y^{i,t}) \hat{D}(x^{i,t}, y^{i,t})$, where $\mathbf{y}^{i,t} = (y^{i,t}_1, \dots, y^{i,t}_m)$.
4. Calculate new efficiency scores, $\hat{D}^*(x^{i,t}, \hat{y}^{*,i,t})$, from the pseudo-dataset constructed in the previous step by using the linear programming problem given in (5.1).
5. Repeat steps 1–4 2,000 times.

One potential problem with using DEA is that the estimator may be biased. To illustrate this, refer to Fig. 5.1 again. The efficiency of the firm represented in the figure is given by ab/ad . However, an estimator must be used since the location of the true frontier is not known. Using the estimated frontier yields an efficiency estimate of ab/ac , which is higher than the true efficiency. This bias can be approximated for each bank by using the Simar and Wilson (1998, 2000a, b) methodology.² Subtracting the estimated bias value from the initial efficiency estimate yields the bias-corrected efficiency estimate. One prominent view holds that the bias-corrected estimate should

not be used if the ratio $\frac{1}{3} \times \left(\frac{(\text{Bootstrap bias estimate})^2}{\text{Sample Variance of the bootstrap estimates}} \right)$ is less than one (Simar and Wilson 2000a, p.790).

² We used FEAR (Frontier Efficiency Analysis with R) software program for all this as well as for all the subsequent calculations. See Wilson (2007) for details.

5.3 Data Issues

There are a number of alternative approaches to the specification of inputs and outputs in 'bank production'. The two most popular approaches are the production and the intermediation approaches. The activity-based production approach treats the number of accounts and transactions processed as outputs. These are produced with the application of inputs of labour and capital. The intermediation approach emphasizes the conversion by banks of loanable funds (obtained from savers) into loans and other assets. We use the intermediation approach, and estimate two alternative models. In the first model, we have total deposits, personnel expenses and fixed assets as inputs, and the nominal value of off-balance sheet items, net loans and other earning assets as outputs. Model 2 specifies a revenue focussed model with interest expense and non-interest expense as inputs, and interest income and non-interest income as outputs (Sturm and Williams 2004 and Park and Weber 2006).

Since data on quantities (number of accounts, etc.) are not available, we use reported nominal values, deflated by the GDP deflator to obtain real values. We exclude observations before 2001 because these are turbulent years of crisis and restructuring that are liable to introduce additional distortions into the data set. The data for the banks come from the Bankscope database. We use both consolidated and unconsolidated data, the latter only in those instances where banks do not provide consolidated accounts. We exclude Islamic banks from the sample as they may be operating under different conditions. Bankscope categorizes accounting data as audited, qualified, unqualified and unaudited.³ In this study, we use audited and unqualified data. We retain the banks that are in liquidation and dissolved in the sample. Pre-merger banks are also retained in the sample. All inputs and outputs that are negative and zero are discarded. All nominal values have been deflated by the relevant national GDP deflators obtained from the IMF *International Financial Statistics* database (base year is 2000). Descriptive statistics for all outputs and inputs are given Table 5.1.

Non-interest income is calculated as the difference between total operating income and net interest revenue. Non-interest expense is equal to the sum of personnel expenses, other administration expenses, other operating expenses, goodwill write-off, and other provisions (almost no bank reports data for the last two items). We retain only those banks in the sample that report positive values for personnel expenses. We do not impose this requirement to the operating expenses and other administrative expenses. Hence, the banks that report zero values on these two items have been retained in the sample.

³ Account statements are classified as qualified or unqualified depending on whether the auditors report the accounts with or without any remarks

Table 5.1 Descriptive statistics of outputs and inputs used in the study (in millions of national currency-deflated by the GDP deflator) 2001–2005

	No. of banks	Mean	Median	Standard Dev.	Min	Max
Indonesia						
OBS items	205	2,0514.9	3,032.4	46,351.5	3.1	28,8373.5
Total loans	205	60,680.6	17,459.2	10,9490.8	65.1	619,252.6
Other earning assets	205	91,704.1	11,034.3	224,797.3	302.0	1,663,772.9
Total fixed assets	205	3,203.3	313.7	6,974.6	3.2	41,577.6
Total deposits	205	139,469.3	22,313.6	291,485.5	514.1	1,732,413.0
Personnel expenses	205	2,251.7	305.0	4,870.4	32.6	29,212.4
Interest income	196	18,716.0	2,376.4	40,288.7	116.3	269,890.3
Interest expense	196	11,129.1	1,504.2	27,235.8	20.7	208,971.7
Non-interest income	196	2,383.4	367.5	5,071.6	6.9	29,669.8
Non-interest expense	196	5,159.3	876.3	9,833.6	95.4	46,437.3
Malaysia						
OBS items	118	198.5	117.5	214.6	1.3	945.2
Total loans	118	169.4	137.2	217.3	0.7	1,032.8
Other earning assets	118	88.8	60.3	111.6	2.2	560.7
Total fixed assets	118	2.3	1.5	3.2	0.0	14.6
Total deposits	118	204.2	158.1	260.4	1.9	1,290.4
Personnel expenses	118	2.0	1.5	2.5	0.0	11.7
Interest income	114	13.30	10.71	16.04	0.19	81.73
Interest expense	114	6.25	5.22	7.37	0.04	40.43
Non-interest income	114	3.13	2.17	4.30	0.04	24.62
Non-interest expense	114	4.30	3.19	5.14	0.08	24.27
Philippines						
OBS Items	49	185.7	39.3	346.4	0.3	1,430.9
Total loans	49	401.2	135.0	557.5	3.6	2,129.4
Other earning assets	49	381.6	107.8	517.9	14.1	2,042.0
Total fixed assets	49	23.5	6.5	33.5	0.1	128.7
Total deposits	49	675.9	168.4	940.1	1.2	3,415.5
Personnel expenses	49	11.9	3.2	16.0	0.3	58.2
Interest income	44	60.1	26.0	75.8	3.3	292.6
Interest expense	44	27.2	12.5	34.6	1.3	148.0
Non-interest income	44	18.3	5.1	24.7	0.4	83.7
Non-interest expense	44	32.4	11.0	40.9	1.4	148.3
Thailand						
OBS items	75	1,813.0	633.1	2,840.6	0.2	17,593.1
Total loans	75	2,341.9	1,125.4	2,291.2	67.6	7,647.3
Other earning assets	75	1,089.9	368.8	1,361.5	26.0	5,008.4
Total fixed assets	75	189.9	150.4	178.9	0.4	707.0
Total deposits	75	3,250.0	2,070.9	3,281.1	57.2	11,327.4
Personnel expenses	75	27.2	13.6	27.0	0.3	92.1
Interest income	71	1,57.8	1,41.3	147.9	1.6	510.3
Interest expense	71	66.6	53.4	66.1	0.3	291.9
Non-interest income	71	39.9	21.7	43.2	0.3	187.4
Non-interest expense	71	74.4	35.9	73.2	0.9	259.5

Table 5.2 Summary statistics for efficiency estimates: Indonesia, Model 1

	Year	Numb. of Banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency estimates	2001	42	0.73	0.72	0.043	0.37	1.00
Bias	2001	42	0.11	0.07	0.011	0.03	0.42
Bias-corrected Eff.	2001	42	0.63	0.63	0.024	0.33	0.90
2002							
Efficiency estimates	2002	41	0.75	0.78	0.035	0.38	1.00
Bias	2002	41	0.09	0.07	0.008	0.03	0.41
Bias-corrected Eff.	2002	41	0.66	0.68	0.023	0.34	0.90
2003							
Efficiency estimates	2003	39	0.78	0.82	0.035	0.39	1.00
Bias	2003	39	0.09	0.07	0.004	0.02	0.36
Bias-corrected Eff.	2003	39	0.69	0.70	0.024	0.36	0.91
2004							
Efficiency estimates	2004	43	0.80	0.84	0.037	0.40	1.00
Bias	2004	43	0.11	0.07	0.009	0.03	0.41
Bias-corrected Eff.	2004	43	0.69	0.70	0.022	0.38	0.93
2005							
Efficiency estimates	2005	40	0.81	0.87	0.037	0.41	1.00
Bias	2005	40	0.14	0.09	0.012	0.02	0.40
Bias-corrected Eff.	2005	40	0.67	0.72	0.018	0.38	0.93
2001–2005							
Efficiency estimates	2001–2005	205	0.78	0.81	0.038	0.37	1.00
Bias	2001–2005	205	0.11	0.07	0.009	0.02	0.42
Bias-corrected Eff.	2001–2005	205	0.67	0.68	0.023	0.33	0.93

5.4 Results

We report the summary statistics for the original and the bias-corrected efficiency estimates in Tables 5.2–5.9. However, our discussion refers to the *original* estimates because for many of the bias-corrected estimates, the ratio given in Sect. 5.2 was less than one.

The results for Indonesia (Tables 5.2 and 5.3) show that mean efficiency increased from 0.73 in model 1 (0.57 in model 2)⁴ in 2001 to 0.78 (0.62) in 2005. At the same time, there is a 16% (25%) decrease in the dispersion of estimates as indicated by the comparison of the end-of-period with the start-of-period variances. A look at what happens at the individual bank level indicates that the proportion of the efficient banks has increased from 19% (14%) to 33% (7%) over the period. In model 1, the year-on-year change in mean efficiency slows down by the end of the

⁴Throughout this section estimates reported in brackets are the ones estimated by using model 2.

Table 5.3 Summary statistics for efficiency estimates: Indonesia, Model 2

	Year	Numb. of banks	Median	Mean	Variance	Min.	Max.
2001							
Efficiency estimates	2001	38	0.57	0.51	0.07	0.212	1.00
Bias	2001	38	0.13	0.06	0.03	0.013	0.90
Bias-corrected Eff.	2001	38	0.44	0.41	0.04	0.099	0.83
2002							
Efficiency estimates	2002	37	0.58	0.54	0.06	0.245	1.00
Bias	2002	37	0.13	0.06	0.04	0.021	0.99
Bias-corrected Eff.	2002	37	0.45	0.44	0.04	0.007	0.79
2003							
Efficiency estimates	2003	38	0.61	0.58	0.06	0.225	1.00
Bias	2003	38	0.11	0.05	0.02	0.029	0.72
Bias-corrected Eff.	2003	38	0.50	0.52	0.03	0.186	0.76
2004							
Efficiency estimates	2004	43	0.65	0.67	0.06	0.283	1.00
Bias	2004	43	0.16	0.07	0.04	0.021	1.00
Bias-corrected Eff.	2004	43	0.49	0.52	0.03	0.003	0.88
2005							
Efficiency estimates	2005	40	0.62	0.68	0.05	0.249	1.00
Bias	2005	40	0.12	0.06	0.03	0.019	0.99
Bias-corrected Eff.	2005	40	0.50	0.57	0.03	0.008	0.80
2001–2005							
Efficiency estimates	2001–2005	196	0.61	0.60	0.06	0.212	1.00
Bias	2001–2005	196	0.13	0.06	0.03	0.013	1.00
Bias-corrected Eff.	2001–2005	196	0.48	0.49	0.03	0.003	0.88

period with the rate of increase gradually dropping from 3.12% in 2002 to 1.38% in 2005. Model 2 results indicate an annual decrease in efficiency in 2005.

Identifying the timing of the best practice during the observation period provides an alternative means to determine whether or not efficiency has improved at the end of the period. If the best practice banks are observed in the last year or two, one can conclude that efficiency has improved during the observation period. Out of the 42 (26) best practice banks, i.e., banks with an efficiency estimate equal to 1, 23 (10) observations occurred in the last 2 years.

In Malaysia, the results from model 1 (Table 5.4) indicate that mean efficiency increased by 9.34% from 0.88 to 0.96 over the period. The mean efficiency has been increasing at a rate in excess of 2.7% before it levelled off to 0.2% in 2005. The Model 2 results (Tables 5.5) indicate that mean efficiency decreased by 4.5% from 0.88 to 0.84 over the period, with decreases in each year except 2002. The variance is 49% (16%) lower in 2005 than in 2001. There are 40 (19) banks on the frontier, of which 24 (7) come from the last 2 years.

As can be seen from Tables 5.6 and 5.7, there are too few banks in the first 3 years of the period to allow a meaningful interpretation of the results for the

Table 5.4 Summary statistics for efficiency estimates: Malaysia, Model 1

	Year	Numb. of Banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency estimates	2001	24	0.88	0.90	0.008	0.70	1.00
Bias	2001	24	0.03	0.03	0.000	0.02	0.08
Bias-corrected Eff.	2001	24	0.85	0.87	0.007	0.67	0.96
2002							
Efficiency estimates	2002	25	0.90	0.89	0.006	0.78	1.00
Bias	2002	25	0.04	0.03	0.001	0.02	0.09
Bias-corrected Eff.	2002	25	0.86	0.86	0.003	0.76	0.96
2003							
Efficiency estimates	2003	24	0.94	0.95	0.004	0.78	1.00
Bias	2003	24	0.04	0.04	0.000	0.02	0.10
Bias-corrected Eff.	2003	24	0.89	0.90	0.003	0.76	0.96
2004							
Efficiency estimates	2004	22	0.96	0.99	0.003	0.82	1.00
Bias	2004	22	0.05	0.04	0.001	0.02	0.10
Bias-corrected Eff.	2004	22	0.91	0.92	0.001	0.81	0.96
2005							
Efficiency estimates	2005	23	0.96	1.00	0.004	0.80	1.00
Bias	2005	23	0.06	0.07	0.001	0.02	0.10
Bias-corrected Eff.	2005	23	0.90	0.91	0.002	0.78	0.96
2001–2005							
Efficiency Estimates	2001–2005	118	0.93	0.95	0.006	0.70	1.00
Bias	2001–2005	118	0.05	0.04	0.001	0.02	0.10
Bias-corrected Eff.	2001–2005	118	0.88	0.91	0.004	0.67	0.96

Philippines. Hence, we focus on the last 2 years.⁵ In model 1, the mean efficiency was 0.93 in 2004 and 2005, while in model 2, the mean efficiency was 0.90 in 2005, which had increased by 3.82% from its 2004 level. The number of efficient banks estimated by model 1 was 8 in both 2004 and 2005, which is roughly half of the banks. The corresponding figures in model 2 are 8 and 7.

In Thailand, the mean efficiency increased from 0.85 (0.74) in 2001 to 0.95 (0.89) in 2005. In model 1 (Table 5.8), slight annual decreases in mean efficiency occurred in 2002 and 2004, and increases of 5% or more in the other years. In model 2 (Table 5.9), mean efficiency increased in each year. The end-of-period variability is lower compared to its value in the beginning of the period for both models. Out of the 20 (19) banks on the frontier, 9 (12) are from the last 2 years.

⁵The low number of observations is due to changes in the reporting standards from local to international in 2004, which required us to discard the data for the majority of the banks that kept their books by using the local standards. We left the data for the few banks that had been reporting their accounts by using international standards throughout in the sample.

Table 5.5 Summary statistics for efficiency estimates: Malaysia, Model 2

	Year	Numb. of Banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency Estimates	2001	23	0.88	0.91	0.017	0.55	1.00
Bias	2001	23	0.04	0.03	0.002	0.01	0.18
Bias-corrected Eff.	2001	23	0.83	0.87	0.014	0.53	0.97
2002							
Efficiency estimates	2002	24	0.88	0.91	0.013	0.61	1.00
Bias	2002	24	0.05	0.03	0.002	0.02	0.19
Bias-corrected Eff.	2002	24	0.84	0.86	0.011	0.58	0.96
2003							
Efficiency Estimates	2003	22	0.88	0.89	0.013	0.59	1.00
Bias	2003	22	0.04	0.04	0.001	0.02	0.12
Bias-corrected Eff.	2003	22	0.83	0.87	0.012	0.55	0.96
2004							
Efficiency Estimates	2004	22	0.86	0.86	0.011	0.67	1.00
Bias	2004	22	0.05	0.03	0.001	0.01	0.18
Bias-corrected Eff.	2004	22	0.81	0.84	0.008	0.65	0.94
2005							
Efficiency estimates	2005	23	0.84	0.85	0.014	0.63	1.00
Bias	2005	23	0.05	0.03	0.002	0.02	0.18
Bias-corrected Eff.	2005	23	0.79	0.82	0.009	0.60	0.95
2001–2005							
Efficiency estimates	2001–2005	114	0.87	0.89	0.014	0.55	1.00
Bias	2001–2005	114	0.05	0.03	0.001	0.01	0.19
Bias-corrected Eff.	2001–2005	114	0.82	0.85	0.011	0.53	0.97

The correction for bias has involved large changes in efficiency for some of the observations that were initially on the frontier. For instance, in 2004, the efficiency of Bank Mandiri, an Indonesian bank, decreased from 1 to 0.53 after correction for bias.

The confidence intervals⁶ for many observations overlap. The efficiency differences between the banks whose confidence intervals overlap are not statistically significant. For example, the bias-corrected efficiency for Malayan Banking Berhad (Malaysia) in model 1 in 2005 is 0.9125 (95%, CI: 0.8333 – 0.9969, $n = 118$), and for United Overseas Bank (Malaysia) is 0.9463 (95%, CI: 0.905 – 0.9976, $n = 118$). The bias-corrected efficiency estimates suggest that the former bank is less efficient than the latter bank. The confidence intervals, however, suggest that there may not be a difference. This is an issue for the other countries as well.

⁶ We used FEAR's percentile option to construct confidence intervals, which is described in Simar and Wilson (2000a) in detail.

Table 5.6 Summary statistics for efficiency estimates: Philippines, Model 1

	Year	Numb. of banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency estimates	2001	3	0.98	0.99	0.001	0.94	1.00
Bias	2001	3	0.05	0.04	0.000	0.04	0.06
Bias-corrected Eff.	2001	3	0.93	0.94	0.001	0.90	0.95
2002							
Efficiency estimates	2002	7	0.93	0.95	0.007	0.79	1.00
Bias	2002	7	0.06	0.04	0.001	0.03	0.11
Bias-corrected Eff.	2002	7	0.87	0.90	0.004	0.76	0.93
2003							
Efficiency estimates	2003	7	0.94	1.00	0.006	0.83	1.00
Bias	2003	7	0.06	0.04	0.001	0.03	0.09
Bias-corrected Eff.	2003	7	0.89	0.91	0.004	0.80	0.96
2004							
Efficiency estimates	2004	17	0.92	0.98	0.011	0.73	1.00
Bias	2004	17	0.06	0.04	0.001	0.03	0.11
Bias-corrected Eff.	2004	17	0.86	0.90	0.007	0.70	0.94
2005							
Efficiency estimates	2005	15	0.93	1.00	0.012	0.70	1.00
Bias	2005	15	0.06	0.05	0.001	0.03	0.11
Bias-corrected Eff.	2005	15	0.87	0.90	0.008	0.67	0.97
2001–2005							
Efficiency estimates	2001–2005	49	0.93	0.99	0.009	0.70	1.00
Bias	2001–2005	49	0.06	0.04	0.001	0.03	0.11
Bias-corrected Eff.	2001–2005	49	0.87	0.90	0.006	0.67	0.97

5.5 Policy Implications

A period of restructuring involving nationalization, re-privatization, re-capitalization, and foreign bank entry, should cause efficiency to increase gradually over the period. Although mean efficiency has increased in our sampled countries by the end of the period, it is still rather low, especially in Indonesia. This means that banks have considerable potential to increase their output without using more inputs.

Loans are one of the bank outputs, which offer scope for improvement. Various observers have noted that bank lending has fallen after the crisis. Insufficient loan demand from the corporate sector combined with increasing risk averseness of banks may account for this decline (Gosh 2006). Risk averseness can be alleviated by taking steps to facilitate information collection, which would help with adverse selection and moral hazard problems, and also with improving corporate governance in the banking as well as in the corporate sector. Corporate governance has improved in the sampled countries after the crisis but much remains to be done according to the latest reports. Further improvements in the legal and regulatory framework, enforcement and supervision, accounting and auditing practices are required.

Table 5.7 Summary statistics for efficiency estimates: Philippines, Model 2

	Year	Numb. of banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency estimates	2001	3	0.89	0.97	0.027	0.70	1.00
Bias	2001	3	0.04	0.04	0.001	0.02	0.07
Bias-corrected Eff.	2001	3	0.85	0.93	0.020	0.68	0.93
2002							
Efficiency estimates	2002	7	0.85	0.87	0.014	0.66	1.00
Bias	2002	7	0.04	0.03	0.001	0.02	0.12
Bias-corrected Eff.	2002	7	0.81	0.83	0.009	0.64	0.93
2003							
Efficiency estimates	2003	7	0.87	0.90	0.020	0.63	1.00
Bias	2003	7	0.04	0.04	0.000	0.02	0.06
Bias-corrected Eff.	2003	7	0.83	0.86	0.016	0.61	0.95
2004							
Efficiency estimates	2004	14	0.91	0.92	0.009	0.66	1.00
Bias	2004	14	0.05	0.03	0.001	0.02	0.10
Bias-corrected Eff.	2004	14	0.86	0.88	0.006	0.64	0.94
2005							
Efficiency estimates	2005	13	0.94	0.99	0.007	0.72	1.00
Bias	2005	13	0.06	0.04	0.001	0.02	0.13
Bias-corrected Eff.	2005	13	0.89	0.90	0.005	0.70	0.97
2001–2005							
Efficiency estimates	2001–2005	44	0.90	0.93	0.012	0.63	1.00
Bias	2001–2005	44	0.05	0.03	0.001	0.02	0.13
Bias-corrected Eff.	2001–2005	44	0.86	0.88	0.008	0.61	0.97

We think that the weak competition in the banking markets of the sampled countries plays an important role in generating inefficiency. Laeven (2005) finds that the degree of competition is low in the countries included in our sample, and that it is the lowest in Thailand. The low efficiency in Thailand may be due to the existence of entry restrictions, low foreign and high state ownership (Gosh 2006). High state ownership seems to be the main problem in Indonesia. The Malaysian and Philippines banking markets are more competitive compared to Indonesia and Thailand, but there are some restrictions on foreign entry (Gosh 2006).

5.6 Conclusions

The 1997 financial crisis generated a significant “shakeout” in the financial sectors of the prominently affected Asian countries. We have exploited this “natural experiment” to examine the effects of the ensuing reorganisation and the restructuring of the national banking sectors on the efficiency of banking in the four sampled countries. Judging by the behaviour of the variances of our productivity measures, it would

Table 5.8 Summary statistics for efficiency estimates: Thailand, Model 1

	Year	Numb. of banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency estimates	2001	14	0.85	0.90	0.037	0.31	1.00
Bias	2001	14	0.04	0.03	0.001	0.01	0.11
Bias-corrected Eff.	2001	14	0.80	0.86	0.031	0.30	0.94
2002							
Efficiency estimates	2002	15	0.84	0.87	0.033	0.30	1.00
Bias	2002	15	0.04	0.03	0.001	0.01	0.15
Bias-corrected Eff.	2002	15	0.80	0.84	0.027	0.28	0.94
2003							
Efficiency estimates	2003	15	0.89	0.96	0.035	0.34	1.00
Bias	2003	15	0.06	0.06	0.002	0.01	0.15
Bias-corrected Eff.	2003	15	0.83	0.90	0.028	0.32	0.94
2004							
Efficiency estimates	2004	16	0.89	0.94	0.018	0.59	1.00
Bias	2004	16	0.05	0.04	0.002	0.02	0.16
Bias-corrected Eff.	2004	16	0.83	0.87	0.014	0.56	0.94
2005							
Efficiency estimates	2005	15	0.95	0.99	0.005	0.77	1.00
Bias	2005	15	0.08	0.04	0.005	0.02	0.22
Bias-corrected Eff.	2005	15	0.88	0.89	0.005	0.75	0.95
2001–2005							
Efficiency estimates	2001–2005	75	0.88	0.95	0.025	0.30	1.00
Bias	2001–2005	75	0.05	0.03	0.002	0.01	0.22
Bias-corrected Eff.	2001–2005	75	0.83	0.88	0.020	0.28	0.95

appear that the crisis has indeed promoted a “shakeout” in the banking sectors of Indonesia, Malaysia, and Thailand. These countries show a preponderance of reductions in the variances towards the end of the period. In the case of the Philippines, the lack of sufficient data for the early part of the observation period precludes any firm conclusions about the secular change in the performance of the banking sector over the period. We note that the variances obtained in the last 2 years have changed in opposite directions.

A second main finding is that mean efficiency in banking has generally improved in the sampled countries over the observation period. Concretely, both specifications consistently show that the mean banking efficiency in Indonesia and Thailand is higher at the end of the period. In Malaysia, the asset based model indicates an increase in mean banking efficiency while the income based model indicates a decrease. The mean efficiency in Philippine banking has been improving during the last 2 years. At the same time, there is little evidence that the efficiency differences among the banks are statistically significant.

Another interesting finding is that banks appear to be less efficient in generating loans than in generating income. Our present investigation does not enable us to

Table 5.9 Summary statistics for efficiency estimates: Thailand, Model 2

	Year	Numb. of banks	Mean	Median	Variance	Min.	Max.
2001							
Efficiency estimates	2001	13	0.74	0.70	0.033	0.46	1.00
Bias	2001	13	0.05	0.04	0.003	0.02	0.22
Bias-corrected Eff.	2001	13	0.68	0.66	0.025	0.44	0.89
2002							
Efficiency estimates	2002	14	0.79	0.78	0.019	0.51	1.00
Bias	2002	14	0.05	0.05	0.001	0.03	0.12
Bias-corrected Eff.	2002	14	0.74	0.73	0.015	0.47	0.89
2003							
Efficiency estimates	2003	14	0.87	0.89	0.015	0.65	1.00
Bias	2003	14	0.07	0.07	0.001	0.02	0.13
Bias-corrected Eff.	2003	14	0.80	0.82	0.011	0.61	0.93
2004							
Efficiency estimates	2004	15	0.88	0.89	0.014	0.67	1.00
Bias	2004	15	0.09	0.07	0.004	0.03	0.24
Bias-corrected Eff.	2004	15	0.79	0.79	0.008	0.62	0.93
2005							
Efficiency estimates	2005	15	0.89	0.93	0.015	0.69	1.00
Bias	2005	15	0.08	0.07	0.002	0.03	0.16
Bias-corrected Eff.	2005	15	0.81	0.84	0.009	0.63	0.94
2001–2005							
Efficiency estimates	2001–2005	71	0.84	0.86	0.021	0.46	1.00
Bias	2001–2005	71	0.07	0.05	0.002	0.02	0.24
Bias-corrected Eff.	2001–2005	71	0.77	0.79	0.015	0.44	0.94

identify a satisfactory reason for this difference. A careful analysis of the regulatory framework within which banks in these countries operate may shed some light on this distinguishing feature.

An important subsidiary issue is the question of the determinants of technical efficiency. The regression methodology outlined in Simar and Wilson (2003) could be used to explore this issue. Another useful extension of the present work would be to pool data across all the sampled countries and to construct a common frontier, which would allow comparisons of efficiency across different institutional and regulatory environments.

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Chapter 6

The Effect of Asset Composition Strategy on Venture Capital Firm Efficiency: An Application of Data Envelopment Analysis

E.J. Jeon, J.-D. Lee, and Y.-H. Kim

6.1 Introduction

The Korean government has driven the venture capital market since KTB Network was created in 1981 to provide capital to the high tech firms. Due to the venture policy, the venture capital market has undergone a compressed growth in a short period of time. In 1986, the government enacted the “Small and Medium Business Start-up Support Act” and “Finance Act to Support New Technology Businesses” to provide legal bases to establish venture capital (VC) firms. The government pushed the VC firms to carry out equity investments on small and medium businesses within the age of 7 years. Hence, the Korea Development Bank Capital and TG Venture, the archetypes of today’s VC firms, have been established to finance high tech firms such as Medison, Mirae, and Sambo Computer (Lee 2003). In spite of the efforts made by the government, until the mid-1990s, there were problems in constructing the venture capital market, due to poor system to finance technology and lack of policy measures to support the high tech firms. There was no exit system to liquidize the equity investments, and most of the investment targets were from mature industries which brought low returns. Further debt financing was preferred to equity investment because of the low risk and high interest rate.

In 1996, the object-oriented economy started growing since the internet rapidly spread out in the entire nation. The Kim Dae Jung Government (1998–2003) enacted the “Special Act to Foster High Tech Firms” in 1997 to overcome the financial crisis (1997–1998) by promoting market efficiency, industrial restructuring, research and development, and job creations. This in effect induced enormous number of start-ups of high tech firms. The KOSDAQ boomed and there was a tremendous growth in the information technology industry and the venture capital market in 1999. The venture policy took a dominant role in creating the venture capital market during the introduction stage in 1981–1986 and market formation

E.J. Jean, J.-D. Lee, and Y.-H. Kim
Technology Management, Economics, and Policy Program, Seoul National University,
Seoul, South Korea

stage in 1986–1995. During and after the financial crisis (1996–2000), the venture policy induced the rapid growth of the venture capital market.

However, the success of the venture policy was only temporary and backfired by inducing high tech firms to devote their resources on rent seeking rather than R&D investment. Moral hazard problems such as, illegal lobbying, window dressing, solicitation to the media for advertisement, and cozy relations between politics and business permeated the venture business society (Ji 2006). When the market crashed due to the dot com crises and the venture gates, the government decided to continuously provide public funds to the venture capital market and focused to amend the fundamentals by increasing transparency and improving the exit system.

The Korean government has been successful in creating a venture capital market and substantially financing the equity gaps. However, the venture capital market settled in an anomalous form with the characteristic of low risk and low return. Park (1997) showed that during 1994–1996, VC firms had lower return on equity than the local banks and lease companies. Kwak (2001) figured that during 1991–1998, the VC firms, compared to the market portfolio and the stock beneficiary certificates, focused on low risk investments and produced relatively low returns. Chung and Ryou (2004) compared the performances of venture capital funds of Korea to those of the United States and suggested that the Korean venture capital had relatively low-risk and low-return.

The questions are continuously raised whether the venture policy induced effective financing to the equity gaps and bore successful high tech firms. Obviously, high tech firms were directly financed by government loans and the problem of screening and monitoring of these firms has been overlooked. Specifically, the venture policy failed to notice the important role of the VC firms as ‘risk controllers’ and ‘high tech firm managers’. Even though the VC firm is the key solution to the innate problems of information asymmetry, uncertainty, and moral hazard, it has not been the interest of the venture policy. To answer the question of why the venture capital market is showing the characteristics of low risk and low return and why there are so few successful high tech firms, the role of the VC firm in attaining the venture policy goal should be studied. This study investigates the asset composition strategies with which the VC firms raise their operating efficiency, and whether these profit maximizing strategies are meeting the policy demands of maximizing the social benefit. The purpose of this study is to figure out the efficiency maximizing strategies of the VC firms in respect to asset composition and configure them with the venture policy in Korea.

This is the first paper to study the *efficiency* of the VC firms in Korea and to focus on the features of asset composition strategies. Not only is the data envelopment analysis (DEA) applied on the venture capital, but also the strategic variations causing such results are analyzed. Furthermore, whether the efficient VC firms are fulfilling the social expectations are examined. In summation, two research questions are raised: How should a VC firm compose its investment assets to raise its operating efficiency? Are the strategies of the efficient VC firms fulfilling the social expectations?

Studying the *efficiency* of the VC firms has two implications. First, the absolute measures of performance such as, revenue, profit, level of investment have

limitations because they only express one dimension of the object in analysis. Also, the management index, which is a comparative measure of performance, such as the return on equity and return on asset is limited to the analysis of one output over one input. These simple measures cannot evaluate multiple conditions and ignores relationships. Thus, the traditional measures of performance are limited in explaining the complex nature of the VC firms in the real world. On the other hand, the performance of using multiple inputs and producing multiple outputs can be quantified by using DEA and the complicated nature of the VC firm is well reflected in the derived technical efficiency. Second, DEA which was used to derive the 'efficiency' is a powerful benchmarking tool. DEA sorts out the efficient firms from the inefficient firms. Comparing these two groups of firms provides some insight regarding formulating strategies and deriving policy implications.

This paper is organized as follows. Chapter 2 presents the literature reviewed and the hypotheses proposed. In Chap. 3, methodologies are presented while in Chap. 4, the data and the variables are presented. In Chap. 5, the effect of asset composition strategies on operating efficiency is estimated and analyzed. In Chap. 6, the estimation results are reviewed and policy implications addressed.

6.2 Strategies of Venture Capital Firms

Many studies suggest that firm performance is affected by strategy (Wernerfelt 1984; Teece et al. 1997; Boeker 1997; Zahra et al. 2000; Canals 2000). According to the resource-based theory (Tobin 1958; Stinchcombe 1965; Timmons and Sapienza 1992; Teece et al. 1997) resources play a vital role in strategy formulation. In particular, among these resources, financial resource is the critical strategic dimension sought by VC firms (Robinson 1987). Two strategic dimensions of the VC firms are studied in this paper: (1) stage of investment and (2) investment horizon.

Much scholarly work has been done on the strategic behavior of the VC firms according to the different focus on stages of investments (Gorman and Sahlman 1989; Gupta and Sapienza 1992; Rosenstein et al. 1990; Carter and Auken 1994). Different from the early-stage investments, VC firms are motivated to focus their investments on late-stage because it requires less risk and yields moderate return. Timmons and Sapienza (1992) suggested that the VC firms shift their investment capital to later stages because the high tech firms require less general partner's assistance. Gifford (1997) theoretically proved that given a choice among ventures of varying maturity, but equal compensation, the general partner will choose the more mature ventures if time is a binding constraint.

As spelled out in the law, the Korean VC firms have a limited role in participating as board members and providing managerial assistance to the high tech firms. Thus, the venture capital firms are not able to control and manage the risk that occurs in early-stage investments. As there are high costs to pay for taking risky investments, expectations on high risk investments are lower than low risk investments. As shown in Fig. 6.1, the Korean VC firms have been changing their investment

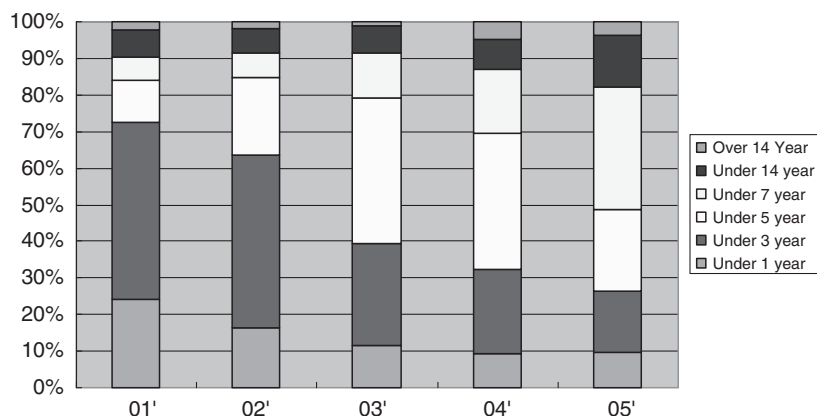


Fig. 6.1 Investment rate of venture capital on high tech firms by age

focus from early-stage to late-stage since the year 2001 and it can be presumed that the return may have decreased continuously.

Therefore, the following hypotheses can be formulated.

Hypothesis 1: Venture capital firms that focus on early-stage investment tend to have lower efficiency than the late-stage focused firms.

Investment horizon is one of the key factors that affect the asset performance. In spite of the scarce literature on VC firms' strategy formulation regarding investment horizon, empirical evidence suggests that VC firms tend to aim for short-term profit than the long-term. As the length of the investment horizon increases, it becomes increasingly difficult for venture capital investors to maintain high rates of return (Petty et al. 1994). This is because, as high tech firms become more seasoned, the required rate of return falls to reflect the lower risk and the greater prospect of liquidity.

Some insights could be generated by looking at the VC firms' focus of investment on certain industries. Figure 6.2 shows the investment focus of the VC firms in various industries. Since the Korean VC firms focuses on the short-term investments such as, information technology (IT), entertainment, and manufacturing, the long-term investments such as the biotechnology (BT) and environmental technology (ET) are neglected. This may be because the government has not been successful in bridging the return gap between the short-term and the long-term investments.

Hypothesis 2: Venture capital firms that aim for short-term profit have higher efficiencies than the ones with long-term objective.

The hypotheses can be briefly reviewed by using Fig. 6.3. The investment asset of a VC firm is composed of current assets, venture capital assets, and operation assets. Hypothesis one can be tested by comparing the effect of current assets and the non-current assets. Hypothesis two can be tested by comparing the effect of venture capital assets and operation assets.

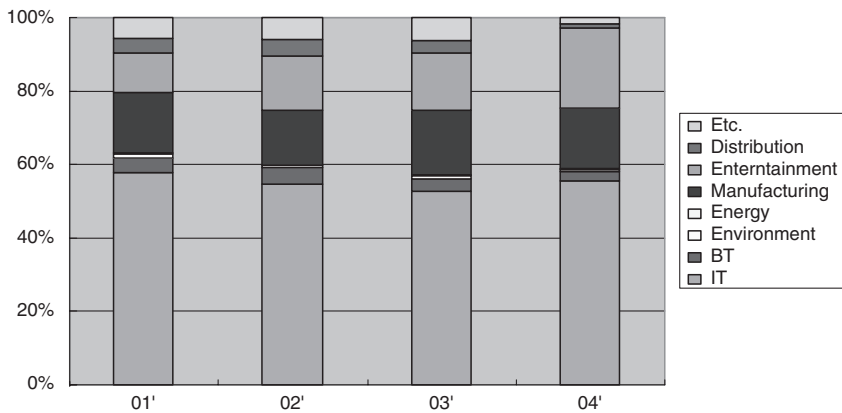


Fig. 6.2 Investment rate of venture capital by industry

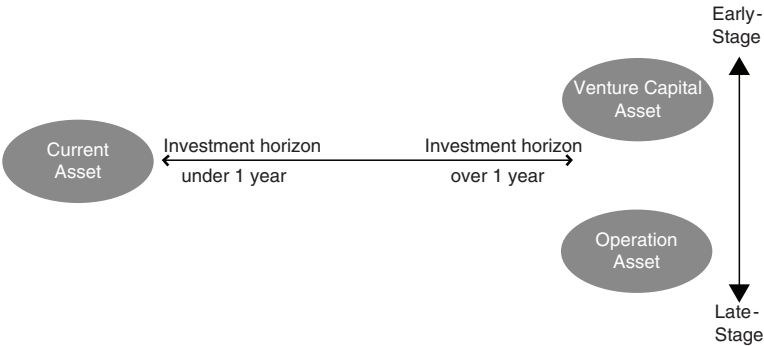


Fig. 6.3 Asset composition strategy and hypotheses testing

6.3 Methodology

6.3.1 Research Design

While the venture capital organizations in the United States are mainly in the form of limited liability partnership, the Korean VC firms are mainly stock companies (Lee et al. 2003). Thus, the analysis on the Korean VC firm should take a different approach. There are two ways of raising capital, that is, by using total assets-equity and debt, and by using venture capital fund. Consequently, there are two ways to analyze the Korean venture capital, one focusing on the VC firm, and the other, focusing on the venture capital fund. In this study, efficiency is estimated based on the operating profit of the VC firm and the resulting efficiency is explained by focusing on the usage of the investment assets resulting from the total asset of the VC firm. In other words, the focus of analysis is on the “VC firm.”

Two steps are followed in the analysis. First, the operating efficiency of each VC firm is measured by using DEA. This study estimates the efficiency of firms by using output oriented multiple variables DEA which assumes a variable returns to scale. Second, the independent sample t-test is used to compare the efficient VC firms to the inefficient firms, and Tobit model is used to analyze the strategic factors affecting the operating efficiencies.

6.3.2 *The Output-Oriented Variable Returns to Scale Model*

The DEA model “Variable Returns to Scale (VRS)” proposed by Banker et al. (1984) is used in this study in estimating the technical efficiency. In the venture capital market, the decision making units (DMUs), that is, the VC firms, are given a fixed quantity of resources from the investors and are asked to produce as much output as possible. As the venture capitalists have most control over the output rather than the input by means of incentives, strategies, and shareholder influences, output-oriented VRS is adopted.

The output-oriented VRS model is specified as follows:

$$\begin{aligned}
 \max_{\theta, \lambda} \quad & \theta \\
 \text{s.t.} \quad & -\theta y_i + Y\lambda \geq 0 \\
 & x_i + X\lambda \geq 0 \\
 & N'\lambda = 1 \\
 & \lambda \geq 0, \text{ where } 1 \leq \theta < \infty
 \end{aligned} \tag{6.1}$$

$\theta - 1$ is the proportional increase in outputs that could be achieved by the i -th DMU, with input quantities held constant.

6.3.3 *The Fixed Effects Panel Tobit Model*

As the fixed effects model is always consistent in panel estimation, and the result of the Hausman test rejected the null hypothesis that the coefficients estimated by the efficient random effects estimator are consistent, the fixed effects model was adopted. However, since the efficiency score, which is the dependent variable, is censored at the upper limit of one, the fixed effects Tobit model was applied. In this study, the efficient venture capital firms have latent technical efficiency of greater than or equal to one, while the inefficient VC firms have below one.

The fixed effects panel Tobit model can be formulated as follows:

$$\begin{aligned}
TE_{it}^* &= \alpha_i + x_{it}'\beta + u_{it} \\
\text{where } u &\sim N(0, \sigma^2) \\
TE_{it}^* &= 1 \quad \text{if } TE_{it}^* \geq 1 \\
TE_{it} &= TE_{it}^* \quad \text{if } TE_{it}^* < 1
\end{aligned} \tag{6.2}$$

The fixed effects model is estimated by maximum likelihood and assumes individual VC firm effects, α_i . The likelihood function of the above standard tobit model is as follows:

$$L = \prod_0 \left[1 - \Phi \left(\frac{x_{it}'\beta}{\sigma} \right) \right] \prod_1 \sigma^{-1} \phi \left[\frac{(TE_{it} - \alpha_i - x_{it}'\beta)}{\sigma} \right] \tag{6.3}$$

where Φ and ϕ are the distribution and density function, respectively, of the standard normal variable.

6.4 The Data and Variables

Data were based on the VC firms' balance sheet, income statement, and statement of cash flows that were obtained from the Financial Supervisory Commission. Approximately 100–140 VC firms were examined during each period from the year 2000 to 2005. A total of 810 observations in the form of an unbalanced panel data were analyzed. The asset compositions were obtained from the balance sheet while the operating revenue and cost were obtained from the income statement.

Super-efficiency of the decision making units were measured to detect outliers that has been contaminated with noise. Approximately 10–15% of the outliers which had super-efficiency values much greater than one were removed and the efficiency of the remaining observations re-estimated. As a result, a normal distribution of the VRS efficiency was obtained. (See Banker and Gifford 1988 for the specific procedures). In case the key variables had zero values, it was excluded from the analysis to prevent the distortion of the DEA results by producing extremely high efficiency score or inefficient values.

The primary purpose of this study is to investigate the effect of financial asset composition on operating efficiency. The empirical model is constructed by the dependent variable, efficiency derived from DEA and the independent variables, strategic asset composition of the venture capital firms.

6.4.1 The Dependent Variable

From the viewpoint of banks, the DEA literature is reviewed because it has been extensively studied in the past decades and it will shed some light in applying the methodology in the new area of VC firms in Korea.

It is commonly acknowledged that the choice of variables in efficiency studies significantly affects the results because the variable selection is often constrained by the paucity of data on relevant variables. The cost and output measurements in banking are especially difficult because many of the financial services are jointly produced and prices are typically assigned to a bundle of financial services (Frexias and Rochet 1997). The most commonly presented approaches to bank production can be summarized under the following three headings: the production approach, the intermediation approach, and the modern approach.

Under the *production approach*, banks are viewed as *service providers* to the customers (Benston 1965). It defines physical variables such as labor, material, space, information and their associated costs as inputs, and services such as the number and type of transactions, documents processed or specialized services provided over a given time period, number of deposit and loan accounts as outputs. This approach has primarily been employed in studying the efficiency of bank branches.

Under the *intermediation approach*, banks are viewed as *intermediates of the funds between the savers and the investors*. The inputs are defined as operating and interest expenses while outputs are defined as loans and other major assets. There are wide variations according to how the deposit should be treated; asset approach (Sealy and Lindley 1997), user cost approach (Hancock 1985), and the value-added approach (Berger et al. 1987).

Under the *modern approach*, measures of risk, agency cost, and quality of bank services are integrated. The ratio-based CAMEL approach devises the financial data to measure the performance of the bank. The *operating approach* (or income-based approach) views banks as business units with the final objective of generating revenue from the total cost incurred for running the business (Leightner and Lovell 1998). Accordingly, it defines banks' output as the total revenue (interest and non-interest) and inputs as the total expenses (interest and operating expenses). Operating approach has been widely used recently. Jemric and Vujcic (2002) adopted an operating approach to measure the banking efficiency in Croatia by setting the inputs as interest and related costs, commissions for services and related costs, labor-related administrative costs, capital-related administrative costs and the outputs as interest and related revenues and non-interest revenues. Das and Ghosh (2006) measured the performance of Indian commercial banks by setting the inputs as the interest expenses, employee expenses, and capital related operating expenses and the outputs as the interest income and non-interest income.

Nevertheless, since the VC firms have similar functions as banks, that is, as financial intermediaries and service providers, the relevant DEA approaches were not appropriate in this study, because there were difficulties in obtaining the related data figures and limitations in analyzing the results. On the other hand, the VC firms in Korea can be viewed as a profit maximizing organizations pursuing greater operating efficiencies. Thus, the operating approach is adopted in this study. Operating expenses and revenues are defined as the inputs and outputs, respectively, in the DEA to calculate the operating efficiency. Specifically, inputs are defined as the selling, general and administrative expenses and costs of investment and financing, while outputs on the other hand are defined as the revenue generated from investments on venture capital funds, high tech firms, and other assets.

Most of the DEA literature has approached the problem of measuring the efficiency in the perspective of labor and capital. However, in this study, the capital structure is viewed as the main cause for the resulting operating efficiency and the efficiency itself is calculated from capital figures from the financial statement. It is assumed that the efficiency itself is caused by strategic variables of how the capital is structured and invested.

There are many constraints in estimating the efficiencies of the VC firms. The main limitation is that the VC firms invest on various kinds of assets which have different investment horizons. However, the financial statements do not reflect such specific information. This is the reason why lagging the variables were not appropriate. Instead, to check the robustness of the results, the VC firms which are older than 3 years are selected and analyzed. It is supposed that these old firms have had enough investment horizons to realize the returns and must have been reflected in the financial statements.

6.4.2 Independent Variables

The variables used in this study are defined in Table 6.1. The dependent variable is defined as the VRS efficiency derived from DEA and the independent variables are defined as the asset composition ratios and control variables.

As the VC firm is defined in law as a public tool for technology-finance to induce innovation, the asset structure is different from the general service industry. Table 6.2 shows the asset structure of a VC firm. According to the accounting standards set by the SMBA (2002), the assets of a VC firm mainly consists of current assets, venture capital assets, and fixed assets.

In generally accepted accounting principles, *current assets* are defined as those assets on the balance sheet which are expected to be sold or otherwise used up in

Table 6.1 Variable definitions

Variable	Definition
Dependent	
VRS	DEA efficiency derived by assuming variable returns to scale
Independent	
Asset composition	
Current asset ratio	Current asset divided by total asset
Venture capital investment ratio	VC investment asset divided by total asset
Management support asset ratio	Management support asset divided by total asset
Operation asset ratio	Operation asset divided by total asset
Current to non-current asset ratio	Current asset divided by non-current asset
Cash outflow from operation to investment ratio	$\frac{\text{Cash outflow from operation}}{\text{Cash outflow from investment}}$
Controls	
Age	Number of months since start-up
Year	Time dummy indicating the year from 2000 to 2005

Table 6.2 Asset structure of venture capital firm

I. Current assets	
II. Venture capital assets	
(1) Venture investment assets	Stock, convertible bond, project investment, venture capital fund, public fund
(2) Management support assets	Committed investment, loan, overseas investment, small and medium business investment
III. Fixed assets	
(1) Operation assets	
(2) Tangible assets	

the near future, usually within 1 year, or one business cycle – whichever is longer. Typical current assets include cash, cash equivalents, accounts receivable, inventory, the portion of prepaid accounts which will be used within a year, and short-term investments.

Venture capital assets are the investments and subsidies carried out on entrepreneurs and high tech firms. Venture capital assets are basically composed of venture capital investment assets and management support assets. *Venture capital investment assets* are the actual investment results approved by the investment companies' regulations and this consists of stock, convertible bond, project investment, fund disbursement, and public disbursement. *Management support assets* are defined as the venture capital assets which are not included in the venture capital investment assets. Management support assets are composed of committed stock, start-up loan, overseas investment, and small and medium business investment.

Fixed assets consist of operation assets and tangible assets. *Operation assets* are defined as investments that have not been committed to the venture capital assets. Thus, operation assets are mainly focused on late-stage investments targeting high tech firms over 7 years old. *Tangible assets* are assets that have a physical form such as machinery, buildings and land.

6.4.2.1 Early-Stage Investments Vs. Late-Stage Investments

- Comparison of VC investment asset ratio with operation asset ratio

The literature has long suggested that the younger a business is, the more tenuous is its viability. Stinchcombe's (1965) proposition regarding the "liability of newness" has been upheld in several empirical studies. Philips and Kirchhoff (1988) reported that the probability of a new venture's survival was quite low in the first 4 years. Gupta and Sapienza (1992) suggested some key reasons why early-stage ventures tend to be riskier investments than late-stage ventures: fewer resolved demand uncertainties, technological uncertainties (in both product and process design), resource uncertainties (in areas such as availability of skilled personnel, raw materials, and channels of distribution), and management uncertainties (in areas such as the leadership capabilities of the founder, compatibility and balance within the top management team, etc.) The venture capital investment assets ratio has been defined

as the variable to represent the degree of investment on early-stage and operation assets ratio has been set to represent the degree of investment on late-stage.

- Cash outflow from operation to investment ratio

To check the robustness of the result on the previous variable, the ratio of cash outflow from operation to cash outflow from investment is devised as the proxy to represent the proportion of early-stage investments to late-stage investments. According to the accounting standards for the VC firms set by the SMBA (2002), the cash flow from operation is generated from the investment activities of the venture capital assets and the cash flow from investment is generated from the investment activities of the operation assets. As the venture capital assets focuses on early-stage investments and the operation assets focuses on late-stage investments, the ratio of the two figures imply the ratio of early-stage investments to late-stage investments. This is an opposite proxy of the previously devised venture capital investment ratio.

6.4.2.2 Short-Term Investments Vs. Long-Term Investments

- Current asset ratio

Current assets are defined as the assets managed to obtain profit within 1 year. It represents the degree of investment on pursuing short-term profit.

- Current to non-current asset ratio

To check the robustness of the results on the previous variable, another proxy variable representing the degree of short-term investments has been defined. This may be a more detailed measure compared to previously defined variable, the current asset ratio, because direct comparison of the current assets with the non-current assets is possible.

6.4.2.3 Controls

- Age

Age of the VC firm was estimated from its start-up date and counted by months. This variable controls the experience of the VC firms.

- Size

Size was represented by the total assets. Size was controlled in the econometric equation by dividing the major asset composition variables with total assets.

- Year

The Korean venture capital market has undergone the venture boom (1999–2000) and cooling (after the year 2000). Thus, taking in the yearly effect would raise the accuracy of the estimation.

6.5 Empirical Analysis Results

6.5.1 Compared Groups Analysis

Independent samples t-test was used to carry out the compared group analysis. Levine's test for equality of variances is rejected when the F-test is significant. See Table 6.3 for the comparison between the efficient frontier ($VRS = 1$) and the non-efficient firms ($VRS < 1$). Even though the results are not statistically significant, the sign of the mean difference may shed some light into the differences between the two groups. It can be conjectured that whereas the efficient firms tend to possess smaller venture capital investment assets and management support assets, they also tend to possess greater current assets and operation assets. It is likely that the results were statistically insignificant because there were other various factors affecting the two groups.

6.5.2 Tobit Estimation

The operating efficiency of the VC firm is mainly caused by the firm's strategic alternatives in respect to asset composition. In particular, four asset composition variables – current assets, venture capital investment assets, management support assets, and operation assets—are devised, controls are defined by age, and year is defined as dummy variables. Size is defined by dividing each asset by total assets. Age is a proxy for experience, total asset a proxy for size, and year is a proxy for the trend effects. The equation is defined as:

$$VRS_{it}^* = \alpha_0 + \alpha_{1it}Current + \alpha_{2it}VentureCapital + \alpha_{3it}ManageSupport + \alpha_{4it}Operation + \alpha_{5it}Age + \alpha_{6it}Year + u_{it} \quad (6.4)$$

On omitting all the firms with zero values from the unbalanced panel data set, 361 observations were left. Table 6.4 shows the descriptive statistics.

Table 6.3 Independent samples t-test efficient frontier vs. non-efficient

	Assumption of variances	t-value	p-value	Mean difference	Std. error difference
Current asset ratio	Inequality	0.9946	0.3272	0.0839	0.0844
VC investment asset ratio	Equality	-0.9335	0.3511	-0.1093	0.1171
Management support asset ratio	Equality	-0.0087	0.9930	-0.0002	0.0249
Operation asset ratio	Inequality	0.9159	0.3669	0.0581	0.0635

Significant at 10 (5,1) % confidence level

Table 6.4 Descriptive statistics (all samples)

	No.	Mean	Std. Dev.	Minimum	Maximum
Current asset ratio	361	0.24	0.19	0.003	0.93
Venture capital investment asset ratio	361	0.45	0.25	1.08E – 11	0.99
Management support asset ratio	361	0.07	0.12	1.25E – 11	0.69
Operation asset ratio	361	0.08	0.12	8.90E–12	0.93
Current to non-current asset ratio	361	0.55	1.29	0.003	12.49
Cash outflow from operation to investment ratio	361	2.30E + 07	3.17E + 08	9.27E–11	5.27E + 09
Age	361	85.38	64.99	2	228

Table 6.5 Correlation coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) VRS	1.00	0.14	–0.04	0.01	0.10	0.03	–0.08	0.10
(2) Current asset ratio	0.14	1.00	0.45	0.15	0.17	0.38	0.02	–0.08
(3) VC investment asset ratio	–0.04	0.45	1.00	0.38	–0.02	0.10	0.01	–0.15
(4) Management support asset ratio	0.01	0.15	0.38	1.00	0.02	–0.07	0.04	0.06
(5) Operation asset ratio	0.10	0.17	–0.02	0.02	1.00	0.13	–0.03	0.03
(6) Current to non-current asset ratio	0.03	0.38	0.10	–0.07	0.13	1.00	0.00	–0.03
(7) Cash outflow from operation to investment ratio	–0.08	0.02	0.01	0.04	–0.03	0.00	1.00	0.01
(8) Age	0.10	–0.08	–0.15	0.06	0.03	–0.03	0.01	1.00

Although the average value of the current asset ratio is low at 0.24, there exist VC firms that have the current asset ratio up to 0.93 and these cannot be distinguished from the general financial institutions.

The mean of the venture capital investment asset ratio is approximately 0.45 which indicates as the law spells out, the VC firms operates the venture capital investment asset up to 50%. Further, the statistics show a wide variation with a minimum of 1.08E–11 to a maximum of 0.99. Compared to the other asset ratios, venture capital investment asset ratio has the largest standard deviation of 0.25. It is obvious that there are large variations among the VC firms, from risk-averse VC firms to risk-loving ones in respect to venture capital investment asset ratio.

The VC firms have a mean age of 85 months, which indicates that the Korean venture capital market is in its early-stage since its formation. In spite of its youth, the venture capital market has its dynamic feature because there are a wide variety of firms from the ones which just entered the market with the age of 2 months to the ones that have been in the market with the age of 228 months.

Table 6.5 shows the correlation coefficients of the variables. The result verifies that there is no problem of multi-collinearity among the variables. From the correlation coefficients, it can be predicted that the technical efficiency of the VC firm may

Table 6.6 Fixed effects tobit estimation on VC firm efficiency (all sample)

	I	II	III	IV
Log current asset ratio	0.035** (0.018)	0.039** (0.019)		
Log current to non-current asset ratio			0.025* (0.014)	0.032** (0.015)
Log VC investment asset ratio	-0.017*** (0.004)	-0.022*** (0.004)	-0.018*** (0.004)	-0.022*** (0.004)
Log management support asset ratio	0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)
Log operation asset ratio	0.007*** (0.002)	0.004** (0.002)		
Log cash outflow from operation to investment ratio			-0.014** (0.006)	-0.020*** (0.007)
Log age	0.016 (0.022)		0.022 (0.022)	
Year 2001	-0.327*** (0.076)		-0.321*** (0.076)	
Year 2002	-0.574*** (0.081)		-0.539*** (0.081)	
Year 2003	-0.511*** (0.080)		-0.462*** (0.079)	
Year 2004	-0.491*** (0.081)		-0.438*** (0.080)	
Year 2005	-0.276*** (0.082)		-0.234*** (0.082)	
Log likelihood	-348.75	-362.77	-350.50	-362.33
No. of observations	361	361	361	361

*(**, ***) Significant at 10 (5,1) % confidence level

increase in line with the current asset ratio, operation asset ratio, and age while on the other hand, decrease in line with the venture capital investment asset ratio.

Four different models were estimated by using fixed effects censored panel Tobit model. The results are presented in Table 6.6. Model III and IV include the substitute variables for the current asset ratio and operation asset ratio. The limits of the efficiency scores in the censored Tobit model were defined from 0 to 1. The independent variables are logged for the sake of clear explanation. This implies that one percentage change in the independent variable will cause the dependent variable to change by one hundredth of the estimated coefficients.

The estimation results are consistent among the different model settings. Current asset ratio was positively significant, venture capital investment asset ratio was negatively significant, and the operational asset ratio was positively significant, and all year effects were negatively significant.

Taking only the significant results from all models, the average effect of the variables on raising the operating efficiencies are as follows. On average, increasing 1% of the current asset ratio resulted in raising the efficiency by 0.00037, while

increasing 1% of the venture capital investment asset ratio resulted in decreasing the efficiency by 0.00019. 1% increase in operational asset ratio contributed to raising the efficiency by 0.00005.

Several implications are conveyed from these results. First, short-term investments raise the efficiency of the VC firms in larger degree than the long-term investments. 1% increase in current asset ratio caused the efficiency to rise seven times more than the case of increasing 1% of current to non-current asset ratio, which raised the efficiency by 0.00028. This supports the previous analysis that the VC firms focusing on short-term investments had greater efficiencies than those focusing on long-term investments.

Second, the early-stage investments via the venture capital investment assets tend to decrease the operating efficiencies. This result is interesting because investment focused on early-stage is what makes the VC firm a VC firm. This implies that the VC firms are far from showing the innate investment behavior of taking high-risk and earning high-return. Rather, the VC firms that take high risks are likely to show lower operating efficiencies. On the other hand, the late-stage focused asset tends to increase the operating efficiencies. Efficient VC firms tend to find profit from rather on late-stage investments than on early-stage investments.

There may be questions of whether the previous analysis is reliable because the young VC firms have been included in the analysis and these firms may not have had enough time to reap returns. To check the robustness of the previous estimation result, estimation on the VC firms older than 3 years was carried out. These firms had enough investment periods to achieve modest returns. The total observation were 259 and Table 6.7 shows the descriptive statistics.

The descriptive statistics are similar to the descriptive statistics of the all sampled firms. The results can be interpreted as follows.

First, there exist VC firms with large current asset ratio up to 0.93 and these firms cannot be differentiated from the general financial institutions. Second, older age did not affect the wide variation of risk-taking behaviors in respect to venture capital investment ratios. It had the largest standard deviation of 0.25 among the variables. There were risk-averse firms with the minimum venture capital investment ratio of 1.08E-11 to risk-loving firms with the maximum ratio of 0.99. It can be noticed that the venture capital investment ratio is highly maintained due to the

Table 6.7 Descriptive statistics (older than 3 year sample)

	No.	Mean	Std. Dev.	Minimum	Maximum
Current asset ratio	259	0.23	0.19	0.005	0.93
Venture capital investment ratio	259	0.43	0.25	1.08E-11	0.99
Management support asset ratio	259	0.08	0.13	1.25E-11	0.69
Operation asset ratio	259	0.09	0.11	8.90E-12	0.70
Current to non-current asset ratio	259	0.58	1.47	0.005	12.49
Cash outflow from operation to investment ratio	259	3.15E + 07	3.71E + 08	0.006	5.27E + 09
Age	259	108.98	60.63	37	228

restraints by the law. However, the VC investment asset ratio of the older than 3 years sample is smaller than those of the whole sample because VC firms gradually seek profit by investing in other assets.

The estimation results of the VC firms older than 3 years are shown in Table 6.8.

Together with the entire sampled cases, the samples including the firms older than 3 years have shown statistically significant results. Most of the findings are consistent with the previous results. While the venture capital investment ratio tends to decrease the operating efficiency, the operation asset ratio and current asset ratio tends to increase the efficiency. It can be concluded that the VC firms focusing on early-stage investments have lower efficiencies than those focusing on late-stage investments. Also, the results from model II and IV concludes that the VC firms aiming for short-term profit tend to have greater efficiencies than those pursuing long-term profit. Based on the previous estimation results and empirical analysis, both hypotheses one and two are accepted.

Table 6.8 Fixed effects Tobit estimation on VC firm efficiency (older than 3 years)

	I	II	III	IV
Log current asset ratio	0.013 (0.016)	0.033** (0.017)		
Log current to non-current asset ratio			0.012 0.012	0.025** (0.012)
Log venture capital asset ratio	-0.005* (0.003)	-0.011*** (0.003)	-0.006* (0.003)	-0.011*** (0.003)
Log management support asset ratio	-0.001 (0.002)	0.002 (0.002)	-0.00005 (0.002)	0.003 (0.002)
Log operation asset ratio	0.004** (0.002)	0.003* (0.002)		
Log cash outflow from operation to investment ratio		-0.012**	-0.016*** (0.005)	(0.006)
Log age	0.038 (0.028)		0.037 (0.028)	
Year 2001	-0.216*** (0.072)		-0.232*** (0.071)	
Year 2002	-0.470*** (0.070)		-0.465*** (0.070)	
Year 2003	-0.375*** (0.065)		-0.361*** (0.065)	
Year 2004	-0.383*** (0.064)		-0.363*** (0.064)	
Year 2005	-0.263*** (0.067)		-0.250*** (0.067)	
Log likelihood	0.943	-26.923	1.099	-24.585
No. of observations	259	259	259	259

* (**, ***) Significant at 10 (5,1) % confidence level

6.6 Conclusion

VC firms that tend to focus on early-stage investments and long-term investments show relatively low efficiency than the firms focusing on late-stage investments and short-term investments. This may not be a problem to the VC firms themselves because their goal of profit maximization is achieved anyway.

However, in the perspective of technology policy, this result is gloomy because the efficient VC firms are taking exactly opposite strategies from the social expectation. The VC firms are neither showing the characteristics of 'high risk and high efficiency' nor meeting the policy demand of maximizing the social benefit. The VC firms are supposed to finance high tech firms with relatively low marginal cost of capital, sort out the potentially successful ones by screening, and add value on them by monitoring. The problem can be summed up in two dimensions – difficulty in inducing risky venture capitals and VC firms themselves being inefficient in managing capitals, especially those focused on early-stage and long-term investments.

The venture capital market in Korea has been created by inducing the cash from the loan market to the venture investments. The underground capital has been transformed in to technology capital empowered by the law. These capitals originally had their focus on short-term investments and late-stage investments as money lenders. The policy failure of financing high tech firms with the objective of inducing investments on early-stage high tech firms and pursuing long-term profit was rooted from its creation. And this paper has confirmed the failure of technology-finance policy via VC firms.

Additionally, several policy implications are suggested. First, the legal institution should be spelled out to provide VC firms with incentives to specialize in early-stage and long-term investments. Current legal system prevents the VC firms from managing the basic problems of uncertainty, information asymmetry, and moral hazard with regard to financing high tech firms. If the VC firms are provided with the necessary bells and whistles, the supportive legal institutions which allow them to fully functional as VC firms by enabling them to carry out effective functions of screening and monitoring, their operating efficiencies with regard to early-stage and long-term investments may be raised. Thus, to maximize the social benefit, the VC firms which specializes in early-stage and long-term investments and raises substantial profit via such investments should be brought up by supportive legal institution.

Second, public capital should be provided to support the VC firms to concentrate their assets on early-stage and long-term investments. The VC firms were not able to accumulate appropriate knowledge and experience in screening and monitoring, especially in the areas of early-stage and long-term investments, due to lack of substantial capital providers such as the government. In case of the United States, the pool of money managed by VC firms grew dramatically over the past 20 years as pension funds became active investors, following the U.S. Department of Labor's clarification of the "prudent man" rule in 1979. In fact, pension funds became the single largest supplier of new funds and during 1990–2002, pension funds supplied

about 44% of all new capital (OECD 2006). Likewise, the Korean venture capital market may need a public investor to provide risky venture capitals. Public capital should be provided to support investment activities on early-stage investments and long-term profit making.

There are several limitations in this study. First, although the results convey the nature of VC firms in Korea, the data obtained from the Financial Supervisory Service maybe imperfect. The Korean accounting standards leave VC firms a room for misreporting and “window dressing.” Furthermore, the supervisory capacity of the Audit Institution is in question to prevent those practices. In particular, venture capitals have more tricks to inflate capital figures, manipulate book profits, etc. In this aspect, capital inflows and outflows from the statement of cash flow may be used to make a better estimation on the VC firm efficiencies.

Second, one of the significant factors affecting the operating efficiency, the human factor, has been excluded from the analysis due to difficulties of obtaining such data. Further studies are recommended to include the quality of human resources in to the econometric equation.

Third, venture capital fund is a significant part of the venture capital market. Although it is a separate entity from the VC firm, it explains approximately 50% of the profit generated and thus, it should not be omitted when studying the venture capital in Korea.

This paper focused on examining the effects of different asset compositions on the VC firms’ efficiency. The methodologies and ideas may be applied to the studies on venture capital funds and private equity.

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Chapter 7

Post Crisis Non-Bank Financial Institutions Productivity Change: Efficiency Increase or Technological Progress?

F. Sufian and M.-Z. Abdul Majid

7.1 Introduction

Non-Bank Financial Institutions (NBFIs) play an important dual role in a financial system. Traditionally, NBFIs comprise of a mixed bag of institutions that includes all financial institutions not classified as commercial banks. They complement the role of commercial banks, filling in financial intermediation gaps by offering a range of products and services that they offered. Nevertheless, they also compete with commercial banks, forcing the latter to be more efficient and responsive to their customers needs. Most NBFIs are also actively involved in the securities markets and in the mobilization and allocation of long-term financial resources. The state of development of NBFIs is usually a good indicator to the state of development of a country's financial system as a whole.

Given the substantial task of the NBFIs, it is worth raising the issue of its role. In particular, since Gerschenkron (1962) classic study emphasizing the role of the banking systems in the economic development of Germany, France and Italy in the nineteenth century, it may appear that the need for NBFIs is largely redundant in the specific circumstances of the developing economies. There are two main reasons why the existence of NBFIs is important; one reason concerns the economic development and the other reason relates to financial stability. As NBFIs are established to avoid tight prudential controls applicable to banks, they play a prominent role in financial system failures. Increased competition from NBFIs could also result in banks increasing their lending volumes, by lowering their lending standards to maintain market shares. This may result in a rapid lending growth, which could indirectly result in a financial crisis.

The importance of investigating the efficiency and productivity of the Malaysian NBFIs could be best justified by the fact that in Malaysia, the NBFIs play important roles in complementing the facilities offered by the commercial banks and are the

F. Sufian

CIMB Bank Berhad, Universiti Putra Malaysia, Kuala Lumpur, Malaysia

M.-Z. Abdul Majid

Monetary and Financial Policy Department, Central Bank of Malaysia, Kuala Lumpur, Malaysia

key players in the development of the capital markets in Malaysia. The existence of Banking Financial Institutions (BFIs) and NBFIs, supported by efficient money and capital markets, keeps the financial sector complete while enhancing the overall growth of the economy. Although Malaysia is moving towards a full market based economy, its capital markets are still at its infancy. As sophisticated and well-developed capital markets are considered as the hallmark for a market-based economy worldwide, a study of this nature is particularly important since the health and development of the capital market rely largely on the performance of the NBFIs. Hence, efficient and productive NBFIs are expected to enhance the Malaysian capital markets in its pursuit to move towards a full market based economy.

The main motivation for this study is the Malaysia's Financial Sector Master Plan (FSMP), a long-term development plan charting the future direction of the financial services industry in Malaysia to achieve a more competitive, resilient and efficient financial system (see Bank Negara Malaysia Financial Sector Master Plan 2001). Among the measures outlined in the plan is further liberalization of the banking sector, ahead of the opening of the financial sector to foreign competitions in 2007. Despite the progress in financial liberalization that was pursued during the 1990s, which saw the banking sector expanding at a rapid pace, earlier findings have suggested that the management of Malaysia commercial banks were inefficient (Okuda and Hashimoto 2004). This study thus attempts to highlight the effectiveness of microeconomic reforms introduced by the Malaysian government to enhance the competitiveness of the Malaysian financial services industry.

The present study will also be the first to investigate the sources of productivity of the NBFIs in a developing economy. Despite the significance of the NBFI sector towards economic development, studies that attempt to investigate this issue are relatively scarce. While there has been an extensive literature examining the productivity and efficiency of banking industries in various countries over the years, empirical work on NBFIs productivity and efficiency is still in its infancy.¹ To the best of our knowledge, there has been no microeconomic study performed in this area of research with respect to the NBFI sector. This study will also consider both productivity growth at the frontier and the spread of the productivity levels, as well as the diffusion of technology across the NBFI sector in a developing economy.

In effect, the paper addresses three important issues relating to the productivity of the Malaysian non-bank financial institutions sector. First, what does the data suggest regarding the convergence of productivity of the Malaysian NBFIs resulting from the increased competition brought by the further liberalization of the banking sector? Second, does NBFIs capital position impinge upon productivity? Third, does productivity vary across specialization patterns? The paper also examines how sources of productivity changes differ among the 'peer groups'. Furthermore, the

¹Berger and Humphrey (1997) surveyed 130 studies that apply frontier efficiency analysis to investigate the efficiency of financial institutions in 21 countries. They report that the majority of these studies are confined to the US banking sector and calls for the need to examine the efficiency of financial institutions outside the US.

Table 7.1 The structure of the Malaysian banking system

	1997			2004		
	Number of institutions	Share in total assets (%)	As a ratio of GDP	Number of institutions	Share in total assets (%)	As a ratio of GDP
Domestic commercial banks	22	55.6	1.34	10	66.1	1.28
Foreign commercial banks	13	15.3	0.37	13	21.1	0.41
Finance companies	16	22.5	0.54	6	7.8	0.15
Merchant banks	12	6.5	0.16	10	4.9	0.09
Total	63	100	2.40	39	100	1.94

Source: Bank Negara Malaysia

paper explores the proximate sources of productivity under both univariate and multivariate framework, and relates the findings to the ongoing liberalization undertaken within the Malaysian banking sector.

By applying the non-parametric Malmquist Productivity Index (MPI) methodology, we attempt to investigate the sources of productivity change of the Malaysian NBFIs during the post crisis period of 2001–2004. The preferred methodology allows us to isolate efforts to catch up to the frontier (efficiency change) from shifts in the frontier (technological change). In addition, the Malmquist index enables us to explore the main sources of efficiency change; either improvements in management practices (pure technical efficiency change) or improvements towards optimal size (scale efficiency change). Furthermore, a multivariate regression technique is employed to investigate possible correlations between the balance sheet and income statement information, as well as the macroeconomic data and the measures of NBFIs performance. A series of parametric and non-parametric tests are also performed to examine whether the merchant banks and finance companies share identical production technology (frontier).

This paper is organized as follows: The following section will provide a brief overview of the Malaysian financial system. Section 7.3 reviews the main literature. Section 7.4 outlines the approaches to the measurement and estimation of productivity change. Section 7.5 discusses the results and finally Section 7.6 concludes.

7.2 An Overview of the Malaysian Financial System

In Malaysia, as in other developing economies, the banking system plays an important role in the economy by channeling funds from those who have excess funds to those who have productive needs for those funds. Unlike in other developed nations where financial markets, as well as the banking system work in unison to channel those funds, in developing countries, however, financial markets are undersized and sometimes completely absent. The banks are therefore supposed to bridge the gap

between savers and borrowers, and perform all the tasks associated with the profitable and secure channeling of funds.

The Malaysian financial system can broadly be divided into Banking Financial Institutions (BFI) and Non-Bank Financial Intermediaries (NBFIs). These two banking institutions are different with respect to their activities. For a well functioning financial market along with the BFIs, NBFIs have an important role to uplift economic activity. These two financial sectors can simultaneously build up and strengthen the country's financial system. The banking system is the largest component, accounting for approximately 70% of the total assets of the financial system. The Malaysian BFIs can further be divided into three main groups, namely commercial banks, finance companies and merchant banks.

The commercial banks are the main players in the banking system. They are the largest and most significant providers of funds in the banking system. As at end-2004, there were ten domestically incorporated and 13 locally incorporated foreign commercial banks in Malaysia. There were ten domestically incorporated finance companies in Malaysia as at end-2004, forming the second largest group of deposit taking institutions. Traditionally, finance companies specialize in consumption credit, comprising mainly hire purchase financing, leasing, housing loans, block discounting, and secured personal loans. The finance companies are allowed to accept savings and fixed deposits from the public, but are prohibited from providing current account facilities. They are also not allowed to engage in foreign exchange transactions compared to their commercial banks counterparts. During the later part of the last decade, the finance companies began to broaden its traditional retail-financing role, to include the wholesale banking.

Table 7.2 Assets of the financial system 1960–2004

Year	Commercial banks		Finance companies		Merchant banks	
	RM million	As a ratio of GDP	RM million	As a ratio of GDP	RM million	As a ratio of GDP
1960	1,231.9	0.21	NA	NA	NA	NA
1970	4,460.2	0.38	531.0	0.05	19.6 ^a	0.002
1980	32,186.1	0.63	5,635.4	0.13	2,228.7	0.05
1990	129,284.9	1.23	39,448.0	0.50	11,063.2	0.14
1995	295,460.0	1.77	91,892.0	0.55	27,062.0	0.16
1996	360,126.8	1.98	119,768.8	0.65	34,072.8	0.19
1997	480,248.1	2.46	152,386.8	0.77	44,300.0	0.23
1998	453,492.0	2.52	123,596.9	0.68	39,227.8	0.22
1999	482,738.3	2.50	116,438.0	0.60	39,184.0	0.20
2000	512,714.7	2.44	109,409.8	0.52	36,876.0	0.18
2001	529,735.5	2.51	121,811.1	0.58	41,025.2	0.19
2002	563,254.1	2.56	130,520.0	0.59	41,415.5	0.19
2003	629,975.3	2.71	141,911.0	0.61	44,103.6	0.19
2004	761,254.8	3.05	68,421.1	0.27	42,691.0	0.17

Source: Bank Negara Malaysia

^aAs at end 1971

The Merchant banks emerged in the Malaysian banking scene in 1970, marking an important milestone in the development of the financial system alongside the country's corporate development. As the country's small businesses prospered and grew into large corporations, the banking needs of the nation became larger and more sophisticated, requiring more bulk financing and complex banking services. The Merchant banks filled the need for such services by complementing the facilities offered by the commercial banks, which were at times more focused on providing short-term credit for working capital and trade financing. They play a role in the short-term money market and capital raising activities, such as financing, syndicating, corporate financing, providing management advisory services, arranging for the issue and listing of new shares as well as managing investment portfolio. As at end-2004, there were ten merchant banks in Malaysia, which were all domestically controlled institutions.

The Malaysian financial system's assets and liabilities continued to be highly concentrated at the commercial banking sector with total assets and liabilities amounting to RM761,254.8 billion or 3.05 times the national GDP as at end 2004. Prior to the Asian financial crisis in 1997/1998, the finance companies' assets and liabilities were seen increasing from only RM531 million or 0.05 times of the national GDP in 1970 to reach a high of RM152.4 billion or 0.77 times in 1997. The ratio however has gradually declined from 0.60 times or RM123.6 billion in 1998 to 0.52 times or RM109,409.8 billion of the national GDP in 2000, before increasing again in the year 2001–2003, to reach a post crisis of 0.61 times of the national GDP in 2003 or RM141,911.0 billion. Due to further consolidation in the Malaysian financial sector, the finance companies assets as a ratio of the national GDP declined again to reach a low of 0.27 times in 2004. As for the merchant banks, a similar trend is observed where its assets and liabilities as a ratio of the national GDP have been increasing since 1971 to reach a peak of RM44.3 billion or 0.23 times the GDP in 1997 i.e. before the Asian financial crisis. During the post crisis period, the merchant banks' assets and liabilities continued to remain stable at 0.17–0.22 times of the national GDP. A combination of both the finance companies and merchant banks total assets would reveal that, the non-commercial banking sector command approximately 22.8% of the banking system's total assets and liabilities.²

7.3 Related Studies

Faced with a changing banking industry's environment, there has been a considerable amount of research performed over the last decade, to examine financial institutions productivity and efficiency, aiming at informing regulators and practitioners

²The figure is at end-2003, prior to the consolidation of finance companies into their respective commercial banking parents.

(Casu et al. 2004). The liberalization of the banking sector and the increasing number of bank failures in the 1980s and early 1990s has contributed to an increasing academic interest in the topic. However, earlier studies had concentrated mainly on the banking industry of the developed countries, while studies on the banking sector of a few of the Pacific Basin countries are conducted only in the latter part of the last decade.

Among the earlier studies on Asian banks' productivity was done by Fukuyama (1995). Fukuyama (1995) studied the nature and extent of technical efficiency and productivity growth of Japanese banks during the 1989–1991 period. He also investigated the relationship between efficiency measures, productivity indexes, organizational status, and bank size. During the early part of the studies, he found that Japanese banks' mean values of the three productivity change indexes were greater compared to the latter part, which he attributed to the collapse of the bubble in the Japanese economy. He also found that during the period of the study, productivity gains were largely due to technological change rather than technical efficiency change. On the other hand, he suggested that the major contribution to productivity losses was technical efficiency rather than technological regress.

Despite there being substantial studies on the developed economies' banking industry with regard to the efficiency and productivity of financial institutions, there are only a handful of studies performed on the Malaysian banking industry partly due to the lack of available data sources and the small sample of banks. As pointed out by Kwan (2003), the lack of research on the efficiency of Asian banks was due to the lack of publicly available data for non-publicly traded Asian financial institutions. Among the most notable researches conducted on Malaysian banks' productivity are Krishnasamy et al. (2004) and Sufian and Ibrahim (2005).

Krishnasamy et al. (2004) investigated the Malaysian banks post-merger productivity changes. Applying labor and total assets as inputs, and loans and advances and total deposits as outputs, they found that during the period of 2000–2001, post-merger Malaysian banks had achieved a total factor productivity growth of 5.1%. Moreover, they found that during the period, eight banks posted positive total productivity growth ranging from 1.3 to 19.7%, one bank exhibited total factor productivity regress of 13.3%, while another was stagnant. The merger has not resulted in better scale efficiency of the Malaysian banks as all banks exhibited scale efficiency regress with an exception of two banks. The results also suggest a rapid technological change of post-merger Malaysian banks ranging from 5.0 to 16.8%. Two banks however experienced technological regress during the period of study.

More recently, Sufian and Ibrahim (2005) applied the Malmquist Productivity Index method to investigate the extent of off-balance sheet (OBS) items in explaining the Malaysian banks total factor productivity changes. They found that the inclusion of OBS items resulted in an increase in the estimated productivity levels of all banks in the sample during the period of study. They also suggested that the impact was more pronounced on the Malaysian banks' technological change rather than the efficiency change.

7.4 Methodology

Three different indices are frequently used to evaluate technological changes: the Fisher (1922), Tornqvist (1936), and Malmquist (1953) indexes.³ According to Grifell-Tatje and Lovell (1996), the Malmquist index has three main advantages relative to the Fischer and Tornqvist indices. Firstly, it does not require the profit maximization, or the cost minimization, assumption. Secondly, it does not require information on the input and output prices. Finally, if the researcher has panel data, it allows the decomposition of productivity changes into two components (technical efficiency change or catching up, and technical change or changes in the best practice). Its main disadvantage is the necessity to compute the distance functions. However, the Data Envelopment Analysis (DEA) technique can be used to solve this problem.

Following Fare et al. (1994) among others, the output oriented Malmquist productivity change index will be adopted for this study. Output orientation refers to the emphasis on the equi-proportionate increase of outputs, within the context of a given level of input. The output based Malmquist productivity change index may be formulated as:

$$M_j^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{D_j^t(y^{t+1}, x^{t+1})}{D_j^t(y^t, x^t)} \frac{D_j^{t+1}(y^{t+1}, x^{t+1})}{D_j^{t+1}(y^t, x^t)} \right]^{1/2} \quad (7.1)$$

where M is the productivity of the most recent production point ($x_t + 1, y_t + 1$) relative to the earlier production point (x_t, y_t). D 's are output distance functions. A value greater than unity indicate a positive factor productivity growth between two periods. Following Fare et al. (1994), an equivalent way of writing this index is:

$$M_j^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{D_j^{t+1}(y^{t+1}, x^{t+1})}{D_j^t(y^t, x^t)} \times \left[\frac{D_j^t(y^{t+1}, x^{t+1})}{D_j^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_j^t(y^t, x^t)}{D_j^{t+1}(y^t, x^t)} \right]^{1/2} \quad (7.2)$$

³Malmquist Total Factor Productivity Index was not invented by Malmquist. In his paper (Malmquist 1953) he brought input functions of distance into an analysis of consumption, developing a method for the empirical measurement of standard of living. The change in living standards is defined as the ratio of two input functions of distance. Before the Malmquist paper, the input function of distance was brought into a paper by Debreu (1951), and the output function of distance was introduced by Shephard in his book (Shephard 1953). The natural development of their papers was the definition of the index of change of total factor productivity as the ratio of two input or output functions of distance. Some 31 years had to pass before it arrived. The Malmquist index of change in total factor productivity was proposed in a paper for the first time in (Caves et al. 1982). Today these indices are entitled partially oriented indices of change in total factor productivity. In the case of production technology that satisfies the constant yields axiom, the indices are the same.

or $M = TE \times TC$

$$\text{Technical Efficiency (TE)} = \frac{D_j^{t+1}(y^{t+1}, x^{t+1})}{D_j^t(y^t, x^t)} \quad (7.3)$$

Technical Change

$$(TC) = \left[\frac{D_j^t(y^{t+1}, x^{t+1})}{D_j^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_j^t(y^t, x^t)}{D_j^{t+1}(y^t, x^t)} \right]^{1/2} \quad (7.4)$$

where M is the product of a measure of technical progress TC as measured by shifts in the frontier measured at period $t + 1$ and period t and a change in efficiency TE over the same period.

In order to calculate these indices it is necessary to solve several sets of linear programming problems. We assume that there are N financial institutions each with varying amounts of K different inputs to produce M outputs. The i th financial institutions is therefore represented by the vectors x_i, y_i and the $K \times N$ input matrix X and the $M \times N$ output matrix Y represent the data of all financial institutions in the sample. The purpose is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. The calculations exploit the fact that the input distance functions, D , used to construct the Malmquist index is the reciprocals of Farrell (1957) output orientation technical efficiency measures.

The (7.5) and (7.6) are applied where the technology and the observation to be evaluated are from the same period and the solution value is less than or equal to unity. The (7.7) and (7.8) are applied where the reference technology is constructed from the data in one period, whereas the observation to be evaluated is from another period. Assuming a constant return to scale, the following output-oriented linear programming is used:

$$\begin{aligned} D_j^t[y^t, x^t]^{-1} &= \max_{\theta, \lambda} \theta \\ \text{s.t. } -y_{jt} + Y_t \lambda &\geq 0 \\ \theta x_{jt} - X_t \lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned} \quad (7.5)$$

$$\begin{aligned} D_j^{t+1}[y^{t+1}, x^{t+1}]^{-1} &= \max_{\theta, \lambda} \theta \\ \text{s.t. } -y_{j,t+1} + Y_{t+1} \lambda &\geq 0 \\ \theta x_{j,t+1} - X_{t+1} \lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned} \quad (7.6)$$

$$\begin{aligned} D_j^{t+1}[y^t, x^t]^{-1} &= \max_{\theta, \lambda} \theta \\ \text{s.t. } -y_{jt} + Y_{t+1} \lambda &\geq 0 \\ \theta x_{jt} - X_{t+1} \lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned} \quad (7.7)$$

$$\begin{aligned}
D_j'[y^{t+1}, x^{t+1}]^{-1} &= \max_{\theta, \lambda} \theta \\
\text{s.t. } -y_{jt+1} + Y_t \lambda &\geq 0 \\
\theta x_{jt+1} - X_t \lambda &\geq 0 \\
\lambda &\geq 0
\end{aligned} \tag{7.8}$$

This approach can further be extended by decomposing the constant returns to scale technical efficiency change into scale efficiency and pure technical efficiency components. This involves calculating further linear programs where the convexity constraint $N_i \lambda = 1$ is introduced to (7.5)–(7.8). It is apparent that (7.6) and (7.7) give the Farrell efficiency scores and the programming problems are the dual form of the Charnes et al. (1978) data envelopment model. Solutions to these programming models give us the efficiency scores of the j th firm in periods t and $t + 1$. By solving the equations with the same data under constant returns to scale and variable returns to scale, measures of the overall technical efficiency, TE , and the pure technical efficiency, PTE , are obtained. Hence, dividing the overall technical efficiency, TE , by pure technical efficiency yields a measure of scale efficiency, SE .

By combining these models and the Fare et al. (1994) approach, it is thus possible to provide four efficiency indices for each firm and a measure of technical progress over time. These are (a) Technical Efficiency Change (TE), (b) Technological Change (TC), (c) Pure Technical Efficiency Change (PTE), (d) Scale Efficiency Change (SECH), and (e) Total Factor Productivity Change (M). M indicates the degree of productivity change; $M > 1$ means that period $(t + 1)$ productivity is greater than period t productivity, whilst $M < 1$ indicates productivity decline and $M = 1$ corresponds to stagnation.

An assessment can be made of the sources of productivity gains or losses by comparing the values of TE and TC . If $TE > TC$, then productivity gains are largely the result of improvements in efficiency. Whereas if $TE < TC$, productivity gains are primarily the result of technological progress.

An important understanding that arises after the calculation of the Malmquist productivity indices is to attribute variations in productivity, efficiency, and technological change to NBFIs specific characteristics and the environment in which they operate. The standard method in the empirical bank studies is to estimate regression equations with pooled ordinary least squares (OLS), which assume that the omitted variables are independent of the regressors and independently identically distributed. Such estimation, however, can create problems of interpretation if bank-specific characteristics, such as bank management, that affect performance are not considered. If those omitted bank-specific variables (both observed and unobserved) correlate with the explanatory variables, then pooled OLS produces biased and inconsistent estimates (Hsiao 1986). Using panel data, however, the fixed-effect model produces unbiased and consistent estimates of the coefficients.

The fixed-effect model assumes that differences across banks reflect parametric shifts in the regression equation. Such an interpretation becomes more appropriate when the problem at hand uses the whole population, rather than a sample from it. Since the sample considers all the Malaysian NBFIs over a particular time period, the fixed-effect model is adopted in this analysis. Using the productivity and

efficiency scores as the dependent variable, we estimate the following regression models:

$$m_{it}^* = z_{it}'\beta + \varepsilon_{it}; i = 1, \dots, N \text{ and } t = 1, \dots, N \quad (7.9)$$

where m_{it}^* is the Malmquist productivity indices, z_{it}' is a $(I \times J)$ vector of explanatory variables posited to explain productivity in NBFIs, β is a vector of parameters to be estimated and $\varepsilon_{it} \sim N(0, \sigma^2)$.

7.4.1 Data, Input, and Output Definitions

For the empirical analysis, all Malaysian NBFIs from 2001 to 2004 are incorporated in the study. Due to homogeneity constraints, Malaysian Islamic banks and development financial institutions are not included in the analyzed sample. Annual data is obtained from published balance sheet information in annual reports of each individual institution. Four NBFIs were excluded from the study due to the unavailability of data resulting from mergers and acquisitions.

Variable definition is one of the most difficult tasks in financial institutions studies. There is consensus concerning the fact that NBFIs are multi-product financial institution. However, disagreement arises on what a financial institution produces and how to measure a financial institution's production. The final decision depends on the underlying concept of a financial institution, the problem at stake and the availability of information. The approach of input and output definition used in this study is a variation of the intermediation approach, which was originally developed by Sealey and Lindley (1977). The intermediation approach posits total loans as outputs, whereas deposits along with physical capital are defined as inputs. Furthermore, Berger and Humphrey (1997) stated that the intermediation approach is more suitable for studying efficiency of the entire financial institutions.

The aim in the choice of variables for this study is to provide a parsimonious model and to avoid the use of unnecessary variables that may reduce the degrees of freedom.⁴ Accordingly, we model the Malaysian NBFIs as multi-product firms, producing two outputs by employing three inputs. All variables are measured in millions of Malaysian Ringgit (RM). The input vectors include *Total Deposits* ($x1$), which include deposits from customers and other banks and *Non-Interest Expenses* ($x2$), which is inclusive of total expenditures on employees, establishment costs, marketing expenses and other administrative expenses and *Total Assets* ($x3$), while *Total Loans* ($y1$), which include loans to customers and other financial institutions is the output vector. To recognize that financial institutions in recent years have increasingly been generating income from "off-balance sheet" business and fee income generally, *Non-Interest Income* ($y2$), defined as fee income, investment

⁴For a detailed discussion on the optimal number of inputs and outputs in DEA, see Avkiran (2002).

income, and other income, is included in the study as a proxy to non-traditional activities as an output. The *Non-Interest Income* (y2) consist of commission, service charges, and fees, guarantee fees, net profit from sale of investment securities, and foreign exchange profit. The variables selected for this study could be argued to fall under the intermediation approach to modeling bank behavior.

Table 7.3 presents the summary of statistics for the outputs and inputs for the Malaysian NBFI. It is apparent that over the four-year period, total assets of the Malaysian NBFI operations grew by 32% to RM9,177 billion in 2004 from RM6,948 billion in 2001. It is also interesting to note that despite the increase in total deposits, total loans on the other hand seems to decline during the period of study. A plausible reason could be that during the period of study, the Malaysian NBFIs have focused more on the capital market activities, i.e. issuance of new shares, bonds, etc., rather than on the traditional banking activities.⁵ The view is

Table 7.3 Descriptive statistics for inputs and outputs

		2001 (RMb)	2002 (RMb)	2003 (RMb)	2004 (RMb)
Outputs					
Total loans	Min	179,370.00	136,731.00	89,774.00	136,552.00
	Mean	1,746,320.30	1,518,397.90	1,163,402.30	1,135,866.30
	Max	7,580,365.00	6,906,825.00	5,582,323.00	5,274,910.00
	SD	2,426,456.60	2,226,298.70	1,847,752.43	1,718,861.98
Non-interest income	Min	799.00	939.00	534.00	3,730.00
	Mean	63,605.25	57,418.13	69,020.44	71,603.63
	Max	350,575.00	207,255.00	313,840.00	392,518.00
	SD	93,480.63	63,768.14	97,747.24	113,478.62
Inputs					
Total deposits	Min	88,858.00	113,195.00	63,782.00	108,898.00
	Mean	1,976,341.00	2,072,613.80	3,914,141.60	2,644,559.30
	Max	6,946,428.00	6,261,464.00	19,609,194.00	5,929,859.00
	SD	2,179,905.56	2,231,923.14	6,487,009.97	2,179,372.61
Non-interest expense	Min	4,362.00	6,707.00	7,670.00	7,604.00
	Mean	86,093.25	96,291.56	111,952.38	125,261.44
	Max	281,966.00	341,767.00	424,433.00	525,775.00
	SD	83,450.79	102,361.42	118,982.19	139,451.70
Total assets	Min	506,331.00	553,523.00	662,855.00	594,538.00
	Mean	6,948,016.94	7,070,498.94	8,898,910.69	9,176,940.81
	Max	20,186,180.00	23,625,038.00	32,529,566.00	33,618,318.00
	SD	6,354,506.67	6,717,443.03	9,076,978.74	8,936,914.42

⁵ The bond market (including both public and private sector bonds) tripled in size, from 44.7% of GDP in 1996 to 80.6% of GDP as at end-June 2003. The private debt securities market accounted for 54% of bonds outstanding and 43.6% of GDP as at end-June 2003 compared to 13.5% of GDP in 1996. Funds raised by the private sector through the bond market increased to 16% of the total private sector debt financing as at end-June 2003 from 9.3% in 1996 (Bank Negara Malaysia Annual Reports, various years).

supported by the increase in non-interest income, which is mainly derived from fee income based services. From Table 7.3, it is also clear that the Malaysian NBFI non-interest expenses have increased by more than 45%, suggesting that the Malaysian NBFIs could have engaged in expense preference behavior. The intensification of competition in the Malaysian financial sector could have resulted in the merchant banks and finance companies to invest heavily in systems and equipments, e.g. up-to-date computer systems, risk management systems, etc., as well as to attain well qualified personnel to help them in staying competitive amidst the keener competition. The increasing non-interest expenses could also be due to the mega merger among the domestic financial institutions, which was completed in the year 2001. As pointed by Sufian (2004), the merger among the domestic financial institutions has resulted in the Malaysian financial sector's costs to swell, arising from systems integration, employee lay offs and branch closures.

Several NBFI's specific and macroeconomic factors may influence NBFI productivity and efficiency levels. Some of these factors may be neither inputs nor outputs in the production process, but rather circumstances faced by a particular NBFI. The independent variables used to explain the NBFI's productivity and efficiency changes are grouped under two main characteristics. The first represent firm-specific attributes, while the second encompass economic conditions during the period examined. The firm-specific variables included in the regressions are, log of total assets (*LNTA*), book value of stockholders' equity as a fraction of total assets (*EQTY*), total loans divided by total assets (*LOANS/TA*) and total overhead expenses divided by total assets (*OVERHEAD*). To distinguish between the merchant banks and finance companies operations, the *SPEC* variable is included in the regression to account for the effects of NBFI specialization. To measure the relationship between economic conditions and NBFIs productivity and efficiency, a proxy measure of economic conditions, the growth rate of the country's gross domestic product, *GDP*, is used.

The *LNTA* variable is included in the regression as a proxy of size to capture the possible cost advantages associated with size (economies of scale). In the efficiency literature, mixed relationships are found between size and efficiency, while in some cases, a U-shaped relationship is observed. *LNTA* is also used to control for cost differences related to NBFIs size and for the greater ability of larger NBFIs to diversify. In essence, *LNTA* may lead to positive effects on NBFIs productivity and efficiency if there are significant economies of scale. On the other hand, if increased diversification leads to higher risks, the variable may have negative effects.

LOANS/TA as a proxy of loans intensity is expected to affect NBFIs productivity and efficiency positively, if loans are the main source of revenue. However, the loan-performance relationship depends significantly on the expected change of the economy. During a strong economy, only a small percentage of loans will default, and the NBFIs profit will rise. On the other hand, the NBFIs could adversely be affected during a weak economy, because borrowers are likely to default on their loans. Ideally, NBFIs should capitalize on favorable economic conditions and insulate themselves during adverse conditions.

EQTY variable is included in the regressions to examine the relationship between productivity and efficiency and NBFIs capitalization. Strong capital structure is essential for NBFIs in emerging economies, since it provides additional strength to withstand financial crises and increased safety for depositors during unstable macro-economic conditions. Furthermore, lower capital ratios in banking imply higher leverage and risk, and therefore greater borrowing costs. Thus, the productivity level should be higher for the better-capitalized NBFIs.

The ratio of overhead expenses to total assets, *OVERHEAD*, is used to provide information on the variations of NBFIs operating costs. The variable represents total amount of wages and salaries, as well as the costs of running branch office facilities. The relationship between the *OVERHEAD* variable and productivity and efficiency levels may be negative, because NBFIs that are more productive and efficient should be keeping their operating costs low. Furthermore, the usage of new electronic technology, like ATMs and other automated means of delivering services, may have caused expenses on wages to fall (as capital is substituted for labor).

We do not have *a priori* expectation on the *SPEC* variable sign. The variable, which is entered into the regression as a proxy of NBFIs specialization, may have positive or negative correlation with NBFIs productivity and efficiency levels. Similarly, the *GDP* variable may have a positive or negative relationship with NBFIs productivity and efficiency levels. Favorable economic conditions are expected to result in higher demand and supply of banking services, and would possibly improve NBFIs productivity and efficiency. On the other hand, during economic downturns, NBFIs productivity, and efficiency levels could adversely be affected, resulting in a negative relationship.

7.5 Empirical Findings

In this section, we will discuss the productivity change of the Malaysian NBFIs, measured by the Malmquist Total Factor Productivity (TFPCH) Index and assign the change in total factor productivity to Technological Change (TECHCH) and Efficiency Change (EFFCH). We will also attempt to attribute any change in EFFCH to change in Pure Technical Efficiency (PEFFCH) and Scale Efficiency (SECH). The summary of annual means of TFPCH, TECHCH, EFFCH, and its decomposition into PEFFCH and SECH for the years 2001–2004 are presented in Table 7.4. The Malmquist analysis is based on a comparison of adjacent years, i.e., indices are estimated for 2001–2002, 2002–2003, and 2003–2004. Because the year 2001 is the reference year, the Malmquist TFPCH index and its components take an initial score of 1.000 for 2001. Hence, any score greater (lower) than 1.000 in subsequent years indicates an improvement (worsening) in the relevant measures. It is also worth mentioning that favorable efficiency change (EFFCH) is interpreted as evidence of “catching up” to the frontier, while favorable technological change (TECHCH) is interpreted as innovation (Cummins et al. 1999). Annual values of the indices for the industry and each NBFIs group are provided in Table 7.4.

Table 7.4 Decomposition of total factor productivity change (TFPCH) in the Malaysian NBFIs

	NBFI			Indices	
	Productivity change (TFPCH)	Technological change (TECHCH)	Efficiency change (EFFCH)	Pure technical efficiency change (PEFFCH)	Scale efficiency change (SECH)
Panel 1:					
ALL_NBFI					
2001	1.000	1.000	1.000	1.000	1.000
2002	0.993	1.045f	0.950	1.028	0.925
2003	0.961	0.943	1.019	0.993	1.026
2004	0.932	0.961	0.970	0.942	1.030
Geometric mean	0.971	0.986	0.984	0.990	0.994
Panel 2:					
MERC_BNKS					
2001	1.000	1.000	1.000	1.000	1.000
2002	0.896	0.985	0.910	1.071	0.850
2003	0.918	0.865	1.061	0.936	1.134
2004	0.828	0.917	0.903	0.904	0.999
Geometric mean	0.908	0.940	0.966	0.976	0.991
Panel 3:					
FIN_COS					
2001	1.000	1.000	1.000	1.000	1.000
2002	1.101	1.109	0.992	0.987	1.006
2003	1.007	1.028	0.979	1.054	0.929
2004	1.048	1.007	1.041	0.982	1.061
Geometric mean	1.038	1.035	1.003	1.005	0.998

Note: The mean scores of the Total Factor Productivity Change (TFPCH) index and its components, Technological Change (TECHCH) and Efficiency Change (EFFCH) that is further decomposed into Pure Technical Efficiency Change (PEFFCH) and Scale Efficiency Change (SECH), for All NBFI (ALL_NBFI) and different forms in the sample, Merchant Banks (MERC_BNKS) and Finance Companies (FIN_COS)

7.5.1 Total Factor Productivity Growth of the Malaysian NBFIs: An Analysis Based on the Levels

As depicted in Panel 1 of Table 7.4, the Malmquist results suggest that during the period 2001–2004, the Malaysian NBFI total factor productivity was on a declining trend exhibiting productivity regress during all years. The average productivity decline was 0.7% in 2002, 3.9% in 2003, and 6.8% in 2004. During the year 2002, the productivity decline of the Malaysian NBFI was mainly due to the decline in efficiency, which fell by 5.0% compared to technological change, which increased by 4.5%. However, in the latter years, it seems that the Malaysian NBFI productivity decline was mainly due to the regress in technological change, which fell by 5.7% and 3.9% in 2003 and 2004 respectively. It is also interesting to note from the

results that during the period of study, while the Malaysian NBFI technological change follows a U-shaped behavior, the efficiency change on the other hand exhibited an inverted U-shaped behavior.

The decomposition of the efficiency change index into its pure technical and scale efficiency components suggest that the dominant source of the decline in the Malaysian NBFI efficiency during the year 2002 was scale related rather than managerially related. This implies that although the Malaysian NBFI was managerially efficient in controlling their costs, they have been operating at the wrong scale of operations during the year. Likewise, during the years 2003 and 2004, the results suggest that the Malaysian NBFI inefficiency was mainly the result of pure technical inefficiency, which declined by 0.7% and 5.8% respectively, suggesting that during the latter years, the Malaysian NBFI turned to be less efficient in controlling their costs despite operating at a relatively more optimal scale of operations.

Panel 2 of Table 7.4 presents the results for the merchant banks operating in Malaysia. As observed, the merchant banks have exhibited productivity regress during all years, i.e. 10.4% in 2002, 8.2% in 2003, and 17.2% in 2004. The decomposition of the productivity change index into its technological and efficiency change components suggest that the decline in the merchant banks productivity was largely due to the decline in technological change of 6.0% during the period of study. The results also suggest that like the total productivity change index, the merchant banks' efficiency change index also follows an inverted U-shaped behavior, while the technological change index exhibit a flat U-shaped behavior. The decomposition of the efficiency change index into its pure technical and scale efficiency components suggest that the dominant source of the decline in the Malaysian merchant banks' efficiency during the period of study was mainly due to pure technical inefficiency or managerially related rather than scale related. The results imply that although the merchant banks have been operating at the optimal scale of operations, they were relatively inefficient at managing and controlling their operating costs.

The results for the finance companies are presented in Panel 3 of Table 7.4. In contrast to the merchant banks, the results seem to suggest that the finance companies have exhibited productivity progress during all years, i.e. 10.1% in 2002, 0.7% in 2003, and 4.8% in 2004. The decomposition of the productivity change index into its technological and efficiency change components suggest that the finance companies productivity progress were mainly attributed to the increase in technological change of 3.5% compared to a smaller 0.3% increase of the efficiency change index. Further decomposition of the Malaysian finance companies' efficiency change index into its pure technical and scale efficiency components depicts interesting findings. The results suggest that while the dominant source of the merchant banks' inefficiency was pure technically related, the opposite was true for the Malaysian finance companies. The results from Panel 3 of Table 7.4 suggest that Malaysian finance companies have exhibited higher pure technical efficiency compared to scale efficiency. Hence, the results imply that while the merchant banks were operating at a relatively more optimal scale of operations, the finance

companies on the other hand were more managerially efficient in controlling their costs. It is also interesting to note from the results that while the merchant banks' efficiency index follows an inverted U-shaped behavior, the finance companies productivity, and efficiency indices on the hand follows a U-shaped behavior during the period of study.

7.5.2 Total Factor Productivity Growth of Malaysian NBFIs: An Analysis Based on the Numbers

As an analysis based on productivity levels of NBFIs can be biased by a few observations, it would thus be beneficial to perform an analysis based on the number of NBFIs, which is less sensitive to possible outliers. As a robustness check, Table 7.5 elaborates the productivity of the Malaysian NBFIs by summarizing the development in the number of NBFIs, which experienced productivity progress or regress. As the results in Panel 1 of Table 7.5 indicate, out of the total 16 NBFIs operating in Malaysia during the 2001–2004 period, nine (56.3%) NBFIs have experienced productivity growth in years 2002 and 2003, before declining to eight (50.0%) in 2004. Likewise, while 11 (68.8%) Malaysian NBFIs have seen progress in their technology in 2002, the majority, nine (56.3%) NBFIs have exhibited technological regress in years 2003 and 2004.

It is also apparent that the number of NBFIs that experienced efficiency increase rose from five (31.3%) in year 2002 to six (37.5%) in 2003, before declining to five (31.3%) in 2004. The number of NBFIs that experienced efficiency decline remained stable at six (37.5%) during the period of study. The decomposition of efficiency change index into its pure technical and scale efficiency components reveals some interesting facts. While the number of Malaysian NBFIs that exhibit pure technical efficiency increase (decrease) fell (rose) from four (three) NBFIs in 2002 to two (five) NBFIs in 2004, the number of Malaysian NBFIs that exhibit scale efficiency increase (decrease) rose (fell) from four (six) NBFIs in 2002 to seven (four) NBFIs in 2004.

As the results in Panel 2 of Table 7.5 indicate, three (18.8%) Malaysian merchant banks have experienced productivity growth in the period 2002 to 2004, with the majority five (31.3%) merchant banks exhibiting productivity regress. On the other hand, the Malaysian merchant banks, which have exhibited progress (regress) in their technology declined (increased) from four (four) in 2002 to two (six) in 2004. It is also apparent from Panel 2 of Table 7.5 that the number of merchant banks that experienced efficiency increase (decrease), increased (declined) from one (four) in 2002 to two (three) in 2004. The decomposition of the efficiency change index into its pure technical and scale efficiency components suggest that, while the number of Malaysian merchant banks that exhibit pure technical efficiency increase (decrease), declined (increased) from one (one) in 2002 to zero (three) in 2004, the number of Malaysian merchant banks that exhibit scale efficiency increase

Table 7.5 Developments in the number (percentage) change of the Malaysian NBFIs with productivity progress (regress) and efficiency increase (decrease)

Period	Productivity change (TFPCH)				Technological change (TECHCH)				Efficiency change (EFFCH)				Pure efficiency change (PEFFCH)				Scale efficiency change (SECH)			
	Progress # (%)	Regress # (%)	No Δ # (%)		Progress # (%)	Regress # (%)	No Δ # (%)		Increase # (%)	Decrease # (%)	No Δ # (%)		Increase # (%)	Decrease # (%)	No Δ # (%)		Increase # (%)	Decrease # (%)	No Δ # (%)	
Panel 1: ALL_NBFI																				
2002–2001	9 (56.3)	7 (43.8)	0 (0.0)		11 (68.8)	5 (31.3)	0 (0.0)		5 (31.3)	6 (37.5)	5 (31.3)		4 (25.0)	3 (18.8)	9 (56.3)		4 (25.0)	6 (37.5)	6 (37.5)	
2003–2002	9 (56.3)	7 (43.8)	0 (0.0)		7 (43.8)	9 (56.3)	0 (0.0)		6 (37.5)	6 (37.5)	4 (25.0)		3 (18.8)	4 (25.0)	9 (56.3)		5 (31.3)	7 (43.8)	4 (25.0)	
2004–2003	8 (50.0)	8 (50.0)	0 (0.0)		7 (43.8)	9 (56.3)	0 (0.0)		5 (31.3)	6 (37.5)	5 (31.3)		2 (12.5)	5 (31.3)	9 (56.3)		7 (43.8)	4 (25.0)	5 (31.3)	
Panel 2: MERC_BNK																				
2002–2001	3 (18.8)	5 (31.3)	0 (0.0)		4 (25.0)	4 (25.0)	0 (0.0)		1 (6.3)	4 (25.0)	3 (18.8)		1 (6.3)	1 (6.3)	6 (37.5)		1 (6.3)	4 (25.0)	3 (18.8)	
2003–2002	3 (18.8)	5 (31.3)	0 (0.0)		1 (6.3)	7 (43.8)	0 (0.0)		3 (18.8)	2 (12.5)	3 (18.8)		0 (0.0)	2 (12.5)	6 (37.5)		4 (25.0)	1 (6.3)	3 (18.8)	
2004–2003	3 (18.8)	5 (31.3)	0 (0.0)		2 (12.5)	6 (37.5)	0 (0.0)		2 (12.5)	3 (18.8)	3 (18.8)		0 (0.0)	3 (18.8)	5 (31.3)		3 (18.8)	2 (12.5)	3 (18.8)	
Panel 3: FIN_COS																				
2002–2001	6 (37.5)	2 (12.5)	0 (0.0)		7 (43.8)	1 (6.3)	0 (0.0)		4 (25.0)	2 (12.5)	2 (12.5)		3 (18.8)	2 (12.5)	3 (18.8)		3 (18.8)	3 (18.8)	2 (12.5)	
2003–2002	6 (37.5)	2 (12.5)	0 (0.0)		6 (37.5)	2 (12.5)	0 (0.0)		3 (18.8)	4 (25.0)	1 (6.3)		3 (18.8)	2 (12.5)	3 (18.8)		1 (6.3)	6 (37.5)	1 (6.3)	
2004–2003	5 (31.3)	3 (18.8)	0 (0.0)		5 (31.3)	3 (18.8)	0 (0.0)		3 (18.8)	3 (18.8)	2 (12.5)		2 (12.5)	2 (12.5)	4 (25.0)		4 (25.0)	2 (12.5)	2 (12.5)	

Note: Malaysian NBFIs are categorized according to the following, Productivity Growth: TFPCH > 1, Productivity Loss TFPCH < 1; Productivity Stagnation: TFPCH = 1; Technological Progress: TECCH > 1, Technological Regress TECCH < 1, Technological Stagnation: TECCH = 1; Efficiency, Pure Technical and Scale increase: EFFCH, PEFFCH and SECH > 1, Efficiency, Pure Technical and Scale decrease: EFFCH, PEFFCH and SECH < 1, No Change in Efficiency, Pure Technical and Scale: EFFCH, PEFFCH and SECH = 1

(decrease), increased (declined) from one (four) in 2002 to three (two) in 2004. The results conforms to our earlier findings that, although the merchant banks are becoming more scale efficient, they however have been inefficient in controlling their operating costs.

As the results in Panel 3 of Table 7.5 suggest, six (two) Malaysian finance companies have experienced productivity growth (regress) in the years 2002 and 2003, before declining (increasing) to five (three) in 2004. Similarly, while only one (6.3%) Malaysian finance company exhibited regress in its technology in 2002, with the majority seven (43.8%) exhibiting technological progress, the number of Malaysian finance companies that exhibit technological progress gradually declined to six (37.5%) and five (31.3%) in 2003 and 2004 respectively. It is also apparent from Panel 3 of Table 7.5 that the number of finance companies that experienced efficiency increase (decrease), declined (increased) from four (2) in the year 2002 to three (3) in the year 2004. The decomposition of efficiency change index into its pure technical and scale efficiency components suggest that, the number of the Malaysian finance companies that exhibit pure technical efficiency increase, declined from three (18.8%) in 2002 and 2003 to two (12.5%) in 2004, while the number of finance companies that exhibit pure technical efficiency decline remained stable at two (18.8%). Conversely, the number of the Malaysian finance companies that exhibit scale efficiency increase (decrease), increased (declined) from three (three) finance companies in 2002 to four (two) in 2004.

Table 7.6 is constructed to examine the major sources of productivity progress (regress) and efficiency increase (decrease) in the Malaysian NBFIs sector during the 2001–2004 period. The results given in Table 7.6 are simply a decomposition of Table 7.5. For instance, of the nine NBFIs that experienced productivity progress in 2002 as shown in Panel 1 of Table 7.6, the majority, seven (43.8%), were attributed to technological progress, while two (12.5%) was mainly attributable to efficiency increase. On the other hand, of the seven (43.8%) NBFIs, which experienced productivity regress in 2002, the majority, six (37.5%), were due to decline in efficiency, while the rest was mainly due to technological regress.

The results from Panel 1 of Table 7.6 indicates that of the five (31.3%) NBFIs that experienced efficiency increase during the year 2002, four (25.0%) NBFIs experienced the increase in efficiency attributed to the increase in pure technical efficiency while one NBFIs experienced increase attributed to increase in scale efficiency. On the other hand, from the six (37.5%) NBFIs that experienced efficiency loss during the year 2002, two (18.8%) NBFIs experienced the reduction in their efficiency mainly due to a decrease in their pure technical efficiency, whereas another four (25.0%) NBFIs faced the reduction mostly due to a decrease in their scale efficiency.

The sub-group results in Panel 2 and 3 of Table 7.6 yield interesting findings. While the finance companies' productivity progress during the years 2001–2004 were mainly attributed to technological progress, their productivity regress on the other hand were mainly due to the decline in efficiency. Likewise, the merchant banks' productivity progress were mainly attributed to technological progress, with an exception of the year 2003 when the results seem to suggest that the merchant

Table 7.6 Major source of productivity progress (regress) and efficiency increase (decrease) in the Malaysian NBFIs

Period	Productivity progress				Productivity regress				No productivity Δ				Efficiency increase due to				Efficiency decrease due to				No efficiency Δ			
	mainly due to				mainly due to				mainly due to				mainly due to				mainly due to				mainly due to			
	Efficiency increase # (%)	Technological progress # (%)	Efficiency decrease # (%)	Technological regress # (%)	Efficiency increase # (%)	Technological progress # (%)	Efficiency decrease # (%)	Technological regress # (%)	Efficiency increase # (%)	Technological progress # (%)	Efficiency decrease # (%)	Technological regress # (%)	PTE increase # (%)	SE increase # (%)	PTE decrease # (%)	SE decrease # (%)	PTE increase # (%)	SE increase # (%)	PTE decrease # (%)	SE decrease # (%)	No efficiency Δ # (%)	SE decrease # (%)	PTE decrease # (%)	SE decrease # (%)
Panel 1: ALL_NBFI																								
2002–2001	2 (12.5)	7 (43.8)	6 (37.5)	1 (6.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	4 (25.0)	1 (6.3)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	5 (31.3)	4 (25.0)	2 (12.5)	4 (25.0)
2003–2002	3 (18.8)	6 (37.5)	2 (12.5)	5 (31.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	4 (25.0)	4 (25.0)	2 (12.5)	4 (25.0)
2004–2003	3 (18.8)	5 (31.3)	4 (25.0)	4 (25.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	5 (31.3)	4 (25.0)	4 (25.0)	4 (25.0)	5 (31.3)	2 (12.5)	5 (31.3)	5 (31.3)	5 (31.3)	2 (12.5)	4 (25.0)
Panel 2: MERC_BNKS																								
2002–2001	1 (6.3)	2 (12.5)	4 (25.0)	1 (6.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	1 (6.3)	0 (0.0)	0 (0.0)	4 (25.0)	0 (0.0)	0 (0.0)	0 (0.0)	4 (25.0)	3 (18.8)	4 (25.0)	0 (0.0)	4 (25.0)
2003–2002	2 (12.5)	1 (6.3)	1 (6.3)	4 (25.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	3 (18.8)	0 (0.0)	0 (0.0)	0 (0.0)	3 (18.8)	2 (12.5)	0 (0.0)	3 (18.8)	3 (18.8)	0 (0.0)	4 (25.0)
2004–2003	1 (6.3)	2 (12.5)	2 (12.5)	3 (18.8)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (12.5)	3 (18.8)	2 (12.5)	3 (18.8)	2 (12.5)	3 (18.8)	0 (0.0)	3 (18.8)	3 (18.8)	0 (0.0)	4 (25.0)
Panel 3: FIN_COS																								
2002–2001	1 (6.3)	5 (31.3)	2 (12.5)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	3 (18.8)	1 (6.3)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)
2003–2002	1 (6.3)	5 (31.3)	1 (6.3)	1 (6.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (12.5)	1 (6.3)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)
2004–2003	2 (12.5)	3 (18.8)	2 (12.5)	1 (6.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	3 (18.8)	1 (6.3)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)	4 (25.0)	2 (12.5)

Note: Malaysian NBFIs are categorized according to the following. (1) Productivity Progress: $TPPCH > 1$, (2) Productivity Regress: $TPPCH < 1$, (3) Productivity Stagnation: $TPPCH = 1$. (1) Technological Progress: $TECCH > 1$, (2) Technological Regress: $TECCH < 1$, (3) Technological Stagnation: $TECCH = 1$. (1) Efficiency, Pure Technical and Scale increase: $EFFCH$, $PEFFCH$ and $SECH > 1$, (2) Efficiency, Pure Technical and Scale decrease: $EFFCH$, $PEFFCH$ and $SECH < 1$, (3) No Change in Efficiency, Pure Technical and Scale: $EFFCH$, $PEFFCH$ and $SECH = 1$

banks' productivity progress were mainly attributed to efficiency increase. In contrast to their finance companies peers, the findings suggest that the technological regress has mainly resulted in the merchant banks productivity decline, particularly during the latter part of the studies.

It is also apparent from Panel 2 and 3 of Table 7.6 that, during the period of study, while the merchant banks efficiency progress were mainly attributed to the increase in scale efficiency, the finance companies on the other hand have exhibited higher pure technical efficiency. It is also interesting to note that, different factors explained the decline in efficiency of the merchant banks and the finance companies. While the merchant banks' efficiency decline was largely due to the decline in pure technical efficiency, the finance companies on the other hand were mainly due to the decline in scale efficiency.

7.5.3 Total Factor Productivity Growth of Malaysian NBFIs: An Analysis Based on the Size

Malaysian NBFI of different sizes might exhibit different operational characteristics. Thus, in this section we divide our sample by size (gross of total assets), to explore the relationship between NBFI size and productivity. Table 7.7 exhibits the TFPCCH and its components according to size. The results from the row view (r %) suggest that, for instance, during the year 2002, six out of nine SML_NBFI experienced productivity progress, of which four SML_NBFI productivity progress were attributed to technological progress, while for the other two SML_NBFI were mainly attributable to efficiency increase. On the other hand, of the three SML_NBFI that experienced productivity regress during the year, all were due to efficiency decline.

From a column view perspective (c %), during the earlier year, the majority of NBFI that experienced productivity progress attributable to technological progress came from the SML_NBFI group (57.1%), followed by the MED_NBFI group (28.6%) and LAR_NBFI group (14.3%). Likewise, the results from Panel 1 of Table 7.7 suggest that, of the only NBFI that experienced productivity regress due to technological regress during the year came from the LAR_NBFI group. However, during the latter years, the results seem to suggest that the majority of NBFI that experienced productivity progress attributable to technological progress came from the MED_NBFI group, followed by the LAR_NBFI group.

The results imply that, the SML_NBFI group with its limited capabilities is at a disadvantage compared to its larger counterparts in terms of technological advancements and shifts to the frontier. The empirical findings do not support the divisibility theory, which holds that there will be no such operational advantage accruing to large banks (NBFI in our case) if the technology is divisible, thus suggesting that small-scale banks could have produced financial services at costs per unit output comparable to those of large banks, implying no or possibly negative association between size and performance. As pointed out by Kolari and Zardkoohi (1987), advances in technology, which has reduced the size and cost of the automated

Table 7.7 The source of productivity progress (regress) in the Malaysian NBFIs with respect to size

Year/Size	Indices															
	No. of NBFi	No. of NBFi with productivity progress						No. of NBFi with productivity regress								
		Due to technological progress			Due efficiency increase			Due technological regress			Due efficiency decrease					
		#	r%	c%	#	r%	c%	#	r%	c%	#	r%	c%			
Panel 1: 2002–2001																
SML_NBFI	9	4	44.4	57.1	2	22.2	100.0	0	0.0	0.0	3	33.3	50.0	0	0.0	0.0
MED_NBFI	2	2	100.0	28.6	0	0.0	0.0	0	0.0	0.0	0	0.0	0.0	0	0.0	0.0
LRG_NBFI	5	1	20.0	14.3	0	0.0	0.0	1	20.0	100.0	3	60.0	50.0	0	0.0	0.0
Total	16	7		100.0	2		100.0	1		100.0	6		100.0	0		0.0
Panel 2: 2003–2002																
SML_NBFI	8	2	25.0	33.3	1	12.5	33.3	3	37.5	60.0	2	25.0	100.0	0	0.0	0.0
MED_NBFI	3	3	100.0	50.0	0	0.0	0.0	0	0.0	0.0	0	0.0	0.0	0	0.0	0.0
LRG_NBFI	5	1	20.0	16.7	2	40.0	66.7	2	40.0	40.0	0	0.0	0.0	0	0.0	0.0
Total	16	6		100.0	3		100.0	5		100.0	2		100.0	0		0.0
Panel 3: 2004–2003																
SML_NBFI	8	1	12.5	20.0	1	12.5	33.3	4	50.0	100.0	2	25.0	50.0	0	0.0	0.0
MED_NBFI	3	2	66.7	40.0	0	0.0	0.0	0	0.0	0.0	1	33.3	25.0	0	0.0	0.0
LRG_NBFI	5	2	40.0	40.0	2	40.0	66.7	0	0.0	0.0	1	20.0	25.0	0	0.0	0.0
Total	16	5		100.0	3		100.0	4		100.0	4		100.0	0		0.0

Note: SML_NBFI is defined as NBFI with total assets < industry's Mean, MED_NBFI is defined as NBFI with total assets in the mean range, while LRG_NBFI is defined as NBFI with total assets > industry's mean. r% indicates row wise (relative to the same size group); c% indicates column wise (relative to other size groups)

equipment would significantly enhance small banks' ability to purchase expensive technology, which imply more divisibility in technology in the banking industry.

Table 7.8 shows the sources of efficiency increase (decrease) of the Malaysian NBFI according to size. The results from the row view (r%) suggest that, for instance, during the year 2002, two out of the three SML_NBFI that experienced efficiency increase were attributed to pure technical efficiency increase, while for the other SML_NBFI was mainly attributable to scale efficiency increase. On the other hand, of the three SML_NBFI that experienced efficiency decline during the year, all were due to scale inefficiency. From a column view perspective (c%), during the year 2002, 50.0% of the NBFI that experienced efficiency increase attributable to pure technical efficiency came from the SML_NBFI group, while MED_NBFI made the rest 50.0%. The results from Panel 1 of Table 7.8 suggest that all of the NBFI that experienced efficiency decrease in year 2002 due to pure technical inefficiency came from the LAR_NBFI group. Likewise, out of the four Malaysian NBFI that experienced efficiency decline due to scale inefficiency, three (75.0%) NBFI came from the SML_NBFI group, while the LAR_NBFI group made up the rest 25.0%.

7.5.4 *Univariate Tests Results*

After examining the Malmquist results, the issue of interest now is whether the two samples were drawn from the same population i.e., whether the merchant banks and finance companies possess the same technology. The null hypothesis tested is that the merchant banks and finance companies were drawn from the same population or environment and have identical technologies. We tested the null hypothesis that merchant banks and finance companies were drawn from the same population and have identical technologies by using a series of parametric (ANOVA and t-test) and non-parametric (Kolmogorov–Smirnov, Mann–Whitney [Wilcoxon Rank-Sum] and Kruskal–Wallis) univariate tests. The results are presented in Table 7.9.

Based on most of the results, we failed to reject the null hypothesis at the 5% level of significance that the merchant banks and finance companies were drawn from the same population and have identical technologies. With an exception of the Kolmogorov–Smirnov test, which indicates that the TFPCH and PEFFCH of the merchant banks and finance companies are different at the 5% level, the other parametric and non-parametric tests failed to reject the null hypothesis at the 5% level of significance. This implies that, there is no significant difference between the merchant banks and finance companies technologies (frontiers) and that it is appropriate to construct a combined frontier. Furthermore, the results from the Levene's test for equality of variances do not reject the null hypothesis that the variances among merchant banks and finance companies are equal, implying that we can assume the variances among merchant banks and finance companies to be equal. Our findings corroborate with the findings by among others, Isik and Hassan (2002) and Sathye (2001).

Table 7.8 The source of efficiency increase (decrease) in the Malaysian NBFIs with respect to size

Year/Size	No. of NBFi	Indices														
		No. of NBFi with efficiency increase						No. of NBFi with efficiency decrease								
		PTE increase			Scale increase			PTE decrease			SE decrease					
		#	r%	c%	#	r%	c%	#	r%	c%	#	r%	c%			
Panel 1: 2002–2001																
SML_NBFi	9	2	22.2	50.0	1	11.1	100.0	0	0.0	0.0	3	33.3	75.0	3	33.3	60.0
MED_NBFi	2	2	100.0	50.0	0	0.0	0.0	0	0.0	0.0	0	0.0	0.0	0	0.0	0.0
LRG_NBFi	5	0	0.0	0.0	0	0.0	0.0	2	40.0	100.0	1	20.0	25.0	2	40.0	40.0
Total	16	4		100.0	1		100.0	2		100.0	4		100.0	5		100.0
Panel 2: 2003–2002																
SML_NBFi	8	0	0.0	0.0	3	37.5	75.0	2	25.0	100.0	1	12.5	25.0	2	25.0	50.0
MED_NBFi	3	1	33.3	50.0	0	0.0	0.0	0	0.0	0.0	1	33.3	25.0	1	33.3	25.0
LRG_NBFi	5	1	20.0	50.0	1	20.0	25.0	0	0.0	0.0	2	40.0	50.0	1	20.0	25.0
Total	16	2		100.0	4		100.0	2		100.0	4		100.0	4		100.0
Panel 3: 2004–2003																
SML_NBFi	8	0	0.0	0.0	2	25.0	40.0	3	37.5	75.0	0	0.0	0.0	3	37.5	60.0
MED_NBFi	3	0	0.0	0.0	1	33.3	20.0	1	33.3	25.0	0	0.0	0.0	1	33.3	20.0
LRG_NBFi	5	0	0.0	0.0	2	40.0	40.0	0	0.0	0.0	2	40.0	100.0	1	20.0	20.0
Total	16	0		0.0	5		100.0	4		100.0	2		100.0	5		100.0

Note: SML_NBFI is defined as NBFI with total assets < industry's mean, MED_NBFI is defined as NBFI with total assets in the mean range, while LRG_NBFI is defined as NBFI with total assets > industry's mean. r% indicates row wise (relative to the same size group); c% indicates column wise (relative to other size groups)

Table 7.9 Summary of parametric and non-parametric tests for the null hypothesis that merchant bank (*mb*) and finance companies (*fc*) possess identical technologies (frontiers)

Individual tests	Test groups				
	Parametric test		Non-parametric test		
	Analysis of variance				
	(ANOVA) test	t-test	Kolmogorov–Smirnov [K–S] test	Mann–Whitney [Wilcoxon Rank-Sum] test	Kruskal–Wallis equality of populations test
Hypotheses	Mean _{mb} = Mean _{fc}		Distribution _{mb} = Distribution _{fc}	Median _{mb} = Median _{fc}	
Test statistics	F (Prb > F)	t (Prb > t)	K–S (Prb > K–S)	z (Prb > z)	χ^2 (Prb > χ^2)
Productivity change (TFPCH)	3.897 (0.054)	1.974 (0.054)	1.732 (0.005)*	–1.897 (0.058)	3.600 (0.058)
Technological change (TECHCH)	2.152 (0.149)	1.467 (0.149)	1.010 (0.259)	–1.495 (0.135)	2.235 (0.135)
Efficiency change (EFFCH)	3.132 (0.083)	1.770 (0.083)	1.155 (0.139)	–0.868 (0.385)	0.754 (0.385)
Pure technical efficiency change (PEFFCH)	3.191 (0.081)	1.786 (0.081)	1.443 (0.031)*	–0.192 (0.848)	0.037 (0.848)
Scale efficiency change (SECH)	0.066 (0.798)	0.257 (0.798)	0.433 (0.992)	–0.320 (0.749)	0.103 (0.749)

Note: Test methodology follows among others, Aly et al. (1990), Elyasiani and Mehdi (1992) and Isik and Hassan (2002). Parametric (ANOVA and *t*-test) and Non-Parametric (Kolmogorov–Smirnov, Mann–Whitney and Kruskal–Wallis) tests test the null hypothesis that merchant banks and finance companies are drawn from the same efficiency population (environment). The numbers in parentheses are the *p*-values associated with the relative test. * indicates significant at the 0.05% level

7.5.5 The Determinants of the Malaysian NBFIs Productivity

The second stage regressions were estimated using GLS fixed-effects and random-effects estimators, where the standard errors are calculated using White's (1980) correction for heteroscedasticity. To conserve space, the full regression results, which include both NBFIs and time-specific fixed effects, are not reported in the paper. Table 7.10 reports the estimation results. Generally, the findings suggest that all explanatory variables have the expected signs, and are statistically different from zero.

The coefficient on the size variable is positive to the efficiency index and statistically significant at the 1% level, indicating that, on average, larger NBFIs attain a higher level of technical efficiency in their operations. This might be the result of the relaxation of asset restrictions in the banking system that allowed NBFIs to grow and venture into different banking business practices, and to accrue some economies of scale and scope. Thus, assuming that the average cost curve for the Malaysian NBFIs are U-shaped, the recent growth policies of medium and small Malaysian NBFIs seem to be consistent with cost minimization.

The level of equity capital is positively related with the level of productivity change, but is not significant at the conventional levels. The findings are consistent with previous research results, which have found that higher productivity levels are usually reported by well-capitalized financial institutions. The findings seem to suggest that, the more efficient NBFIs, *ceteris paribus*, use less leverage (more equity) compared to its peers. In addition, the results seems to suggest that the more efficient NBFIs involved in riskier operations and in the process tend to hold more equity, voluntarily or involuntarily, i.e., the reason might be NBFIs deliberate efforts to increase safety cushions, or perhaps regulatory pressures that mandate riskier NBFIs to carry more equity.

NBFIs with higher ratio of loans to assets are not related to either higher level of productivity or efficiency. Higher level of overhead expenditures is found to significantly explain the lower level of NBFIs productivity and efficiency. This finding is in consonance with the 'bad management hypotheses' of Berger and DeYoung (1997). Low measure of technical efficiency is a signal of poor senior management practices, which apply to input-usage, day-to-day operations and managing the loan portfolio. Sub par managers do not sufficiently monitor and control their operating expenses. Managers in these financial institutions might not practice adequate loan underwriting, monitoring, and control.

The GDP variable is negatively correlated to productivity and efficiency growth. The economic activities may influence level of productivity as NBFIs could be affected differently by changes in macroeconomic performance, depending on their cost structures. Finally, the dummy variable representing NBFIs specialization is significant and positively related indicating that specialization to some extent tend to reduce cost such as screening and monitoring associated with loan, thus, it promotes the production of more outputs with a given level of inputs.

Table 7.10 Results of panel regression analysis

Explanatory Variables	TFPCH	TECHCH	EFFCH	PEFFCH	SEFFCH
CONSTANT	-0.452 (0.467)	1.484*** (0.255)	-0.236 (0.322)	0.205 (0.300)	0.951*** (0.498)
Bank characteristics					
SIZE	0.029 (0.026)	-0.034* (0.019)	0.079** (0.028)	0.046** (0.019)	0.001 (0.001)
EQTY	0.393*** (0.067)	0.039 (0.033)	0.461*** (0.057)	0.236*** (0.007)	0.049 (0.101)
LOANS/TA	-0.366** (0.157)	0.012 (0.076)	-0.425 (0.299)	-0.175 (0.313)	-0.036 (0.051)
OVERHEAD	2.502 (4.303)	-4.815*** (1.006)	-2.324 (3.191)	1.569 (2.247)	-2.064 (2.507)
SPEC	0.434*** (0.049)	0.157*** (0.013)	0.319*** (0.071)	0.232 (0.203)	0.010*** (0.060)
Economic conditions					
GDP	-0.217** (0.009)	-0.024*** (0.004)	-0.007 (0.005)	-0.012*** (0.003)	-0.016*** (0.005)
R ²	0.38	0.52	0.39	0.39	0.64
Adjusted R ²	0.21	0.37	0.22	0.21	0.53
F-statistic	2.07*	3.39**	2.05*	2.01*	5.66***
No. of observations	48	48	48	48	48

$q_t = \beta_0 + \beta_1 SIZE_{it} + \beta_2 EQTY_{it} + \beta_3 LOANS/TA_{it} + \beta_4 OVERHEAD_{it} + \beta_5 SPEC_{it} + \beta_6 GDP_{it} + \varepsilon_{it}$. The dependent variables are NBFIs' total factor productivity change (TFPCH), technological change (TECHCH), technical efficiency change (EFFCH), pure technical efficiency change (PEFFCH) and scale efficiency change (SEFFCH) indices. *SIZE* is a proxy measure of size, calculated as a natural logarithm of total NBFIs assets; *EQTY* is a measure of capitalization, calculated as book value of shareholders equity as a fraction of total assets; *LOANS/TA* is used as a proxy measure of loans intensity, calculated as total loans divided by total assets; *OVERHEAD* is a proxy measure for management quality, calculated as personnel expenses divided by total assets. *SPEC* is a dummy variable to capture the effects of NBFIs specialization. *GDP* is the country's gross domestic product growth rate and is used as a proxy for economic conditions. Values in parentheses are standard errors. ***, **, and * indicate significance at 1%, 5% and 10% levels

7.6 Conclusions and Directions for Future Research

This paper attempts to investigate the productivity changes of the Malaysian Non-Bank Financial Institutions (NBFI) during the post crisis period of 2001–2004, by applying a non-parametric Malmquist Productivity Index (MPI) method. The preferred methodology has allowed us to isolate efforts to catch up to the frontier (efficiency change) from shifts in the frontier (technological change). In addition, the Malmquist index enables us to explore the main sources of efficiency change: either improvements in management practices (pure technical efficiency change) or improvements towards optimal size (scale efficiency change). Additionally we have also performed a series of parametric and non-parametric tests to examine whether the merchant banks and finance companies were drawn from the same set of population.

The empirical findings suggest that the Malaysian NBFIs have exhibited productivity regress during all the years under study. The decomposition of the productivity change index into its efficiency change and technological change components indicates that, the Malaysian NBFIs productivity regress was mainly due to efficiency decline rather than technological regress. We have also examined the productivity progress/regress of different NBFI groups operating in Malaysia. The results suggest that while the finance companies have exhibited productivity growth during all years attributed to technological progress, the merchant banks on the other hand have exhibited productivity regress during all years due to technological regress.

We have also explored the relationship between different NBFI size and productivity. The findings indicate that, while the majority of Malaysian NBFI, which experienced productivity progress due to technological change, came from the large NBFI group, on the other hand, the majority of NBFI that experienced productivity regress due to technological regress came from the small NBFI group. The results imply that the small NBFI group with its limited capabilities has lagged behind its larger counterparts in terms of technological advancements and shifts to the frontier. The results thus do not support for the divisibility theory, which suggest that there is no size advantage accrued to the larger NBFI during the period of study.

Further, to address the issue whether the merchant banks and the finance companies were drawn from the same sample of population or environment, or whether the merchant banks and finance companies have the same technological (frontiers) attribution, we have performed a series of parametric and non-parametric univariate tests. Our results from the parametric and non-parametric tests could not reject the null hypotheses at the 5% levels of significance that the merchant banks and finance companies were operating in and were drawn from the same population or environment, suggesting that it is appropriate to construct a single frontier for both the merchant banks and finance companies.

The results of the multivariate regression analysis suggest that higher productivity levels are associated with size and well-capitalized NBFIs. Consistent with most

prior research, higher level of overhead expenses are associated with lower productivity levels. Favorable economic conditions seem to reduce the level of productivity and efficiency. Finally, specialization in the nature of operating environment between finance companies and merchant banks contributed to productivity and efficiency gain.

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Chapter 8

The Impact of the Wallis Inquiry on Australian Banking Efficiency Performance

S. Wu

8.1 Introduction

Since the deregulation of the Australian financial system in early 1980s, the banking industry has undergone sweeping changes. As of December 2005, there were 53 authorised banks in Australia, including eleven foreign subsidiary banks and 29 branches of foreign banks (APRA 2005). With the entry of foreign banks and former domestic building societies into the market, domestic banks have reacted to the intensified competition by performing more efficiently and engaging more actively in mergers and acquisitions. However, the four major banks generally hold the view that the consolidation of the financial services industry and the competitiveness of the industry in the international market have been hindered by a restrictive political and regulatory environment, such as the four pillars policy prohibiting mergers among the four major banks (Guy and Whyte 2002). Therefore, it is important to analyse the performance of the Australian banking industry, with particular reference to the Wallis Inquiry into the Australian Financial System (hereafter the Inquiry) in 1996, to which the Australian Federal Government responded by adopting the four pillars policy.

A series of inquiries into the financial system has been conducted by the Government, including the Campbell Inquiry in 1981, the Martin Inquiry in 1991 and the Wallis Inquiry in 1996, aiming at deregulating the financial system and enhancing the competitiveness in the financial market. The final report for the Wallis Inquiry (hereafter the FSI) evaluated the overall effects of past deregulatory process and set the direction for future policy. Whilst the Inquiry has focused on “enhancing competition and contestability in the Australian financial system” (Harper 1997), the FSI contained 115 recommendations in three broad categories, namely new regulatory structure to safeguard the financial system, consideration of mergers and acquisitions and recommendations concerning managing changes.

The FSI recommended the abolition of the “six pillars” policy, which had prohibited mergers among the four major banks and the two largest life insurance companies

S. Wu

School of Accounting, Economics and Finance, Deakin University, Burwood, Toorak, Geelong, Warrnambool, Victoria, Australia

in Australia (FSI 1997, p.429).¹ Nevertheless, there has been no formal banking legislation backing the policy. Under the Banking Act and Trade Practices Act, a bank merger proposal is required to obtain approval by the Australian Competition and Consumer Commission (ACCC) on competition grounds,² the Reserve Bank of Australia (RBA) and its successor Australian Prudential Regulation Authority for prudential consideration, and by the treasurer under his reserve power to veto.³ The six pillars policy, in fact, was initiated by the Keating Government in 1990 when it decided to block the proposed merger between the Australia and New Zealand Banking Group and the National Mutual Life Association of Australia. In a released statement of 23 May 1990, the Government stated that the proposed merger would have reduced the “diversity of institutions and effective competition in banking, in life insurance, and more generally the provision of financial services” and indicted that any mergers between any of the four major banks or the two largest life insurance companies would not be permitted.⁴ The policy was then reiterated by the Dawkins Government in 1993.

Prudential supervision has been used to justify the adoption of four pillars policy, a modified version of the previous six pillars policy. In its submission to the Financial System Inquiry, the RBA raised prudential concerns over the reduction of four major banks to two major banks as a result of the removal of six pillars policy (RBA 1996, p.76). The “too big to fail” argument arises from the assumed guarantee by the RBA for meeting all the deposits liabilities in the event of a bank collapse. In the case that any two of the major banks merge, moral hazard problems may kick in where the resultant “mega” bank tends to be more risk-taking with the expectation that the government will intervene if the business is in trouble. When such a mega-bank is in trouble, it is also difficult to arrange a domestic takeover. However, the Inquiry did not support such argument. It did not believe that the management of a failed mega bank differed much from that of an existing major bank should it fail (FSI 1997, p.428). Combining with other considerations, including competition policy, the Inquiry recommended the discontinuation of the six pillars policy, or any modified version of it. The FSI also recommended a replacement of the implicitly guaranteed lender-of-last resort with a preference for depositors in a liquidation situation. Although acknowledging foreign acquisitions of the big four should be allowed, the Inquiry still considered that some restrictions on foreign ownership might be imposed in the national interest. The Inquiry also advocated that financial mergers and acquisitions

¹References to the four major banks are ANZ, Commonwealth, NAB and Westpac, while for the two largest insurance companies are AMP and NML.

²Banks which want to engage in merger and acquisitions are governed by section 50 of the Trade Practices Act, as administered by the ACCC.

³Under Section 63 of the Banking Act 1959, the Treasurer has veto powers over bank mergers.

⁴Keating (1990) Proposal for Merger of ANZ Banking Group (ANZ) and National Mutual Life Association. Press Release by the Acting Prime Minister and Treasurer, 23 May, Canberra.

be subject to the same criterion as other sectors under the Trade Practices Act 1974, namely, whether the movement would substantially lessen competition. And merger among financial institutions should be assessed by the ACCC on a case-by-case basis.

While adopting most of the recommendations made by the Inquiry, the government clearly took a different viewpoint regarding bank mergers. With strong public and political opposition to the mega bank mergers, it decided to adopt a modified version of the six pillars policy instead (Bakir 2004). Since the release of the FSI, the Government quickly announced that mergers among the four major banks would not be permitted until there was a satisfactory degree of competition in the financial sector, particularly in respect to small business lending. The so-called four pillars policy was in place as of April 1997. Presently, mergers between any of the four major banks remain to be prohibited, while foreign takeover of any Australian bank is allowed. However, it is generally believed that sooner or later, the government will re-examine the issue of bank mergers in order to relax the four pillars policy.

This paper examines the efficiency performance of individual banks, banks of different types and the banking industry in Australia during the post-deregulation period. A four-stage data envelopment analysis (DEA) method is adopted to determine efficiency differences between banks of different groups after removing intra-group managerial inefficiency. Two sub-sample time periods are examined individually, one during the period of 1983–1995 and the other from 1996 through 2001. The cut-off year is 1996 when the Wallis Inquiry was established.

This paper makes the following contributions. Firstly, the study examines bank efficiency during the sample period from 1983 to 2001 inclusive. No prior study of the Australian banking sector has covered such a long time period in order to capture the full effects of financial deregulation on efficiency. Secondly, it is the first quantitative study on the Australian banking efficiency in relation to the Wallis Inquiry into the financial deregulation. Third, to the best of our knowledge, the number of sampled banks included in the study is the largest among all the studies on Australian banking industry. Sample sizes of many previous studies, particularly those applying Malmquist productivity index, are relatively small. In DEA literature, it is recommended that the sample size should be not less than, the product of the number of inputs and number of outputs, or three times the sum of the number of inputs and outputs, whichever is larger (see Cooper et al. 1999, p.252). Finally, the study has adopted a four-step DEA approach, which is initiated by Charnes et al. (1981). Under the approach, a distinction between managerial efficiency and program efficiency has been made to examine efficiency difference within groups and between groups respectively.

This paper is divided into the following sections. The next section provides an overview of Australian banking industry. Section 8.3 reviews the relevant banking efficiency literature in Australia and in the world. Section 8.4 introduces the four-step DEA model to assess the impact of bank status on bank efficiency. The following section presents and analyses the empirical results. Conclusion is drawn in Sect. 8.6.

8.2 An Overview of the Australian Banking Sector

The Australian banking industry is modestly concentrated, with the four nationally-operated banks dominating the market. Banks can be broadly classified into four groups: major banks, State-owned banks, other regional banks and foreign banks. In anticipation of the entry of foreign banks in 1986, Australian banks strategically formed larger banking operations, the four major banks, to compete against the incoming banks (Wright 1999).⁵ These major banks are nationally operating banks with extensive branch and agency networks. Deregulation of the banking industry enabled them to compete more effectively with non-bank financial institutions in many fields of financial services. However, the entry of foreign banks and former building societies into the banking market also posed great challenges to these major banks. Given the pressure and opportunities, the major banks responded by diversification into non-traditional banking business, continuous product innovation and expansion into the world market. They provide a comprehensive range of financial services via well-developed distributional networks around Australia and overseas.

In the past, State banks have been created by the state governments to facilitate fund transfer to special groups in the economy. These banks were state-owned and their liabilities were guaranteed by the relevant state government. They used to operate principally within each state, although some extended their operations to other states later on. All the formerly state-owned banks are no longer in existence, either taken over by other banks because of their own poor performance (e.g. State Bank of Victoria) or privatised and then merged with other banks as long-term strategies (e.g. State Bank of NSW).⁶

The newly established regional banks are commonly former permanent building societies that have been converted to banks via demutualisation in the late 1980s and the early 1990s.⁷ As building societies, they concentrated solely on retail banking business and residential lending.

Financial deregulation induced major challenges for them as their position was eroded by the powerful-than-ever banks. They reacted to the situation by choosing to convert to banks. The new corporate structure and bank status allowed them to equally compete with existing banks in the market by providing a wider range of products and services and via geographic diversification.

⁵In 1981, National Bank of Australia and Commercial Banking Company of Sydney, and Bank of New South Wales and Commercial Bank of Australia merged.

⁶The Victorian government sold the State Bank of Victoria to the Commonwealth Bank in 1991, the NSW government sold the State Bank of NSW to Colonial Mutual Life in 1992, while the South Australian government sold the State Bank of South Australia to Advance Bank in 1995 (FSI 1997, p.592).

⁷Examples include Advance Bank, Bank of Melbourne, Bendigo Bank, Challenge Bank and etc. Until the implementation of the Wallis report in 1997, building societies and credit unions were unable to convert to bank status under mutual ownership structure.

Foreign banks entered into the Australian market since 1986 as either subsidiaries of their parent bank⁸ or branches⁹ and have been mainly operating in the wholesale banking sector. The few that engage or have attempted to engage in retail banking are those large international banks, such as Citibank, Hong Kong Bank of Australia and Chase Manhattan Bank. The presence of foreign banks in the Australian financial market has enhanced competition, especially in the wholesale banking sector (FSI 1997, pp.348–349). As for the retail market where the impact of foreign entry is modest, the threat of potential competition from foreign bank has also forced established banks to operate more efficiently (Thompson 1992).

The degree of market concentration in the Australian banking industry tends to decline over time. The four-firm concentration ratios in terms of total assets held fell from 80.7% in 1983 to 64.5% in 1996, improving slightly to 68.3% in 2001.¹⁰ According to the contestable markets theory, if the barriers to entry are low, firms with substantial market power will behave competitively by charging a price close to its true cost. Otherwise, potential entrants will enter to deplete market share. As early as the mid-1980s, Harper argued that the Australian banking industry is contestable (Harper 1986). In recent years, natural barriers to entry continued to be reduced substantially in the presence of modern technology, globalisation and enhanced consumer awareness. A new entrant may not necessarily incur the cost of establishing an extensive branch network in order to penetrate into the market. Instead, the bank can set up its business via telephone banking and on-line banking.¹¹ Licensing requirements is one of the regulatory barriers to entry. Any applicant who satisfies certain criteria can obtain a license for bank operation.¹²

The threat of takeover is a major source of competitive pressure over existing firms in the market (Shranz 1993). Among many recommendations made in the FSI that have been implemented by the government, the removal of the policy that prohibits foreign takeover of Australian major banks would undoubtedly enhance the contestability of the market. As expected, the release of the Wallis report was to give an intense and lasting impulse to competitive forces in the banking market, pushing banks to operate more efficiently. However, the four pillars policy, which

⁸ In February 1985, 16 foreign banks were permitted to establish local banking subsidiaries. They were subject to the same legislative and prudential requirements as locally-owned licensed banks.

⁹ In 1992, foreign banks were allowed to establish branch operations to conduct wholesale banking activities.

¹⁰ Based on the author's calculation using data from the Australian Economic Statistics (various issues) and the Australian Banking Statistics (various issues).

¹¹ Examples include the ING bank, which entered the market with direct banking in August 1999.

¹² The general criteria involves an applicant being able to demonstrate an on-going ability to meet APRA's prudential standards, such as a minimum capital base 50 million dollars, suitable legal and managerial structures, shareholders of appropriate quality (subject to approval under the Financial Sector (Shareholdings) Act), comprehensive risk management strategies, and suitable multi-year strategic and financial plans. Where the applicant is foreign-owned, confirmation that the home supervisor does not object to the granting of an authority is also sought.

prevents mergers among the four major banks, is another remaining regulatory constraint adopted by the government. Nevertheless, under the threat of takeover by incumbents or potential entrants, existing banks are forced to operate competitively and efficiently. In addition, given the trend of enhanced contestability over time, banks are under pressure to become more efficient as long as there is room for it.

The efficiency performance of individual banks, banks of different groups and the banking industry should be examined because of its usefulness for assessing the effect of changing regulatory policies in the industry. The implementation of the FSI has seen a replacement of the six pillars policy with a modified four pillars policy, making mergers between large banks and insurance companies possible. The Inquiry also allows foreign acquisitions of domestic banks, including the four major banks. If the threat of takeovers serves as an efficiency-enforcement mechanism, then higher level of pure technical efficiency of banks or lower gaps among banks of different groups would be observed since the removal of the six pillars policy.¹³ In the current study, we adopt a four-step DEA method to assess efficiency performance of banks in Australia prior to and after the conduct of the Inquiry.

8.3 Literature Review of Banking Efficiency

The U.S.-based studies dominate the literature on banking efficiency where most of the studies focus on X-inefficiency and economies of scale or scope (see the review conducted by Berger and Humphrey 1997). They have largely ignored the implications of government policies of deregulation for the productivity and efficiency of financial institutions. The few exceptions include Grabowski et al. (1994), Wheelock and Wilson (1999), and Mukherjee et al. (2001). A number of studies in Canadian and European banks examine efficiency performance among banks during the period of deregulation (see Grifell-Tatje and Lovell 1996; Amoako-Adu and Smith 1995; Berg et al. 1993). Researchers on Asian countries in this field include Fukuyama (1995) for Japanese banks, Bhattacharyya et al. (1997) for Indian banks, Leightner and Lovell (1998) for Thai banks, Shyu (1998) for Taiwanese banks, and Gilbert and Wilson (1998) for Korean banks and so on. Although financial deregulation aims at improving efficiency of the financial system, the results from these studies are mixed. For instance, Grifell-Tatje and Lovell (1996) found that deregulation had some negative impacts on bank efficiency in Spain.

There has been few attempts made to measure the performance of the Australian banks in terms of productivity and efficiency levels and changes. Table 8.1 summarises past DEA studies on efficiency performance of banks operating in Australia. Avkiran (1999, 2000) adopted non-parametric DEA method to measure technical efficiencies of twelve Australian trading banks in the post-deregulated period from

¹³ Scale efficiency may not necessarily be improved as some banks may choose to get larger in order to avoid being the target of takeover.

Table 8.1 A summary of the Australian banking efficiency studies using DEA

Authors	Returns-to-scale assumption		Inputs	Outputs	Sample period	Sample size
Avkiran (1999)	Constant	Model A:	Interest expenses, non-interest expenses	Net interest income, non-interest income	1986–1995	183
		Model B:	Deposits, labour	Net loans, non-interest income		
Avkiran (2000)	Constant		Interest expenses, non-interest expenses	Net interest income, non-interest income	1986–1995	100
Sathye (2001)	Constant		Labour, capital, loanable funds	Loans, demand deposits	1996	
Neal (2004)	Variable		Number of branches, loanable funds	Loans, demand deposits, other operating income	1995–1999	115
Sturn and William (2004)	Variable/constant	Model A:	Labour, deposits, equity capital	Loans, off-balance sheet items	1988–2001	273
		Model B:	Interest expenses, Non-interest expenses	Net interest income, non-interest income		
Kirkwood and Nahm (2006)	Constant	Model A:	Labor, capital, interest-bearing liabilities	Interest-bearing assets, non-interest income	1995–2002	79
		Model B:	Labor, capital, interest-bearing liabilities	Profit before tax and abnormal items		

1986 to 1995. His findings showed that efficiencies generally rose in the sample period, but the main reason of total factor productivity change was technical change. Using the same technique, Sathye (2001) conducted empirical studies on the x-efficiency in Australian banking industry in 1996. His study of 29 locally incorporated banks, 17 of them domestically-owned and 12 foreign-owned, concluded that Australian banks were relatively inefficient by international standards.¹⁴ Based on the same group of sampled banks, Neal (2004) investigated X-efficiency and productivity change in the banking industry by bank type between

¹⁴ This conclusion is drawn from a simple comparison of mean efficiency scores among studies on different countries. As noted in this study, such a comparison may not be appropriate since the sampled banks differ.

1995 and 1999. He found that regional banks were less technically and allocatively efficient than other banks. Significant productivity improvement had occurred during the period, mainly through rapid technical progress.

Sturm and Williams (2004) examined the impact of foreign bank entry on banking efficiency in Australia. Their sample contained 39 banks, including both domestic banks and foreign banks, operating in Australia between 1988 and 2001. Using DEA and stochastic frontier analysis, they found that foreign banks were more efficient but less profitable than domestic banks due to their superior scale efficiency. Consistent with Avkiran (2000) and Neal (2004) findings, was a rise in bank productivity during the post-regulation period, driven more by technical change than efficiency improvement. A recent study conducted by Kirkwood and Nahm (2006) used DEA to evaluate cost efficiency and profit efficiency of ten domestically-owned retail banks between 1995 and 2001. They found that whilst major banks had improved both cost and profit efficiencies, the regional banks had shown little change in the cost efficiency of producing banking services and a decline in the profit efficiency.

Some of the above-mentioned studies also devoted some discussion to issues on bank mergers and their implications for public policy. The Policy Forum: Merger Policy in Australia published in March 2000 issue of the Australian Economic Review overviewed both the state-of-the-art merger regulations and the directions of academic research in the field. In regard to the Australian bank mergers, the effects in terms of efficiency, market share, profitability, competition or social welfare, and sometimes a combination of them, have been examined in some empirical studies. Beal and Ralston (1998) found no evidence to suggest that Australian consumers adversely reacted to bank merger announcements by moving their business elsewhere due to relatively high concentration of the Australian banking market. Avkiran (1999) examined the efficiency gains from four cases of bank mergers in Australia and the benefits to the public. Evidence from the few cases supported the hypothesis that acquiring banks are more efficient than target banks. However, the acquiring banks do not always maintain their pre-merger efficiency level. They present mixed evidence on whether some positive social gains in the form of increased market penetration by more efficient banks have been generated from bank mergers. Neal (2004) discussed the mergers with a regional bank as at least one of the parties to the merger and found it was the more efficient banks that took over less efficient banks.

8.4 Data and the Model

In the current study, we use the DEA approach to examine whether the Wallis Inquiry into the Australian Financial System leads to an improvement in banking efficiency performance. A four-step DEA method is applied to banks operating in two sub-sample periods, the pre-Wallis period and the post-Wallis period. Under the approach, some non-parametric statistical tests are conducted to compare efficiency

scores across banks of different organisational types. It is generally expected that the difference in banking efficiency between different bank groups, if exists, would be smaller, or would have disappeared since the conduct of the Wallis Inquiry in 1996, when regulatory policies over bank mergers and acquisitions were expected to be and later on were in fact further relaxed.

8.4.1 *The DEA Model*

DEA is a non-parametric approach for measuring technical efficiency of firms. It involves an application of linear programming (LP) to observed data to form an industry production frontier, against which the efficiency of each firm is measured. Mathematically, the efficiency of an individual firm can be calculated by solving a series of linear programs. Assume that there are K firms, each producing N outputs with M inputs. Denote the vectors of inputs and outputs as X and Y and the inputs and outputs for the i th firm as x_i and y_i . Technical efficiency (TE) under input-oriented variable returns-to-scale (VRS) technology is derived from solving the following linear program K times, once for each firm:

$$\begin{aligned}
 & \min_{\theta, \lambda_i} \theta, \\
 & \text{s.t. } \theta x_i \geq \lambda X \\
 & \quad y_i \leq \lambda Y \\
 & \quad \lambda_i \geq 0, i = 1, \dots, k \\
 & \quad \sum \lambda_i = 1
 \end{aligned} \tag{8.1}$$

where θ is a scalar and λ is a $K \times 1$ vector of constants. This involves finding the smallest value of θ for projecting the firm onto the industry frontier formed by all the observations at the point $(\lambda X, \lambda Y)$. The vector λ is the weights of peer observations in producing the projected point on the industry frontier. The value of θ is between 0 and 1.

8.4.2 *The Four-Step DEA Model*

We then follow Charnes et al. (1981) to apply the VRS DEA model in four steps to bank data for pre-Wallis and post-Wallis Inquiry periods. The procedures are specified as follows:

1. Firstly, all banks are classified into two groups namely incumbents and entrants. Apply standard DEA to banks within each group to identify their corresponding production frontiers.
2. Secondly, project all the remaining inefficient banks to their corresponding best-practice frontiers formed in step 1.

3. Thirdly, apply super efficiency DEA to the revised pooled data to compare efficiency of the two efficient frontiers derived in step 2. Super-efficiency DEA is a type of modified DEA where the observation under evaluation is excluded from forming the reference production frontier (Andersen and Petersen 1993). The efficiency scores can be larger than one.
4. Fourthly, use some non-parametric statistics tests to assess any difference in terms of efficiency level between the two sub-samples.

Note that the DEA efficiency scores estimated from step 1 and step 3 are managerial efficiency and program efficiency respectively, following the terminology used in Charnes et al. (1981). The two types of efficiency differ in terms of reference sets of observations that we shall be studying. Managerial efficiency measures the within-group efficiency, i.e. relative efficiency of an individual bank benchmarked against banks within the group. Program efficiency measures the relative efficiency of an individual bank in an across-group comparison after within-group inefficiencies are removed. Therefore, in our study, any program efficiency difference can be attributed to the group difference associated with entry type. It is also worth noting that super efficiency rather than standard DEA efficiency is used as a measurement of program efficiency.

In step 4, non-parametric rank statistics technique is adopted to examine the inter-group difference in super efficiency. The previous DEA studies use either parametric tests or non-parametric tests. For example, Banker (1993) developed some parametric hypothesis tests in his statistics-related DEA study. The test was applied to DEA efficiency scores derived for two programs in order to detect whether there is any statistically significant difference between the two programs. However, the work was limited in some aspects, including restrictive parametric assumptions concerning the distribution of inefficiencies. Earlier work, such as Charnes and Cooper (1980), used Kullback–Leibler statistic and found that the programmatic efficiency difference was statistically insignificant. However, further work done by Brockett and Golany (1996) showed that the use of this statistic was inappropriate as it measured the distance to a uniform distribution rather than the deviation from the uniformly-distributed unity efficiency. Similar to the procedures proposed in their paper, we use the Mann–Whitney test to detect whether the two bank groups have the same mean of efficiencies within a pooled DEA dataset.

The Mann–Whitney test is a non-parametric test which examines the hypothesis that two independent samples come from populations having the same median. It is equivalent to the parametric independent group t-test, but requires less stringent assumptions. It also reduces or eliminates the impact of outliers by using rank-order data. However, when numeric figures are transformed into rank-order data, some useful information may be lost. The following steps are followed to conduct the test¹⁵:

1. Rank order all n DMUs ($n = n_1 + n_2$ where n_1 and n_2 are the number of observations in group 1 and 2 respectively) by their super-efficiency scores in step III

¹⁵ The test is available from SPSS11.0.

from the smallest to largest. By using the super-efficiency score for ranking, we avoid the situation of having a tie for all the efficient observations on the production frontier.¹⁶ In case of a tie, the mid-rank for the tied observations is used for correction.

2. Compute the sum of ranks of DMUs in each group.
3. Compute the Mann–Whitney rank test statistic:

$$U = n_1 \cdot n_2 + \frac{n_1 \cdot (n_1 + 1)}{2} - R.$$

4. Where R is the sum of ranks of DMUs in the first group.
5. For $n_1, n_2 \geq 10$ compute Z-statistic:

$$Z = \frac{U - \frac{n_1 \cdot n_2}{2}}{\sqrt{\frac{n_1 \cdot n_2 \cdot (n_1 + n_2 + 1)}{12}}}$$

6. Z has an approximately standard normal distribution.

8.4.3 Data

The data set is composed of information from commercial banks operating in Australia for the financial years 1982/1983–2000/2001 inclusive. It is an unbalanced panel data with 505 observations, ranging from a minimum of 14 banks in 1983 to a maximum of 36 in 1989. The data sets are broken into two time periods: 1986–1995 (pre-Wallis Inquiry period) and 1996–2001 (post-Wallis Inquiry period).¹⁷ Each bank is defined as either incumbent or entrant depending on whether it became a bank prior to the beginning of financial deregulation in Australia (here we take the year 1983 when the Martin Committee of Review was formed). As noted earlier, any bank operating in Australia can fall into one of the following four categories: major banks, existing regional banks, newly-established regional banks and foreign banks. In general, major banks and existing regional banks are the incumbents while newly-established regional banks and foreign banks that entered into the Australian banking industry since 1983 are the entrants.

In this study, we follow the intermediation approach, under which banks are viewed as financial intermediaries that transfer financial assets between savers and

¹⁶ However, the super-efficiency DEA model's ability of differentiating efficient DMUs is restricted by the presence of infeasibility problem when the model is estimated under variable returns-to-scale. The work done by Xue and Harker (2002) concluded that those DMUs with infeasibility problem are in fact extremely efficient. In this study, we follow their work to assign observations with infeasibility problem (labelled as “big” in EMS program) the highest ranking.

¹⁷ The Inquiry was established in May 1996 under the chairmanship of Mr. Stan Wallis.

investors. The outputs are defined as net loans, investment and number of branches.¹⁸ The inputs chosen are labour, physical capital, and loanable funds. Net loans are the amount of loans, advances and bills discounted net of provisions. Investment comprises financial securities, inter-bank deposits and other investments, which are part of revenue-earning assets. Number of branches is the number of full-service branches in a bank, excluding those agencies. Labour is defined as the number of full-time equivalent staff employed in the bank. Physical capital represents the book value of premises and fixed assets. Loanable funds are measured as the value of total liabilities.¹⁹ The monetary units are measured in thousands of Australian dollars and have been deflated to constant 1982–1983 prices by GDP deflator.

DEA models will estimate the same industry frontier regardless of input and output orientations. Therefore, the same group of firms will be identified to operate efficiently on the frontier. However, the efficiency estimates of inefficient firms may differ under variable returns-to-scale technology. As pointed out by Coelli and Perelman (1999), the choice of orientation often has only a minor influence upon the efficiency scores derived. For the Australian banking sector, both input-orientation and output-orientation are arguably appropriate for DEA modeling. The majority of the banking sector have experienced downsizing during the 1990s in order to ensure the efficient use of resources, while they competed with each other fiercely for the market share. As profit-maximisers, they could have adopted cost-minimisation or revenue-maximisation or both depending on the banking environment that they were operating in. Given the evolution of the industry over time, different orientations are adopted to measure bank operation for the pre- and post-Wallis period.

Banks have competed actively for market share in the retail and wholesale banking markets among themselves and with other non-bank financial institutions during the early deregulation period. Thus, an output-oriented DEA model is run for the pre-Wallis Inquiry period. However, for the post-Wallis Inquiry period, an input orientation model is used to measure the efficiency of banks in terms of their potential to reduce inputs given the same level of outputs. This is because the majority of the banking sector, in particular the four major banks, have experienced restructuring of business through centralisation of processing function, increased technological automation, as well as staff and branch rationalisation in recent years. See Fig. 8.1 for the trend of movement in employment and fixed assets in the industry by bank group. Both number of employees and amount of fixed assets in the existing banks increased rapidly till the early 1990s and then started to decrease substantially. The down-sizing strategies adopted by these banks have experienced big loss of jobs in the industry.

¹⁸ The number of branches of a bank is used as a proxy for the quality and convenience of bank services that the bank offers to its customers. Previous works that have this variable as an output measure include Grifell-Tatje and Lovell (1996) and Berg et al. (1993).

¹⁹ A more accurate measurement is deposits and borrowings. However, inconsistency persists in the presentation of the liability side of banks' balance sheet. No separation of deposits and borrowings from other liabilities for earlier data set.

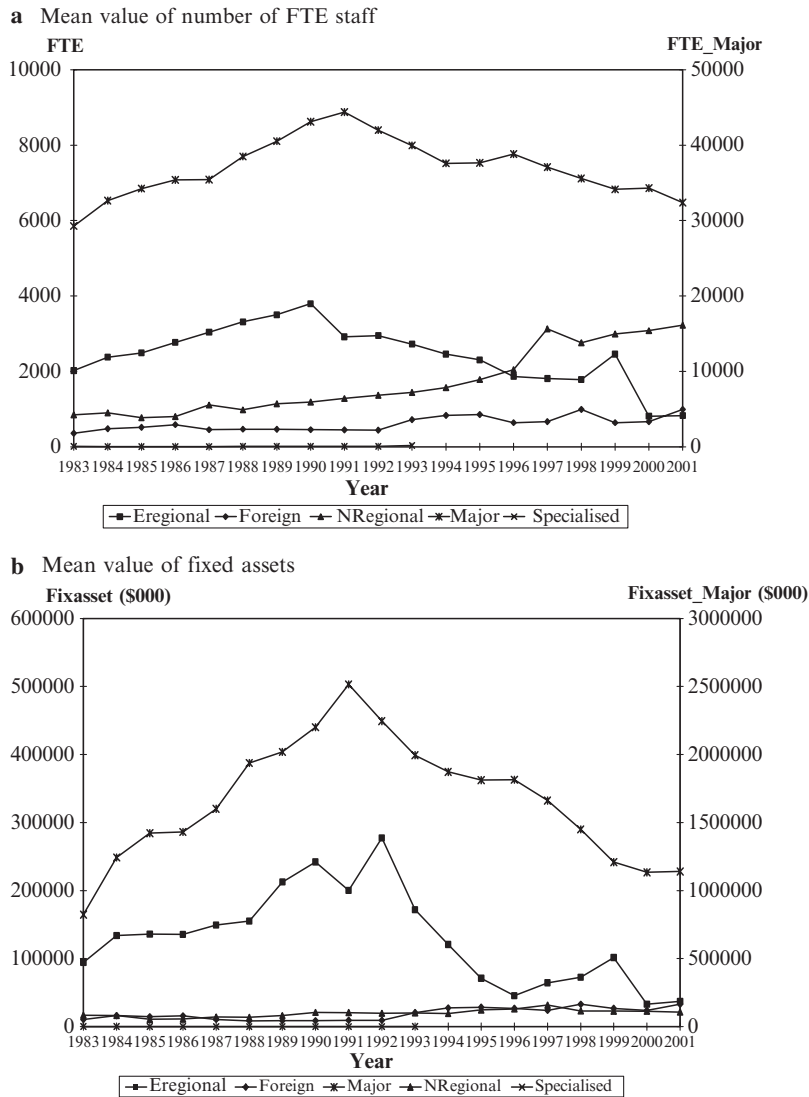


Fig. 8.1 Trend of employment and fixed assets by bank type (1983–2001)

The primary data source is the banks’ annual reports. Missing data were obtained from the Financial Institutions Performance Survey edited by KPMG, the Australian Banking Statistics and the Reserve Bank of Australia Bulletin, wherever possible. The KPMG survey provides annual survey information on a number of size, growth, profitability, efficiency and credit quality measures of a broad cross-section of financial institutions operated in Australia. The latter two

are monthly publication by the Reserve Bank of Australia.²⁰ They contain individual bank data, including monthly data on average of weekly balances of selected liabilities and assets recorded on banks' Australian books in a month and yearly data on income statement and balance sheet figures at balance date. Information on number of branches and agencies of individual bank is also published once a year. In case that any discrepancies exist for data collected from the different data sources, figures from the individual bank annual report are used except where otherwise indicated.

Table 8.2 provides the descriptive statistics of all input and output variables by bank group. The data shows that incumbents as a group are, on average, much larger than entrants as a group in both sub-sample periods. Both types of banks are getting larger over time.

8.5 Empirical Results

Summary statistics of DEA managerial efficiency scores and program efficiency scores are presented in Tables 8.3 and 8.4 respectively. As shown, the data are examined according to the time period and the bank type. Efficiency scores within each group have a negatively skewed distribution. For both pre- and post- Wallis Inquiry periods, incumbents have higher mean managerial efficiency than entrants. And the distribution of the efficiency scores is less for the incumbents than for the entrants. On removing the managerial inefficiency within each group, entrants exhibit higher mean program efficiency for both periods. Incumbents excluding major banks, on average, are the least efficient group, while incumbents including major banks perform slightly better. Efficiency distribution within the latter group is slightly less dispersed. Entrants are the most efficient but the least dispersed group.

Figures 8.2 and 8.3 show the relationship between program efficiencies derived from super efficiency DEA and bank sizes (measured in terms of natural log of total assets) for sampled banks during the pre-Wallis Inquiry period and during the post-Wallis Inquiry period, respectively.²¹ As the industry frontier is formed by fully-efficient banks, the figures can be interpreted as an illustration of thick industry frontiers formed by banks with super efficiency scores equal to or higher than one, as well as those inefficient banks operating under the frontier. As shown, the

²⁰ The Australian Banking Statistics was formerly published by the Australian Bureau of Statistics in the Commonwealth of Australia Gazette. From January 1990, it was published monthly by the Reserve Bank of Australia. Since July 1998, the Australian Prudential Regulation Authority regulates the Australian banks and therefore publishes the data.

²¹ The super efficiency scores assigned to extremely efficient observations that have infeasibility problem are two in Figure 8.2 and three in Figure 8.3. The values are higher than super efficiency scores obtained by any observations with feasible solutions. Alternatively, we can follow Lovell and Rouse (2003) to assign super efficiency scores equal to a scale defined by the maximum of variable ratios observed in the sample. However, the values of these scalars are so large relative to the efficiency scores in our sample, and will distort Figs. 8.1 and 8.2 to some extent.

Table 8.2 Descriptive statistics by bank group (1983–2001)

Variable	Entrants 1983–1995	Incumbents 1983–1995	Entrants 1996–2001	Incumbents 1996–2001
Net loans (\$000,000)				
Mean	1,763.87	19,195.79	5,195.57	61,018.02
Standard deviation	1,773.89	21,866.37	6,907.57	46,981.47
Maximum	12,031.63	78,216.57	30,029.12	153,976.47
Minimum	63.26	86.89	132.32	1,175.57
Investment (\$'000,000)				
Mean	590.90	6,623.15	1,332.60	14,897.41
Standard deviation	534.35	7,280.56	1,697.42	12,661.60
Maximum	2,446.77	28,569.51	8,489.18	47,491.83
Minimum	20.588	32.87	0.01	170.64
Branch (#)				
Mean	46.07	561.06	62.19	710.38
Standard deviation	71.82	571.35	111.49	453.81
Maximum	299.00	1,794.00	513.00	1,390.00
Minimum	1.00	1.00	1.00	47.00
Loanable funds (\$'000,000)				
Mean	2,401.74	30,210.86	6,677.57	89,313.55
Standard deviation	2,264.16	34,247.71	8,223.58	72,537.75
Maximum	14,012.15	114,304.88	34,987.80	260,209.91
Minimum	57.36	138.99	128.91	1,382.73
Staff (#)				
Mean	768.53	15,628.02	1,572.90	23,572.22
Standard deviation	732.73	17,569.48	1,954.62	17,377.14
Maximum	3,780.00	48,267.00	7,886.00	47,417.00
Minimum	44.00	50.00	47.15	438.00
Fixed assets(\$'000,000)				
Mean	41.77	753.03	63.39	931.37
Standard deviation	71.62	864.54	110.15	739.15
Maximum	380.47	3,330.22	532.42	2,147.51
Minimum	0.84	0.49	0.76	13.57
Number of observations	233	142	93	37

Table 8.3 Summary statistics of the DEA managerial efficiency scores

Year	Bank type	N	Mean	Median	Standard deviation	Maximum	Minimum
1983–1995	Incumbent	142	0.946	0.966	0.064	1.000	0.723
1983–1995	Entrant	233	0.867	0.904	0.137	1.000	0.473
1996–2001	Incumbent	37	0.971	1.000	0.051	1.000	0.819
1996–2001	Entrant	93	0.956	0.989	0.074	1.000	0.621

latter parts of both pre-Wallis inquiry and post-Wallis inquiry industry frontiers are formed by the major banks only.

This is because banks are benchmarked against each other of similar size when estimating efficiency under variable returns-to-scale technology for the industry.

Table 8.4 Summary statistics of DEA program efficiency scores

Year	Bank type	N	Mean	Median	Standard deviation	Maximum	Minimum
1983–1995	Incumbent ^a	142	0.926	0.998	0.125	1.000	0.533
1983–1995	Incumbent ^b	90	0.883	0.951	0.140	1.000	0.533
1983–1995	Entrant	233	0.993	1.000	0.018	1.000	0.823
1996–2001	Incumbent ^a	37	0.990	1.000	0.021	1.000	0.925
1996–2001	Incumbent ^b	13	0.981	0.991	0.024	1.000	0.925
1996–2001	Entrant	93	0.999	1.000	0.002	1.000	0.984

^aIt contains both major banks and existing regional banks

^bIt contains existing regional banks only

^cDue to infeasibility problem with super efficiency DEA model first raised in Xue and Harker (2002) and discussed in this paper in footnotes 16 and 21, mean and standard deviation statistics is calculated using standard efficiency scores.

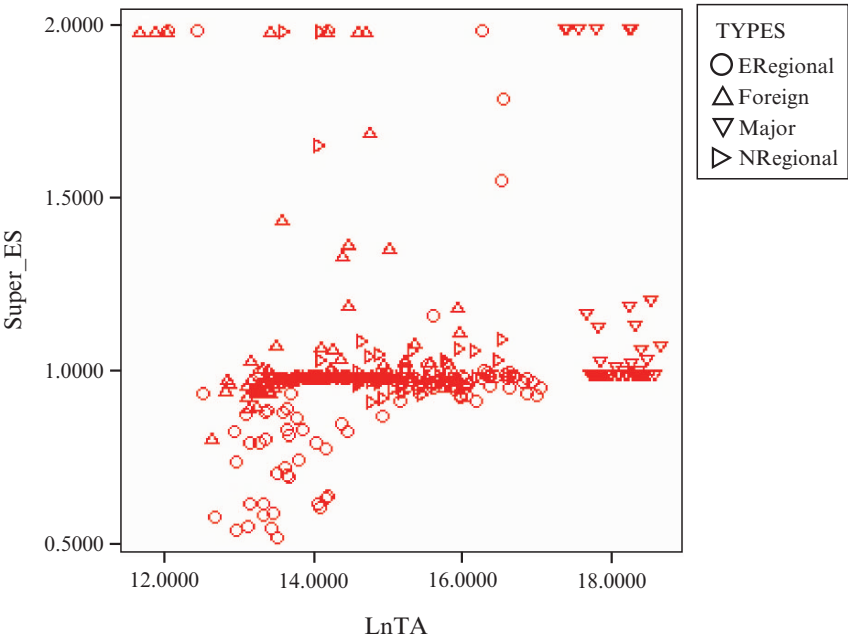


Fig. 8.2 Program efficiencies and sizes by bank type (1983–1995)

The major banks, which are operating nation-wide, are of much larger size than banks of other types. The relative efficiency performance of an individual major bank is generally derived from benchmarking against other major banks. However, the two figures differ in terms of efficiencies of existing regional banks relative to other banks. In Fig. 8.2, relative performance of existing regional banks are much poorer than banks of other types, and consequently, the incumbents as a group is found to be relative inefficient than the entrants as a group. In Fig. 8.3, the perform-

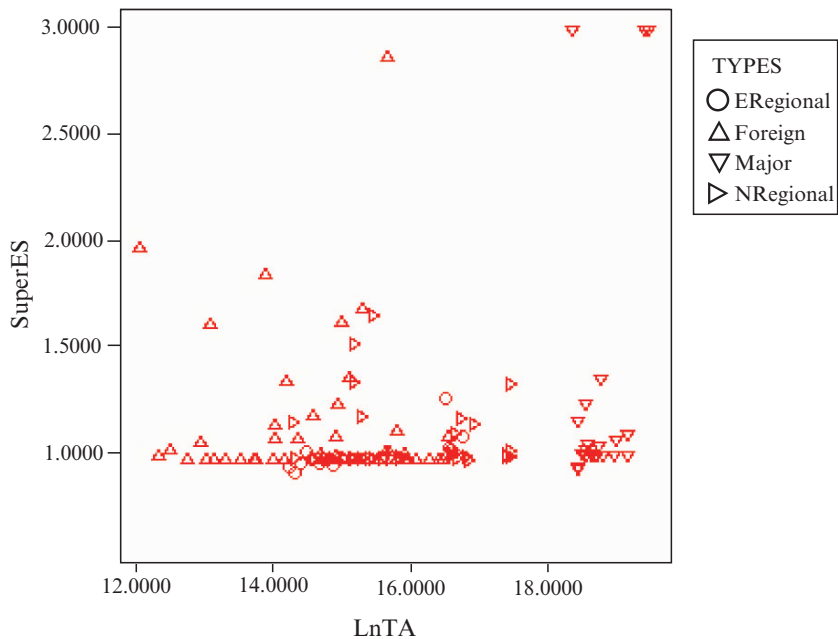


Fig. 8.3 Program efficiencies and sizes by bank type (1996–2001)

Table 8.5 Summary of the non-parametric Mann–Whitney U test results

Data	Incumbent		Entrant N	Mean rank ^a	Mann–Whitney U test	Exact significance for H_0 : $ES_{INC} \geq ES_{ENT}$
	N	Mean rank ^a				
1983–1995 ^b	142	157.58	233	206.54	12,223.0	0.000
1996–2001 ^b	37	59.08	93	68.05	1,483.0	0.106
1996–2001 ^c	13	33.54	93	56.29	345.0	0.004

^aA full rank is ordered based on super-efficiency scores, following Xue and Harker (2002)’s approach to solve infeasibility problem with super-efficiency DEA

^bIt contains all the banks for the sample period between 1995 and 2001

^cIt excludes major banks from the full sample data

ance of existing regional banks seems to have improved since the conduct of the Wallis Inquiry. Banks of all types exhibit high efficiency.

Table 8.5 reports the non-parametric statistical test results from step 4. Using a one-tailed test, we examine the directional null hypothesis $H_0: ES_{INC} \geq ES_{ENT}$, which states that the incumbents are at least as efficient as the entrants are. For pre-Wallis sampled banks, we reject the null hypothesis at a 1% level of significance and conclude that the incumbents are less efficient than the entrants during the period of 1983–1995. When the test is applied to the sample data for post-Wallis Inquiry period, we fail to reject the null hypothesis at a 10% significance level. This implies that since the Inquiry, entrants have lost much of their efficiency advantage over the incumbents identified in the pre-Wallis Inquiry period.

As pointed out by Brockett and Golany (1996), there is still a possibility that one group outperforms the other up to a certain point (input level or size indicator), and then the frontiers intersect and the other group becomes the more efficient (see Fig. 8.2 of their paper). In that case, when Mann–Whitney test is applied to the whole range of data, it may fail to reject the null hypothesis of same mean of efficiency, although the two groups exhibit different distributions of efficiency rankings over a certain range of data. It is most likely to be the case in Fig. 8.2, where existing regional banks may perform slightly worse than other small-sized banks while the majority of the major banks are found to be fully efficient. Overall, it is difficult to tell whether the incumbents are less efficient than the entrants.

Therefore it is necessary to conduct further test for sub-groups of the sampled banks categorised by magnitude of inputs or size. By truncating the sampled banks for the post-Wallis period to those whose total assets are below \$40 million in real value,²² the Mann–Whitney test result shows that at a 1% level of significance, the incumbents are on average less efficient than the entrants.

We also use Kruskal–Wallis test²³ to see whether there is any difference in efficiency level among the different types of banks during the post-Wallis period: major banks, existing regional banks, newly established banks and foreign banks. Table 8.6 displays the two-tailed statistical test results. As shown in the table, efficiency levels do not significantly differ across the four types of banks at a 5% level of significance. When major banks are excluded from the data, the test results show that efficiency levels exhibit statistically significant difference across the other three types of banks at a 5% level of significance. This is consistent with the Mann–Whitney test results which conclude that the existing regional banks are statistically less efficient than the new entrants. However, being more conservative, we may fail to reject the hypothesis of no difference across bank types at a 1% level of significance ($1\% < p < 5\%$) from the Kruskal–Wallis test.

The non-parametric statistical test results show that although entrants have advantage over incumbents in terms of program efficiency in both periods, we have less evidence for the rejection of the null hypothesis about the existence of inter-group efficiency differences across bank entry types for the post-Wallis Inquiry period. Combined with the information presented in Table 8.4 on mean program efficiencies for entrants and incumbents in each period, we find that the magnitude of efficiency differences between entrants and incumbents are getting much smaller during the post-Wallis Inquiry period. The implications are that the banking sector is virtually under more pressure to improve efficiency performance since the Wallis Inquiry was conducted. Any inefficient banks, particularly those of small or medium size, will eventually fall over as a takeover target. As a matter of fact, the

²² The truncated sample data contains all the existing regional, newly established regional and foreign banks during the sample period. All the major banks are excluded from the new subset of data.

²³ The Kruskal–Wallis test is employed with rank-order data for hypothesis testing involving two or more independent samples. The null hypothesis involved is that the samples medians are equal for all the samples. The alternative hypothesis is that at least two of the sample medians will not be equal.

Table 8.6 Summary of the non-parametric Kruskal–Wallis test results

Data	Major N	Mean rank	ERegional N	Mean rank	NRegional N	Mean rank	Foreign N	Mean rank	Chi-square	Degree of freedom	Asymp. significance (two-tailed)
1996–2001 ^a	24	68.92	13	40.92	36	64.72	57	70.16	6.945	3	0.074
1996–2001 ^b			13	33.54	36	53.42	57	58.11	7.243	2	0.027

^aIt contains all the banks for the sample period between 1996 and 2001

^bIt excludes major banks from the full sample data

group of incumbents has shrunk since the 1987 stock market crash and the 1991 recession. All the former state banks, which were relatively inefficient compared to other banks, were either taken over or sold to other banks. Currently, only one existing regional bank – Bank of Queensland, is still in operation.

8.6 Conclusions

In this study, we examine whether the Wallis Inquiry into the Australian Financial System improves banks of different groups and the banking industry's efficiency performance. As pointed out in FSI (1997, p.473), a key issue in the Australian banking sector is whether there should be merger between the existing four major banks. The Inquiry led the Government to adopt the four pillars policy, which still banned mergers among the four major banks. However, it is generally believed that sooner or later, the government will look at the issue of bank mergers again: should the policy be relaxed or removed? From examining the relative efficiency performance of individual bank groups prior to the Inquiry and after the Inquiry, this paper attempts to gauge the efficiency effect of further relaxation (or removal) of the four pillars policy.

The four-step DEA results validate the claim that newly-established banks have an advantage over the existing banks in terms of program efficiency. However, new entrants have lost much of their efficiency advantage since the conduct of the Wallis Inquiry, as incumbents have managed to dramatically improve their efficiency performance. It seems that all the banks are under increasing pressure to operate efficiently and competitively in a more deregulated industry.

In conclusion, the abolition of the four pillars policy may further intensify competition and improve efficiency in the banking industry as all the banks are under the threat of domestic takeovers. Even without actual mergers and acquisitions, the threat of takeover itself can serve to press for efficiency improvements since inefficient banks are more likely to be targets of takeover by other firms within or outside the industry. In addition, the actual takeover may facilitate the exit of relatively inefficient banks and increase efficiency at remaining banks.

The limitation of this paper is that there is no examination of competition effect of actual mergers and acquisitions. Merger among the four major banks will be socially beneficial if and only if the market remains competitive and contestable. Financial deregulation, globalisation and technological advances have worked together to improve competitiveness in the Australian banking industry in the past. These forces will continue to influence the industry at various degrees. Therefore, the primary role of the government is to focus on promoting deregulation and competition in the banking industry and in the economy.

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Part III
Efficiency in Public Sector
and the Role of Public Policy

Chapter 9

Performance Ranking and Management Efficiency in Colleges of Business: A Study at the Department Level in Taiwanese Universities

T.-T. Fu and M.-Y. Huang

9.1 Introduction

Empirical analysis of the efficiency of higher education institutions has commonly involved the use of data envelopment analysis (DEA). Leading studies in this area include those that measure efficiency at the school level, such as Ahn et al. (1988) on US universities in 1981–1985, Glass et al. (1998) on UK universities in 1989–1992, and Avkiran (2001), Abbott and Doucouliagos (2003) and Carrington et al. (2004) on Australian universities. There are also a few studies that measure efficiency at the departmental level. For example, Madden et al. (1997) assessed the efficiency of economics departments in Australian universities, Johnes and Johnes (1993) assessed the efficiencies of economics departments in the UK in 1984–1988, Haksever and Muragishi (1998) and Colbert et al. (2000) studied the efficiency performance of MBA programs in the US, and Ray and Jeon (2003) employed a production model and DEA to examine the reputation and production efficiency of MBA programs in general.

The efficiency ranking provides useful management information for managers of educational production decision-making units in terms of providing effective resource allocation. Such quantitative evidence on school performance is often used by government educational authorities as an indicator for allocating public funding and subsidies to institutions of higher education. It is however arguable whether such efficiency ranking information is useful to prospective students or employers. Will prospective students use the information regarding the relative efficiency of institutions in their decisions on which college to join? The possible answer is inconclusive. Intuitively, if the resource use efficiency ranking can reflect the ranking in terms of a school's reputation, then such information can be used by students when choosing a college. It is often the case that prospective students do

T.-T. Fu

Institute of Economics, Academia Sinica and National Taiwan University, Taipei City, Taiwan

M.-Y. Huang

Department of Economics, National Taipei University, Taipei, Taiwan (ROC)

not really pay attention to how resource efficient a school has become or how many resources are invested in that school. They usually pay more attention to the outcome of schooling, i.e. (1) the value-added of the school programs: whether the school programs can enhance their levels of human capital which will result in a high salary or make it easy to be hired by employers upon graduation, and (2) the school's quality: whether they can enjoy a quality learning environment (campus, teaching and research) and curriculum in that school. Therefore, the performance ranking to determine the best schools from the prospective students' point of view may be quite different from the school rankings' based on the efficiency of the resources used in those schools.

Recently, several studies have been aware of such a gap between the information demanded by prospective students and information regarding the efficiency rankings of schools. Breu and Raab (1994) measured the relative efficiency of the best 25 US News and World Report-ranked universities. They found that the quality ranking of the list of universities contained in the US News and World Report, which was aimed at allowing prospective students and parents to choose a university, had an inverse relationship with the efficiency ranking implied by the narrow productivity criterion that characterized DEA. Haksever and Muragishi (1998) measured the value-added in US MBA programs, and demonstrated how their efficiency rankings based on DEA were useful to prospective MBA students. In contrast to the rankings provided by the Business Week or the US News and World Report, which were based on subjective responses from constituent groups such as the CEOs of firms, school deans, recruiters or graduates, Tracy and Waldfogel (1997) proposed a market-based ranking for the business schools using the labor market performance of each program's graduates. They identified the value-added of each MBA program using regression analysis and then used the estimated value-added for ranking programs.

The number of higher education institutions in Taiwan has increased fivefold over the last three decades, whereas the corresponding government budget has only increased about four times. As a result of the reduction in public funding appropriated per school, many schools have faced financial plight recently. Also in recent years, a few colleges or universities have encountered low student enrollment problem. This problem is expected to worsen in the future since the Taiwanese fertility rate has declined over time and became the lowest in the world in 2005. Under such an increasingly competitive higher education industry in Taiwan, school managers must enhance their school quality or reputation to ensure that enough prospective students register. Moreover, to accommodate the reduction in government education funding and to report the school's performance to its board of directors, they must attempt to show that their resources are efficiently allocated and that they are performing as best as they can. It is therefore important for school managers to achieve the best performance in terms of attracting prospective students and the highest efficiency in terms of resource allocation.

Previous studies have indicated that the selection of outputs or inputs used in the analysis will significantly affect the resulting efficiencies. By using the school outputs as educational functions such as teaching, research and extension, a few studies have adopted a number of proxy variables, among others, such as student

enrollments (teaching), paper or book publications (research) and lectures or service to communities (extension) as outputs of a university or the department in question (Ahn et al. (1988); Glass et al. (1998); Avkiran (2001); Abbott and Doucouliagos (2003); and Carrington et al. (2004). However, some studies have doubted that the provision of these three functions is the ultimate goal of higher education. Hanushek (1986) found that most studies failed to show any systematic relationship between student outcomes and school inputs and expenditures. Lovell et al. (1994) proposed a multistage education production process, in which these three previously mentioned functions and their related services and activities are regarded as the intermediate goods of education. The test scores in school, grades and more subjective assessments of performance can be regarded as intermediate outcomes, whereas the student's performance after graduation, educational attainment, and income levels as long-term outcomes. In their evaluation of the value or efficiency of MBA programs, Haksever and Muragishi (1998) used average starting salary and jobs upon graduation as outputs of MBA programs. Recognizing that an MBA program must satisfy both students and recruiters, Colbert et al. (2000) employed measures related to student and recruiter satisfaction measures as outputs in evaluating the efficiencies of MBA programs.

In this paper, the final educational outcomes, namely the student's job market performance and the student's satisfaction in school, are used as outputs in our evaluation of both relative performance and efficiency in terms of the education process for departments in colleges of business. This performance evaluation is aimed at providing useful information to prospective students in terms of their choices regarding which college to join. To achieve our objectives, we have used appropriate methods of evaluating performance. The output-oriented BCC type of DEA model has been applied to evaluate of the relative resource use efficiency of schools for school administrators. Further, we have also identified appropriate best practice benchmarks for different types of inefficient school departments. Finally, we have compared the results based on both performance and efficiency evaluation.

The remainder of this paper is structured as follows. The methods used to evaluate the performance, that is, the DEA and the output-oriented BCC model are introduced in Sect. 9.2. This is followed by Sect. 9.3 which looks at the data and variables used. Section 9.4 includes all of the empirical results where the scores and rankings based on performance using the DEA method for prospective students are presented, whereas various resulting efficiency rankings based on the BCC model for school administrators are presented in Sect. 9.5. The paper ends with a discussion and concluding remarks in Sect. 9.6.

9.2 Methods for Performance Evaluation and Efficiency Measurement

To aggregate the performance indicators of the school for school administrators, the DEA is used in this study. DEA is a set of linear programming techniques that assist in identifying the set of decision-making units (DMUs) that may be considered

as the best practice. The best practice units are regarded as DMUs with full efficiency and efficiency scores are assigned to other units by comparing them with the best practice units (Coelli et al. 2000). Compared to alternative popular methods for performance evaluation such as the stochastic production frontiers, DEA is appealing to researchers since it can assess the technical efficiency of DMUs with multiple inputs and multiple outputs using only information on input and output quantities, apart from other benefits such as a free model functional form and a residual distribution. Such unique data requirement characteristics, without requiring information on prices, have resulted in DEA being widely employed in evaluating non-profit organizations or government-regulated industries where the prices of outputs are generally not available in the market or else do not reflect market value.

9.2.1 *Performance Ranking and the Performance DEA Model (PDEA)*

To provide appropriate assessment based on a set of performance related indicators, we have employed a simpler version of DEA which is proposed by Kao (1994). In his study on the evaluation of junior colleges of technology, Kao (1994) formulated a linear programming model to aggregate a set of measurements. In such a model, each college is allowed to select the weights which will result in the highest possible efficiency or performance score for itself. Conceptually, this model allows each college to develop its favorable output set (performance indicators) based on its own resource endowments, constraints or preferences.

The model proposed by Kao (1994) can be expressed as a simpler form of the DEA model that only considers outputs. Since this model is used to evaluate the performance of departments from the prospective students' or employers' point of view, it is referred to as a performance DEA model (or PDEA model) in this paper. By denoting Y_{ij} as the j -th output of the i -th department, and P_i as the performance score, defined as the total value or weighted sum of multiple outputs, the performance of the i -th department is calculated via the following objective maximization linear programming model:

$$\begin{aligned}
 P_i = \max \quad & \sum_{j=1}^m u_j Y_{ij} \\
 \text{s.t.} \quad & \sum_{j=1}^m u_j Y_{ij} \leq 1, \quad i = 1, \dots, n \\
 & u_j \geq 0, \quad j = 1, \dots, m
 \end{aligned} \tag{9.1}$$

where m is the number of outputs and n is the number of departments. The u_j is the weight assigned to the corresponding j -th output. Note that this PDEA model will use the information of outputs of the decision making unit (DMU) only, no information on inputs is needed.

9.2.2 Resource use Efficiency and the Resource DEA Model (RDEA)

To assess resource use efficiency for each DMU, we adopted the output-oriented DEA model which was developed by Banker et al. (1984) (the BCC model), which allows for the measurement of variable returns to scale. Unlike the PDEA model, the resource use output-oriented DEA model (referred to as the “RDEA” model in this paper), is a standard DEA model, which evaluates the efficiency of each DMU based on a set of outputs given a set of resource inputs.

Given output vector $\mathbf{Y}$ and input vector $\mathbf{X}$, the Farrell’s technical efficiency for the i -th DMU (E_i) can be formulated as the following BCC model:

$$\begin{aligned}
 E_i = \min \quad & \sum_{r=1}^s v_r X_{ir} + v_0 \\
 \text{s.t.} \quad & \sum_{j=1}^m u_j Y_{ij} = 1 \\
 & \sum_{r=1}^s v_r X_{ir} \geq \sum_{j=1}^m u_j Y_{ij} - v_0, \quad i = 1, \dots, n \\
 & u_j \geq 0, v_r \geq 0 \quad j = 1, \dots, m \quad r = 1, \dots, s
 \end{aligned} \tag{9.2}$$

where X_{ir} is the r -th input of the i -th DMU, and Y_{ij} is the j -th output of the i -th DMU. The v_r is the weight of the r -th input, u_j is the weight of the j -th output, and v_0 is a random variable and free in sign. In addition, n is the number of DMUs, m is the number of outputs, and s is the number of inputs.

9.3 School Performance Indicators: Data and Variables

Most of the previous studies on the performance evaluation of higher educational institutions used secondary data obtained from educational institutions or government authorities, and some used data obtained from MBA institutions, or from the US News and World Report or Business Week. In this study, a survey of recent college graduates was conducted in 2003 for our research purposes. Since the survey was a primary survey, we were able to collect different dimensions of performance indicators, including college graduate performance in the job market after graduation and student satisfaction with regard to the school environment and curriculum, as well as the student’s devotion to the school and its related activities. These are important outcomes of college education.

In our survey, a stratified random sampling framework was used to survey recent graduates in Taiwanese universities with a College of Business or Management. College graduates who were full time students in selected departments of these business or management colleges and had graduated from that college 3 years before (or 5 years for males) were the targeted samples. In the survey, the graduates

were asked, among other things, regarding their performance in the job market after college graduation and their satisfaction with the school's services and curriculum. We then averaged out the variables according to departments to obtain two categories of performance (output) variables for each department. These output measures are used for the evaluation of both performance and efficiency in the sections that follow in this paper.

9.3.1 Definitions of Performance Indicators

Two categories of variables representing two dimensions of performance, namely the student's job market performance and the student's satisfaction with the school, are defined as follows. The first, three measures relate to the "student job market performance". These measures may also be referred to as the "recruiter's satisfaction" since they reflect the employer or the recruiter responses to the performance of these graduates. They include:

- Y1 – the average monthly starting salary of graduates
- Y2 – the average search duration of graduates for the first job. Empirically, the reciprocal is used to indicate that the shorter the search length, the better the performance
- Y3 – the average monthly current salary of graduates. Since this salary is a 3-year work- experience wage, it is intended to represent the student's ability to maintain a sustainable work performance

The starting salary (Y1) has been used extensively as the satisfaction expressed by recruiters towards college graduates or MBA graduates upon graduation. Since the recruiters may not know the implicit productivity of a college graduate very well at first sight, a higher salary may also imply a higher reputation attached to a school in the past by the recruiter. Another variable often used in previous researches to represent the job market performance is the number of jobs offered upon graduation. The higher the quality of a graduate, the more job offers he/she will receive. However, we do not have such a measure. Instead, we use the length (duration) of searching for the first job (Y2) as a proxy for the quality of a graduate. The shorter the length of searching the job, the better is the quality of the graduate. The current salary (Y3) of a graduate also represents the graduate's ability to maintain a sustainable work performance after graduation. Since the graduates in our sample have three years of work experience, the current salary is the wage after having three years of work experience.

The second dimension of the performance variable relates to the college graduate's satisfaction with the environment, curriculum or activities of the school attended. This category of variable is particularly important to college students. This is because, unlike the outcomes of MBA programs, the outcomes of higher education should consist of capacities for building both monetary value and non-monetary value. The provision of a good learning environment and excellent extracurricular

activities by a school may be more appreciated by students than the formal classroom training to enhance cognitive skills for achieving better earnings in the job market. The measures related to student satisfaction in school include:

- Y4 – student satisfaction with the quality of the curriculum in his/her major field
- Y5 – student satisfaction with the quality of the curriculum in non-major fields

Since the respondents were asked to rate their satisfactions on a five-point Likert scale, with 1 for not very satisfactory, 2 for not satisfactory, 3 for indifferent, 4 for satisfactory, and 5 for very satisfactory, to simplify our analysis, we classified the answers using a dummy variable, with 1 for satisfactory (including those who answered 4 or 5) and 0 otherwise (including those who answered 1, 2 or 3). Therefore, empirically, the percentage of graduates who were satisfied with the quality of the curriculum in the major field was used for Y4, and the percentage of graduates who were satisfied with the quality of the curriculum in non-major fields was used for Y5. These two variables were used as proxies for student satisfaction with regard to the learning environment and services provided by the school attended. The higher the values of Y4 and Y5, the better the performance the school is deemed to have.

9.3.2 Data on Performance Indicators of Sampled Departments

The descriptive statistics of the performance variables (Y1–Y5) for sampled departments are shown in Table 9.1. Table 9.1 indicates that the average starting salary (Y1) was about NT\$31,000 per month, of which the average salary of a public school graduate was about NT\$4,000 higher than that of private school graduate. The mean value of the average search duration of the graduates for the first job (Y2) was about 2.2 months ($1/0.48$) with the public school graduates having a shorter job search duration and a higher salary in the first job than the private school graduates. In addition, on comparing the current salary (Y3) with the starting salary for graduates with three years of work experience, we found that the salary growth rate was higher for public school graduates than for private school graduates. Therefore, recruiters in Taiwan tend to prefer and more highly reward graduates from public schools.

The performance of the sampled departments in terms of the student's satisfaction in school (Y4, Y5) is shown in the last two columns of Table 9.1. On average, about half of the sampled graduates were satisfied with the quality of the curriculum related to their major field (Y4), while 40% of the sampled graduates were satisfied with the quality of the curriculum in regard to their non-major field (Y5). The quality of the curricula of Colleges of Business in Taiwan universities apparently needs to be improved to meet the expectations of their college graduates. Nevertheless, among the departments that were included in the sample, the departments in public schools have provided greater satisfaction in relation to both types of curriculum than those in private schools.

Table 9.1 Performance indicators of sampled departments by type: Mean and standard deviation ()

Type	Measures of job market performance			Measures of student satisfaction in school	
	Y1	Y2	Y3	Y4	Y5
Total	31,322 (3,028)	0.48 (0.33)	39,311 (5,633)	0.48 (0.2)	0.4 (0.17)
Public	34,064 (2,105)	0.61 (0.43)	43,897 (5,023)	0.58 (0.19)	0.51 (0.19)
Private	30,011 (2,480)	0.42 (0.24)	37,118 (4,503)	0.44 (0.19)	0.35 (0.13)

Y1 – Average monthly starting salary of graduates, NT dollars/month; *Y2* – average search duration of graduates for the first job, and empirically the reciprocal is used to indicate that the shorter the search length the better the performance; *Y3* – average monthly current salary of graduates, NT dollars/month; *Y4* – student satisfaction with quality of curriculum in major field; *Y5* – student satisfaction with quality of curriculum in non-major fields

9.4 The Relative Performance of Sampled Departments Via PDEA

9.4.1 Performance Scores and Rankings Regarding the Interests of Prospective Students

In this section, we evaluate the performance of departments from the point of view of prospective students and recruiters. As for the interests of prospective students, we used three sets of outputs for assessment: (Y1, Y2), (Y4, Y5) and (Y1, Y2, Y4, Y5). There were no resource inputs included in the models. The first set of outputs (Y1, Y2) represented the college graduate’s job market performance or the recruiter’s satisfaction, whereas the second set of outputs (Y4, Y5) represented the student’s satisfaction with the school’s services. The third set of outputs combined both output measures, and represented the joint or overall performance of a school. We used the proposed PDEA for performance assessment.

The results of the performance scores and ranks for all sampled departments for the three sets of outputs (outcomes) are shown in Table 9.2. The first three rows of Table 9.2 show the average performance scores and rankings of all the schools, as well as of the public and private schools for the three different output sets. In terms of the score for job market performance, Table 9.2 indicates that the average score for the overall sample is 81.29%, whereas the corresponding scores for the departments in public and private schools are 89.02% and 77.59%, respectively. These results imply that, on average, the sampled department has about a 19% capacity to improve to become the best practice school. In addition, the departments in public schools perform better than those in private schools in the job market. Similarly,

Table 9.2 Relative performance and rankings by performance DEA models (PDEA)

DMU no.		PDEA (Y1, Y2) for job market performance		PDEA (Y4, Y5) For student satisfaction		PDEA (Y1, Y2, Y4, Y5) for joint performance	
		Score	Rank	Score	Rank	Score	Rank
Total		81.29	—	60.24	—	83.71	—
Public		89.02	16.50	72.56	22.59	92.26	15.09
Private		77.59	43.04	54.35	40.13	79.63	43.17
N1 ^a	NTU-AC ^b	90.98	9	100	1	100	1
N2	NTU-IB	85.42	22	91.77	6	92.75	12
N3	NTU-IA	91.98	6	100	1	100	1
N4	NTU-FI	90.41	12	96.4	4	100	1
N5	NTU-EC	89.71	14	100	1	100	1
N6	NCH-AE	91.94	7	62.5	31	91.94	14
N7	NCK-AC	100	1	70.05	22	100	1
N8	NCC-BA	80.69	35	65.43	29	82.68	33
N9	NCC-FI	89.27	15	75.46	13	92.39	13
N10	NCC-IT	100	1	65.43	30	100	1
N11	NCC-AC	95.9	4	85.73	8	100	1
N12	NCC-FM	100	1	75.56	12	100	1
N13	NCC-RM	90.75	10	58.67	40	90.75	16
N14	NCC-PF	89.77	13	44.87	52	89.77	18
N15	NCC-EC	90.52	11	88.56	7	96.55	10
N16	NCU-BA	84.61	23	54.53	41	84.61	29
N17	NCU-EC	83.58	26	72.87	15	87.21	23
N18	NSU-BA	79.56	41	68.16	24	82.61	34
N19	NTPU-BA	86.8	18	43.62	54	86.80	25
N20	NTPU-AC	83.58	27	72.74	16	87.12	24
N21	NTPU-EC	78.60	43	62.27	33	80.11	43
N22	NTPU-CE	84.39	24	41.62	57	84.39	30
P23	SCU-BA	80.86	32	46.51	49	80.86	39
P24	SCU-AC	86.46	20	76.34	11	90.44	17
P25	SCU-IT	76.23	48	42.52	55	76.23	53
P26	SCU-EC	89.07	16	54.53	42	89.07	20
P27	CYU-AC	79.99	37	60.63	36	80.71	41
P28	CYU-BA	71.79	58	66.63	27	76.16	54
P29	CYU-IT	78.76	42	40.41	59	78.76	47
P30	TKU-AC	81.88	31	72.74	17	85.78	28
P31	TKU-FI	80.80	33	78.52	10	86.65	26
P32	TKU-EC	69.10	64	61.40	34	72.40	61
P33	TKU-BA	84.06	25	70.29	21	86.15	27
P34	TKU-IT	75.22	51	50.00	46	75.22	55
P35	TKU-IE	85.99	21	74.59	14	89.56	19
P36	THU-AC	86.49	19	51.12	45	87.42	22
P37	THU-EC	87.65	17	66.62	28	89.05	21
P38	THU-BA	67.05	67	54.53	43	68.75	67
P39	THU-IT	74.47	53	91.86	5	91.86	15
P40	FCU-AC	71.69	60	52.48	44	71.69	63
P41	FCU-FI	82.20	29	41.62	58	82.20	35
P42	FCU-EC	69.12	62	60.63	37	72.18	62
P43	FCU-BA	74.20	55	60.00	38	76.26	52
P44	FCU-PF	77.96	44	44.93	51	77.96	50

(continued)

Table 9.2 (continued)

		PDEA (Y1, Y2) for job market performance		PDEA (Y4, Y5) For student satisfaction		PDEA (Y1, Y2, Y4, Y5) for joint performance	
DMU no.		Score	Rank	Score	Rank	Score	Rank
P45	FCU-IS	76.12	49	61.40	35	81.10	38
P46	FCU-IT	67.51	66	69.79	23	73.63	59
P47	FCU-CE	75.72	50	62.50	32	78.14	48
P48	CCU-AC	74.30	54	18.21	68	74.30	57
P49	CCU-EC	68.79	65	45.47	50	68.79	66
P50	CCU-BA	82.01	30	22.75	66	82.01	36
P51	PRU-AC	71.79	59	68.16	25	76.51	51
P52	PRU-BA	70.91	61	31.25	64	70.91	64
P53	PRU-IT	76.65	47	59.25	39	78.11	49
P54	FJU-AC	80.75	34	44.12	53	80.75	40
P55	FJU-EC	82.90	28	46.78	48	82.90	32
P56	FJU-BA	77.15	45	67.71	26	80.22	42
P57	FJU-IT	91.25	8	72.74	18	95.06	11
P58	YZU-BA	92.29	5	82.65	9	96.73	9
P59	ISU-AC	62.28	68	36.31	60	62.28	68
P60	ISU-FI	79.65	40	72.74	19	84.04	31
P61	MCU-AC	77.05	46	70.58	20	81.17	37
P62	MCU-FI	79.87	38	42.43	56	79.87	45
P63	MCU-BA	75.14	52	46.87	47	75.14	56
P64	MCU-IS	79.76	39	35.09	63	79.76	46
P65	MCU-IT	73.83	56	35.22	62	73.83	58
P66	CHU-IA	80.01	36	36.31	61	80.01	44
P67	ALU-BA	69.12	63	31.25	65	69.12	65
P68	ALU-IT	73.04	57	21.81	67	73.04	60

^aN and P initials in column 1 representing national and private schools

^bAbbreviations of the names of the sampled universities and departments are listed in the Appendix in Table 9.8

Table 9.2 shows that the departments in public schools perform better than the departments in private schools in terms of the students' satisfaction with school services (Y4, Y5), although the average score (60.24%) for student satisfaction is much lower than the average score in relation to the job market. In the case of joint performance, the results in terms of the overall outputs (Y1, Y2, Y4, Y5) give rise to the same conclusions with regard to the comparisons. The rankings accorded to the public schools in Table 9.2 also outperform those for the private schools, for all the three sets of output. Such information can be useful information for prospective students and their parents when it comes to choosing between publicly- and privately-owned schools.

Detailed information on the relative performance of each department, as shown in Table 9.2, can also be useful information for prospective students choosing specific departments of interest. For instance, the Department of International Trade of National Chinch University (N10/NCC-IT) ranks first in terms of job market performance (Y1, Y2), whereas both the Department of Industrial Administration

(N3/NTU-IA) and the Department of Economics (N5/NTU-EC) of National Taiwan University rank as the best departments in terms of the student's satisfaction with the curriculum (Y4, Y5). We also found that NTU-IA was the best department in terms of overall performance, the job market and student satisfaction (Y1, Y2, Y4, Y5). In addition, it was found that the ranking for the Department of Business Administration, Yuan-Ze University (P58/YZU-BA) appeared to be impressive among the private schools. The YZU-BA ranked fifth in terms of job market performance, ninth in student satisfaction, and ninth in terms of overall performance. Another interesting example was the Department of International Trade of Tunghai University (P39/THU-IT). The THU-IT ranked the 55th in terms of job market performance. However, it ranked fifth in terms of student satisfaction with the school curriculum. Therefore, this department may be a good choice for prospective students looking for a good learning environment rather than a job market performance in the future. Likewise, one may find a department with good performance in the job market yet poor performance with regard to student satisfaction with the curriculum, such as NCC-PF (N14), as shown in Table 9.2.

9.4.2 Performance Ranking and Reference Peers

Although the performance of the sampled university departments has been evaluated for three kinds of outcomes, Table 9.3 shows that the correlations between the resulting ranks are positive. The Spearman rank correlations are 0.476 for PDEA (Y1, Y2) and PDEA (Y4, Y5), 0.940 for PDEA (Y1, Y2) and PDEA (Y1, Y2, Y4, Y5), and 0.683 for PDEA (Y4, Y5) and PDEA (Y1, Y2, Y4, Y5). To investigate whether the performance rankings calculated from our PDEA models were quite intuitively correct based on the impression of the general public in Taiwan, we used the College Entrance Exam Score (CEES) index in 2000 as the proxy for the quality-based school choice of the sampled departments. The rank correlations between the ranks of the three PDEA models and CEES were quite high, as shown in Table 9.3. Among these, the performance rank based on joint performance (PDEA (Y1, Y2, Y4, Y5)) had the highest correlation coefficient (0.721) in relation to the CEES.

Since the performance DEA is a variant of DEA, we were able to find the referenced peers. The DMUs that performed best with a full performance score (score = 1) were benchmarks for those DMUs without a full performance score. Table 9.4 shows the referenced sets and the numbers of citations as reference peers for each performance DEA. Note that a school code with N (P) as its initial is a department in a national (private) university. One can easily identify that the referenced peers with a full performance score are departments in national universities. The results in Table 9.4 also indicate that benchmarks for job market outcomes (Y1, Y2) are different from for student satisfaction (Y4, Y5). Therefore, strategies for enhancing performance in the job market will be different from for increasing performance in terms of student satisfaction for the sampled departments without a full performance score.

Table 9.3 Correlations between PDEA rankings and college entrance exam scores

	PDEA (Y1, Y2)	PDEA (Y4, Y5)	PDEA (Y1, Y2, Y4, Y5)
PDEA (Y1, Y2)	1	476(**)	940(**)
PDEA (Y4, Y5)	476(**)	1	683(**)
PDEA (Y1, Y2, Y4, Y5)	683(**)	940(**)	1
CEES ^b	684(**)	508(**)	721(**)

** denotes statistically significant at the 1% level. CEES college entrance exam scores

Table 9.4 Referenced peers for performance DEA (PDEA) models

PDEA	Reference set and (No. of citations as a reference peer)
PDEA (Y1, Y2)	N12(64), N10(13), N7(3)
PDEA (Y4, Y5)	N5(41), N1(20), N3(19)
PDEA (Y1, Y2, Y4, Y5)	N12(57), N5(22), N3(12), N10(10), N7(4), N4(2), N11(2), N1(1)

9.5 The Efficiencies of Sampled Departments based on Resource DEA Models (RDEA)

9.5.1 Definition and Data of the Resource Inputs of the Sampled Departments

With regard to the school performance variables, most recruiters will prefer applicants with good quality training, skills and knowledge, while the students will prefer a good quality school environment. However, such school performance or reputation building has to do with the quantity and quality of the resources invested by a school. School resource input measures are measured at the department level. Inputs include:

- X1 – faculty–student ratio, representing teaching quality
- X2 – average College Entrance Exam (CEE) score of sampled students in the department, representing the selectivity of the department and the quality of student
- X3 – male graduate ratio in the class, representing the effect of gender on the job market
- X4 – number of credit hours offered per week by faculty members in a department, representing the diversified learning environment of a school
- X5 – ratio of faculty ranked at least as Assistant Professor, representing the research and teaching quality in a school

Since the male graduate ratio (X3) is a control variable which captures the effect of gender on the wage, it will not be used to evaluate the performance of departments from the employer's perspective. Furthermore, in the efficiency ranking analysis for the school administrators assumed later in this study, the indicated performance indicators are used as outputs while the five resource input measures are used as input variables.

The mean and standard deviation of the five resource input variables (X1–X5) for the sampled departments are shown in Table 9.5. Table 9.5 indicates that the faculty–student ratio (X1) of public schools was two times that of private schools, which implies a high degree of appreciation for teaching quality and resources invested in

public schools. The College Entrance Exam score (X2), which is also the CEES, is a proxy for student quality. It also represents the selectivity of a department since such a score determines the acceptance or rejection of a student's application to college. In Taiwan, a student will submit a list of departments that he or she wishes to join to the College Entrance Committee for consideration. The College Entrance Committee will then compare all possible competitors' exam scores and match a favorable department for that student. Table 9.5 shows that public school students will have higher exam scores (X2) than students in private schools. Since higher exam scores may imply better quality in terms of acquiring knowledge, the freshmen in public schools will be regarded as being of better quality than their counterparts in private schools.

The male student ratio (X3) is used here to capture the effect of gender on the wage in the current job market, where male graduates are paid a higher wage than female graduates, or may have been hired earlier than their female counterparts in Taiwan. In our sample, about 35% of the sampled graduates are male, and the percentage tends to be higher in public schools. The number of credit hours offered by the department (X4) represents the variety of academic courses provided for students. The variety of courses is assumed to enhance students' job market performance or satisfaction with the program's curriculum. In our sample, public schools tend to offer more courses to students than private schools. The last input variable, the ratio of faculty ranked at least as Assistant Professor (X5), represents the quality of the faculty in a department. Table 9.5 shows that about 74% of faculty members are at least at the level of an Assistant Professor in public schools, whereas the corresponding percentage is 61% for private schools. The high quality of the faculty members in public schools is assumed to have a positive impact on the performance of the departments in those schools.

9.5.2 *The Relative Efficiencies of Sampled Departments Based on Different Trials Using RDEA*

Most school administrators will focus on maximizing a set of school outputs given a set of underlying resource inputs, in addition to performance evaluation. The resource efficiency DEA model, or RDEA, is employed for such a purpose. In this section, we include one set of inputs with all the five resource variables (X1, X2, X3, X4 and X5), with the performance indicators regarded as outputs in the RDEA

Table 9.5 Resource inputs of the sampled departments by type: Mean and standard deviation ()

Type	X1	X2	X3	X4	X5
Total	0.04 (0.02)	338.54 (40.41)	0.35 (0.17)	139.94 (44.48)	0.65 (0.18)
Public	0.05 (0.01)	386.63 (23.55)	0.39 (0.12)	148.79 (52.51)	0.74 (0.12)
Private	0.03 (0.01)	315.54 (22.39)	0.33 (0.19)	135.70 (40.02)	0.61 (0.19)

X1 faculty–student ratio; X2 average College Entrance Exam Score (CEES) of sampled students in the department; X3 male graduate ratio in the class***; X4 number of credit hours offered per week by faculty members in a department; X5 ratio of faculty ranked at least as Assistant Professor

model. Since each output set with all the inputs forms one model trial, we have carried out four trials to determine the relative efficiency ranking of the departments. The first trial includes two outputs representing the recruiter’s satisfaction with the graduate’s job market performance, namely, Y1 (the starting salary) and Y2 (the search duration for the first job). In the second trial, we use outputs related to the student’s satisfaction with school services, including Y4 (satisfaction with the quality of the curriculum in the student’s major field) and Y5 (satisfaction with the quality of the curriculum in non-major fields). The third trial uses mixed outputs based on both the recruiter’s and the student’s satisfaction, namely, Y1, Y2 and Y4, Y5, representing joint performance or overall satisfaction. In the fourth trial, we add the current salary (Y3) to reflect the sustainability of the student’s ability in the job market. If the training or skills learned from school are sustainable and good, then the current salary (with 3 years of work experience) will be affected by learning at the school.

Table 9.6 summarizes the means and standard deviations of the efficiency scores calculated from these four RDEA trials. The results of Trial 1 in Table 9.5, which is based on the job market performance, indicate that the average efficiency score of the sampled departments is 93%. A total of 21 DMUs have a full efficiency score. This result implies that the average sampled department can be further improved by 7% to become a best practice DMU given the levels of their resource inputs. By further comparing the schools based on ownership, we find the mean efficiency score of public schools (95%) to be higher than that of private schools (92%) (see Table 9.6). Public schools are thus more efficient than private schools in terms of the recruiter’s degree of satisfaction or the graduate’s job market performance. In the case where the school output set is the student’s satisfaction with the curriculum, our results in Trial 2 in Table 9.6 show that the mean efficiency score is 82% with a relatively large standard deviation (19%), which means that on average 18% of the college graduates’ satisfaction with the school curriculum needs to be improved in the colleges of Business in Taiwanese universities. Since the coefficient of variation (CV) for Trial 2 (0.23) is also much higher than that for Trial 1 (0.08), the student rates of satisfaction with the curriculum are much more diversified than recruiters’

Table 9.6 RDEA efficiency scores of the sampled departments by different trials and types

Type	Job market performance	Student satisfac- tion in school	Joint performance	
	Trial 1	Trial 2	Trial 3	Trial 4
	(Y1, Y2)	(Y4, Y5)	(Y1, Y2, Y4, Y5)	(Y1, Y2, Y3, Y4, Y5)
Public	95.13 (5.22)	84.21 (17.37)	96.98 (4.81)	97.24 (4.67)
Private	92.25 (7.64)	81.88 (20.03)	94.09 (6.97)	95 (6.28)
Total	93.18 (7.05)	82.64 (19.11)	95.02 (6.46)	95.72 (5.87)
C.V.	0.08	0.23	0.07	0.06
Full range	47	41	35	33
No. of efficient DMU	21	27	33	35

satisfaction with the job market. Table 9.6 shows that public schools perform better in terms of resource efficiency than private schools in relation to the student’s satisfaction with the school curriculum.

In Trials 3 and 4, where we include both the recruiter’s and the student’s satisfaction as joint outputs in the models, we find that the mean efficiency scores are quite high, 95% for Trial 3, and 96% for Trial 4. Since Trial 3 has included both output sets (Y1, Y2 and Y4, Y5), such a mixed model has shown that the sampled departments on average have a high level of technical efficiency. The addition of the Y3 output in Trial 4 seems to have a very limited impact on the efficiency scoring. It should also be noted that the average efficiency score for public schools is also shown to be 2% higher than for private schools in Trial 3 and Trial 4, on assessing the overall performance.

9.5.3 Referenced Peers for Inefficient DMUs in RDEA Models

The referenced peers or benchmarks for inefficient DMUs in different trials of RDEA models are summarized in Table 9.7. Detailed information on the efficiency scores and ranking for each sampled department is available upon request. On comparing the results of Trial 1 and Trial 2 in Table 9.7, we find that the referenced peers in Trial 1 are different from those in Trial 2. For example, the most referenced DMU in Trial 1 is a department in a national university N12(NCC-FM), which is followed by DMUs in private universities: P64, P58, P24, and P30. However, the most referenced DMU in Trial 2 is a department in a private university P39 (THU-IT), followed by P58, P31, P61 and P60. Since the referenced DMUs are departments with full efficiency and are targeted references to the inefficient DMUs, the selection of output components in the RDEA model has a strong influence on the efficiency results and thus on the corresponding benchmarks. This finding indicates that inefficient departments aiming at promoting the graduate’s job market performance

Table 9.7 Referenced peers by trials for resource efficiency models (RDEA)

RDEA Trial	Output mix	Reference set and (No. of citations as a reference peer)
Trial 1	(Y1, Y2)	N12(36), P64(35), P58(34), P24(22), P30(12), N11(10), N13(9), P 66(7), P36(6), N6(6), P48(5), N7(4), N10(4), P61(4), P59(2), P60(2)
Trial 2	(Y4, Y5)	P39(36), P58(22), P61(16), P60(15), N1(14), P64(12), P30(10), N5(9), P31(8), N9(5), P33(5), P44(5), P48(4), P47(3), N4(3),N3(2), N12(2), P27(2), P36(2), P57(2), P59(2)
Trial 3	(Y1, Y2, Y4, Y5)	P58(34), N12(29), P64(22), P24(14), P30(12), P61(8), N5(7), P39(7), N9(6), P33(6), P36(6), N1(5), P31(5), P60(5), P66(5), N6(4), N11(4), P48(4), N13(3), N3(2), N4(2), N7(2), N10(2), N17(2), P57(2), P59(2)
Trial 4	(Y1, Y2, Y3, Y4, Y5)	P58(36), P64(21),N12(16), P30(13), N10(11), P50(11), P61(11), P24(8), P39(8), P48(8), P66(7), N3(6), P33(6), P60(6), N9(5), N1(5), N5(4), N11(4), P31(4), N4(3), N6(3), P36(3), P57(2), P59(2), N7(2), P44(2), N13(2), N17(2), P68(2)

should choose different sets of referenced peers as benchmarks, compared with those inefficient departments attempting to promote their students' satisfaction with the school services provided. Therefore, each department must choose those benchmark peers specific to that particular department in order to improve resource use efficiency to the level where it should be.

As for the referenced peers in Trials 3 and 4, Table 9.7 shows that the number of referenced peers becomes higher than in the previous two trials due to the increase in the number of output variables in the DEA. The referenced peers in Trials 3 or 4 will not be the sum of the referenced peers in Trials 1 and 2. A Venn diagram of the "best practice" departments for Trial 1 (set A), Trial 2 (set B) and Trial 3 (set A&B) in Fig. 9.1 shows that there are 9 DMUs (N12, P30, P36, P48, P58, P59, P60, P61, P64) that overlap in Trials 1 and 2, but there are also three DMUs (P27, P44, P47) in Trial 2 (set B), but not in Trial 3 (set A&B). In addition, N17 is the one DMU in Trial 3 that is not in Trial 1 or Trial 2.

One important observation for these RDEA models in Table 9.7 that must be mentioned is that, unlike the results in the PDEA models where the referenced peers are departments in national universities, the referenced peers in our RDEA models are departments in both national and private universities. In fact, the proportion of departments in private universities is higher than 50% in most of the trials in this paper. This finding has an important implication: departments in private schools with full efficiency, can serve as models for the inefficient departments in either public or

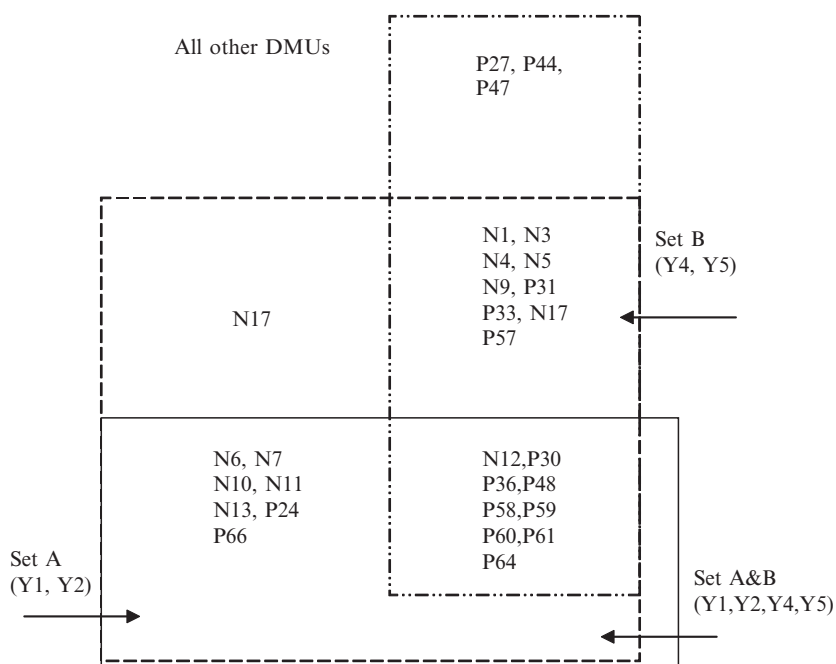


Fig. 9.1 Venn diagram of "best-practice" departments in colleges of business

private schools for improving their resource use efficiency, although they cannot be the best performing schools as defined by the performance evaluation.

9.6 Discussion: Performance Versus Efficiency

This study investigated whether the efficiency ranking information was useful to prospective students, and whether the prospective students would use information regarding the relative efficiency of institutions in their decisions to join college. Previously, Breu and Raab (1994) measured the relative efficiency of the best 25 US News and World Report-ranked universities and found that the quality ranking provided by the US News, which was aimed at allowing prospective students and parents to choose a university, had an inverse relationship with efficiency ranking that is implied by the narrow productivity criterion of DEA. In this paper, we plotted the performance ranks and the efficiency ranks of our sampled departments in a two dimensional diagram (see Fig. 9.2), using the ranking results of PDEA (Y1, Y2, Y4, Y5) and RDEA (Y1, Y2, Y4, Y5). The scattered DMU points in Fig. 9.2 indicate that the relationship between the performance ranking and the efficiency ranking is positive in this study. In fact, the rank correlation coefficient between these two ranks is about t6.

Moreover, most departments in national universities, located at the left-half area of Fig. 9.2, are shown to be better than those of private universities on both performance and efficiency ranks. Those departments in private schools, located at the upper part

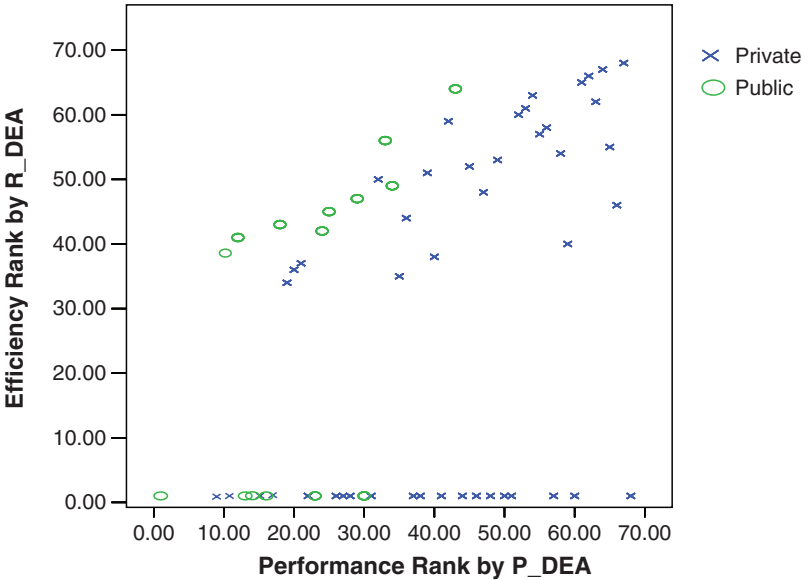


Fig. 9.2 Performance ranks vs. efficiency ranks of Taiwanese University Departments

of Fig. 9.2, have relatively poor ranks on both performance and efficiency. This finding implies that the efficiency ranking information regarding colleges of business in universities can still be useful to prospective students in their decisions to select a college to join in Taiwan. This also confirms the hypothesis that good management, good performance, and reputation goes hand-in-hand with higher education.

One last observation that deserves to be mentioned in this study is related to the sampled departments with full resource use efficiency. These departments, which consist of 12 from public schools and 14 from private schools, are plotted at the lower area (efficiency rank = 1) of Fig. 9.2 within the rectangular block. All these departments have full resource efficiency score but with different levels of performance score. Most private school departments (marked with “x” in Fig. 9.2) are relatively poor on performance ranking, but are the best practice schools in term of resource use efficiency. Therefore, it is plausible for this study to suggest that private schools in Taiwan may wish to place greater emphasis on the strategies of improving of resource use efficiency at least in the short run. The school reputation building or the enhancement of performance ranking, which take time to be effective, can be regarded as a relative long run strategy.

Appendix

See Table 9.8 here.

Table 9.8 Abbreviations of schools and departments

School		Department	
Abbreviation	Full name	Abbreviation	Full name
Public school:		AC	Accounting
NTU	National Taiwan University	IB	International business
NCH	National Chung Hsing University	IA	Industrial administration
NCK	National Cheng Kung University	FI	Finance
NCC	National Cheng chi University	EC	Economics
NCH	National Central University	AE	Agricultural Economics
NSU	National Sun Yat-sen University	BA	Business Administration
NTPU	National Taipei University	IT	International Trade
Private School:		RM	Risk Management
SCU	Soochow University	PF	Public Finance
CYU	Chung Yuan University	CE	Cooperative Economics
TKU	Tamkang University	IE	Industrial Economics
THU	Tunghai University	IS	Insurance
FCU	Feng Chia University		
CCU	Chinese Culture University		
PRU	Providence University		
FJU	Fu Jen Catholic University		
YZU	Yuan Ze University		
ISU	I-Shou University		
MCU	Ming Chuan University		
SCU	Shih Chien University		
CHU	Chung Hua University		
ALU	Aletheia University		

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Chapter 10

Efficiency of the Korean Defense Industry: A Stochastic Frontier Approach

Kyong-Ihn Jeong and A. Heshmati

10.1 Introduction

The defense market, which is composed of a sole demander and few suppliers, is generally regarded as a monopolistic market. In this sense, it has its own characteristics that are different from other common competitive markets. High precision technology and a huge amount of capital investment in the initial stage of production are essential in the defense industry, and this necessitates subsidy policy of the government. Most of the supplies are produced in an order-based manner due to the special specification requirements and this hampers the market-driven pricing mechanism. The price is determined based on negotiations between the two parties, considering the cost of production, retrieval of the investment, and efficient allocation of the government budget.

The following statements provide a general understanding on the Korean defense industry. The separation of R&D activities, which is overseen by the Korea Agency for Defense Development (ADD), from production activity, has weakened the defense related firms' own R&D abilities. This policy offers little incentives for the firms to seek cost-saving measures through improvements in management or R&D activities. It also deters autonomous cooperation between the assembly plants and the component companies. The government's demand on the defense industry has been limited because sustaining operation rates of the firms can be achieved by the production quantity based on the "early adoption plan" of the late 1990s, completion of the "basic arm equipping plan" and shortened equipment lifecycle timetable. The current operation rate of the Korean defense industry is 20% lower than that of the manufacturing industry.

Obtaining adequate data for an analysis is difficult in defense area studies. Rogerson (1994) observed that getting data on individual programs and accounting

K.-I. Jeong

Defense Acquisition Program Administration, Seoul, South Korea

A. Heshmati

University of Kurdistan Hawler, Hawler, The Federal Region of Kurdistan, Kurdistan, Iraq

data are well-known limitations to analyzing of the defense firms. This study overcomes the data problem by employing the Korean defense industry's data ranging from 1990 to 2005 into the analysis, which encompasses nearly all usable data from the industry. Moreover, this is the first attempt to use a SFA model to measure and decompose efficiency of the Korean defense industry with large set of panel data. This study uses real cash flows about labor, capital, material, and sales output. It also uses data of R&D, employees, and other characteristic data.

The objective of this study is to analyze the technical efficiency and technical changes in the defense industry and identify the determinants of individual firms' inefficiency. In the parametric approach, the model is specified and estimated using panel data techniques such that it allows for an estimation of firm-specific rate of technical change and technical efficiency. Each factor's contribution to the technical efficiency is quantified and their effects on efficiency tested using parametric and non-parametric techniques.

This study applies a stochastic frontier production model to analyze the efficiency and technical change of the Korean defense industry (1990–2005). After analyzing the effectiveness of policies in the aspect of efficiency, some directions on policy are presented from a technical efficiency point of view. An inefficiency model of the frontier production functions involves nine factors that affect the level of firm's technical inefficiency. These factors are the rate of defense part, the rate of operation, the length of time a firm has operated as a defense firm, firm size, specialization, serialization, implementation of a cost monitoring system, R&D investment, and competition. The influence levels of the nine factors are tested and linked to policy implementations. In the analysis of the above subjects, the levels and differences in efficiency score, technical change and returns to scale are measured by the sector, firm size, ratio of defense part to total sales, specialization, serialization, and the level of competition.

The second objective of this study is to measure TFP growth using a parametric method and decompose it into the underlying technical change, scale and efficiency change, and allocative efficiency components. From a policy perspective, the decomposition of TFP growth into efficiency changes and technical changes provides useful information for productivity analysis. The main factors dominating the TFP growth are presented. Policy makers in national defense can recommend policies that are more effective in terms of improving the productivity of firms if they can understand the sources of variation in productivity growth.

This study is organized as follows. The history of the Korean defense industry and policies are summarized in Sect. 10.2. The data is described in Sect 10.3. In Sect 10.4, this study sets out the stochastic frontier production function for the analysis of efficiency and the model for decomposition of TFP. The results of the estimation of the stochastic frontier model are presented in Sect 10.5, where technical efficiency, testing results on factors affecting efficiency and decomposition of TFP are discussed. Lastly, Sect 10.6 presents the conclusions of this study.

10.2 The Korean Defense Industry and Policies

10.2.1 *The History and Characteristics of the Korean Defense*

The Korean defense system built its foundation through a special fostering plan, which was introduced in the 1970s due to the tension between South and North Korea and a South Korea's strong will for self-reliant national defense. Moon (1991) concluded that despite its late beginning, the Korean weapon industry has made a remarkable progress due to several factors: a security environment conducive to the defense industry; an assertive defense industry policy; the availability of capital and manpower; timely linkage with the "Heavy-Chemical industrialization Plan"; and the supportive role of the United States.

In the 1970s, the South Korean government launched the Korean defense industry and the Agency for Defense Development (ADD), which is aimed at fostering local development of weapon systems. This policy was strongly emphasized as the priority in terms of national security policy. As a part of the policy, "The Special Law on the Protection of the Defense Industry" was enacted in 1973. Once a company is designated as a defense firm, it is eligible to receive benefits from the government, such as several political supporting systems and tax deductions. The defense firms supply the government with military-specific products which cannot be delivered by the market in a competitive mechanism. The suppliers (i.e., defense firms) have the privilege of being in a monopolistic position in terms of production.

However, most of the defense companies in Korea are privately owned, and are in the form of a commercially owned-commercially operated (Co-Co) structure. The design of the Co-Co structure seems like an efficiency-oriented industry structure at the time of the so-called "Economic Construction Era", a period in which efficiency was an important factor. While this Co-Co structure can maximize efficiency when there is enough demand for products, it can also suffer when no one wants to invest in the defense industry due to a perceived lack of demand for its products.

In the 1980s, the defense acquisition strategies preferred purchasing equipments from overseas in order to boost the Korea's defense capability. This resulted in a shortage of R&D in the domestic defense industry and disconnection of the defense industry with other manufacturing industries, especially the heavy-chemical industry. Decreased demand for military products also lowered the operating rate of the defense companies in the late 1990s.

Until 2005, the defense acquisition and procurement programs had been handled by different agencies. These include: the Office of Acquisition at the Ministry of National Defense, the Defense Procurement Agency, the Defense Quality Assurance Agency, and the Army, the Navy, and the Air Force headquarters. The Korea Ministry of National Defense (KMND) launched a defense acquisition agency called the Defense Acquisition Program Administration (DAPA) by integrating

agencies involved in acquisition and procurement projects. The new agency is designed to ensure more transparency and efficiency in the defense acquisition and procurement.

10.2.2 Specialization, Serialization and Competition

10.2.2.1 Specialization and Serialization

In defense acquisition, the weapon system is classified as the end-item of equipment and components/parts according to their characteristics such as required technology, plant type and so on. The end-item of equipments and components/parts are divided into several specialized products and serialized units according to sector and product types. The specialized products and serialized units are then produced by assemblers and component producers. Thus, specialization (serialization) is meant to put specialized (serialized) firms in charge of production of specialized products (serialized units).

The specialized firms produce end-item equipments by assembling components produced by serialized firms. The specialized firms are in cooperation with serialized firms and associates for a R&D or construction of production system. The priority of supporting the financial incentives such as defense industry promotion fund, industrial foundation establishment fund and subsidy as well as technical support is given to the specialized or the serialized (SOS) firms.

The “Special Law on the Protection of the Defense Industry” characterizes the Korean defense industry together with “Specialization and Serialization Policy (SSP)”. The “Special Law on the Protection of the Defense Industry” has been stabilizing the supply market since 1973, but increased demand for defense products and improvements in technology stimulated the competition among the defense industry related companies. The KMND introduced SSP to prevent overlapping of investment and to encourage R&D on technology by defense companies. While the designation system has prevented non-defense related companies from entering into the defense industry, SSP is intended to control competition and to protect the defense companies.

The SSP is a kind of grouping method, which aggregates the companies which have similar equipment and facilities for production or R&D. The specialized firms are guaranteed with the priority right to participate in the weapon system acquisition projects or R&D projects. The specialized firms are in charge of the integrating equipment system and the serialized firms are responsible for developing components or parts for the equipment.

10.2.2.2 Competition Policy

This research addresses whether competition improves the efficiency of defense firms. In this study, the effect of changes in competitive environment on technical

efficiency is examined by overall competitive environment change and policy changes on SOS firms. The results can provide defense decision makers with useful information for choosing the best policy practices.

Competition can be described as: 'a rivalry between individuals (or groups or nations), and it arises whenever two or more parties strive for something that all cannot obtain' (Vickers 1995). Many policy makers and researchers believe that competition not only increases the pressure for firms to adopt and develop new technologies, but also induces innovative managerial effort, and that these innovative activities lead to improvement in efficiency. According to many researches, the relationship between market competition and productivity performance is mixed. Supporters of the positive relationship insist that competition reduces managerial slack introduced by monopoly power, and generates incentives to improve efficiency through product, process and organizational innovation (Tang and Wang 2005).

There are also some arguments in the literature for a negative relationship between competition and productive performance (Griffith 2001; Hermalin 1992; Horn et al. 1994; Kamien and Schwartz 1982; Porter 2000). They claim that increased competition lowers the managers' expected income, and hence reduces their managerial effort, which has been argued along the line of the Schumpeterian hypothesis that monopoly power enables firms to spend more on innovative activities. This study analyzes the overall effect of competition to defense industry as well as to each sector.

The changes of competitive environment are decided by accounting for the rate of products which are produced under competitive condition, and by considering the competition level the SOS firms being pressured. The SSP has been changed into monopolistic, competitive, oligopolistic systems since its introduction in 1983. The degree of competition, given in Table 10.1, is classified according to the number of companies existing in a sector. When only one company exists in a sector, it is classified as monopoly, limited competition in case of two companies and competition, when the number of firms is more than three. In this study, competition is classified when more than two companies are subjects of competition for production after they have been designated as SOS firms, because, by nature only one defense firm enters into a contract with the government for defense products, even if there are several firms in a sector.

Table 10.1 History of policies on specialization and serialization

	Time	Operating system	Number of firms in a sector
Introduction	June 1983	Monopoly	Main firm: 1, Reserve firm: 1
First revision	July 1990	Competition	Competitive environment with 2–5 firms
Second revision	December 1993	Oligopoly/Monopoly	Specialized firm: 2, Serialized firm: 1
Third revision	December 1998	Oligopoly/Monopoly & Extended competition	Oligopoly, monopoly and competition
Fourth revision	December 2001	Oligopoly/Monopoly	Oligopoly and monopoly

The policy for SOS firms has been revised four times and after each revision, there was a change in the competitive system in the defense industry. Since the beginning of the SSP up to the 1990s, only one company was selected as the main producer for conducting R&D activities or handling production projects by technology transfer. The others were operated as reserves. The conversion to a competitive system between two and five companies was adopted in the first revision.

In the second revision, two specialized companies were selected for each product and one company was selected as a serialized one. The third revision was implemented during the Korean financial crisis focusing on restructuring. A monopolistic system was maintained in sectors that needed enormous investment or that suffered due to overlapped investments. The others were changed into a competitive system. Wheeled vehicles, ship, communication and electronics, information, command, control and optical equipment sectors, which are closely compatible with a commercial market, were the ones that were changed into a competitive environment. The number of designated companies was reduced and items of products in competitive condition were increased in the fourth revision.

Decreased demand for defense products increases the level of competition for defense contracts and it restricts defense contractors' ability to pass any increased cost to the government. The competition environment can be changed by the policy or by decreased demand from the government. This study introduces the change of competition environment. An overall change of a competitive environment was made at the third revision in 1998. The whole period can be divided into two periods according to the level of competition. One was before 1998 and the other from 1999 onwards.

The third revision was selected as a critical point because of the following reasons. Many sectors, with an exception of firms that play exclusive roles for defense products, became competitive. After the third revision of SSP, the number of specialized and serialized companies was reduced and the number of items which was produced under the competitive condition was increased. Moreover, the bidding system for 40% of the specialized items and 60% of the serialized items became competitive. After the fourth revision in 2002, more than 30 items out of 143, which had been produced by the specialized or the serialized firms, were included in the items that could be produced by competitive bidding.

10.2.3 Research and Development

One of features of the Korean defense industry on R&D is that the ADD, established in 1970, has been taking the monopolistic position in defense related R&D. Although a defense firm actually produces weapons, the special law forces that it closely cooperates with the ADD in R&D.

Characteristics and limitations in R&D of the Korean defense industry from the existing studies can be summarized as follows: the technological foundation for the defense industry has been weakened because of the ADD's central role in defense

R&D and the defense firms have only been in charge of production the amount of domestic defense production has decreased due to the defense acquisition policy that was mainly dependent on foreign acquisition; the defense firms are not interested in innovation and new product development, but concentrate their attention on profit margin and output; there is a low demand for R&D that can be assigned to domestic defense firms, and a shortage of government effort in searching for new R&D; for a quick achievement of increased defense capability, the government does not have enough time to consider newly developed indigenous technologies or products, rather, it puts its priority on acquiring, introducing, and adapting technologies from abroad. These reasons caused a vicious cycle of weak foundation of the defense firms for technology development.

The problem in technology development is that there is no incentive for defense firms to invest in R&D. The firms bear all the expenses of activities for technology development and take full responsibility for failed R&D. The government does not compensate firms for their loss brought by failed R&D activities. Further, the government provides very limited economic compensation system and does not guarantee procurement after a successful development. There is no difference in firms' profit level between using parts developed by Korean firms and applying parts imported from abroad or made by subcontracting firms.

The KMND determines the appropriate amount of profit regarding the effort for technology development, especially for the amount of investment cost for R&D. A new incentive policy to reimburse some level of cost invested by assessing the effort of management type has been in force since 2006, but its incentive level for R&D is very low, accounting for 3 points of 36 total points. We can identify the decreasing tendency of mean number of R&D employees in the defense part from the data set. Mean R&D expenditure was 4.5% of GDP in Korea, while it was 13, 12 and 11% in United States, United Kingdom, and Russia, respectively. In this study, the effect of R&D investment in the defense part on technical change and technical efficiency is tested.

10.3 The Data

The data used in this study is from the annual reports of the defense firms. They are published by the Korean Defense Industry Association (KDIA). The report includes annual data related to the management and the defense part of the firm. The data contains information for the years from 1984 through 2005. Over this period, some firms have been revoked of their position as defense firms, due to lack of demand or changed defense policies.

An unbalanced panel of firms that has been engaged in the defense industry from 1990 to 2005 was constructed. Only few firms were excluded due to their shortage of characteristic data. The sample covers over 95% of the defense firms that existed from 1990 to 2005. The data from 1984 to 1989 is not included because the firms do not have a complete data for the analysis. The empirical analysis is

based on 155 firms. A total of 1,221 observations were made. The number of firms in year wise is given in Table 10.2.

This study considers total sales of the defense part as output (Y). Number of labor (L), tangible fixed asset (K), and material cost (M) are taken into consideration as inputs for the frontier function. Total costs (C) are calculated as the total sum of labor costs (C_L), tangible fixed asset (K), and material cost (M). The factor share in total costs (S_L, S_K, S_M) is calculated as the factor's share out of the total costs ($S_j = C_j/C, j = L, K, M$).

Sales (Y) and material cost (M) were deflated using Producer Price Index (PPI) deflator (2,000 Yr = 100) of each industry. Labor cost (C_L) and tangible fixed asset (K) were deflated using GDP and capital deflator (2,000 Yr = 100).

To better understand the composition of a defense firm, the definitions of each part and factory are required. A defense firm is composed of a commercial part and a defense part. The defense part produces pure defense products while the commercial part makes products only for commercial purpose. Thus, a firm can divide the input and output factors of production into factors for defense and commercial activities. The defense (commercial) part represents a pure defense (commercial) part of a defense firm. A defense factory is authorized to produce the defense products, and the defense part represents the part that produces pure defense products in the factory. Thus, the definition of a defense part is the sum of the defense part in the defense factory and the defense part in the commercial factory. If a firm has only one factory, then a firm can be divided into a defense part and a commercial part in a defense factory. If a firm has both the defense factory and commercial factory, then each factory has a defense part and a commercial part.

A number of variables including those above, except for the input and output data, can explain the characteristics of defense firms. These variables are included in the inefficient part of the model in order to test their effects on technical efficiency. The ratio of the defense part can tell the concentration level of a firm in the defense industry. The defense ratio is measured as the sales by the defense part divided by the total sales of the firm.

The rate of operation is the basis of capturing the level of facility utilization, and to evaluate the efficiency level of the firm. The variable 'AGE' is measured as the total sum of years the firm operated as a defense firm. The mean period of service of 155 firms from 1990 to 2005 is 10.9 years. Small and medium enterprises are classified by the "Framework Act on Small and Medium Enterprises". A firm is a large sized firm if the total number of employees is greater than 300. The same definition is applied in annual reports of the defense industry.

Table 10.2 Number of defense firms and sample size

Year	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05
Number of firms	81	81	81	81	81	83	82	81	80	78	76	78	80	82	85	86
Sample size	79	83	82	81	77	79	78	78	79	73	68	71	70	76	77	70

Source: KDIA (1991–2006)

Table 10.3 Summary statistics for variables

Variables	Measure	Mean	Std dev	Minimum	Maximum
Output					
Sales (Y)	Million Won	42,283.0	97,318.5	4.9	986,541.8
Inputs					
Labor (L)	Number	351.8	645.4	2.0	6,509.0
Capital (K)	Million Won	155,488.8	590,535.6	10.6	10,372,019.2
Material (M)	Million Won	22,183.7	56,734.6	1.4	709,922.0
Inefficiency inputs					
Defense ratio (DRT)	%	32.8	34.9	0.1	100
Rate of operation (ORT)	%	60.5	20.1	0.1	100
Serving period (AGE)	Year	10.9	4.5	1	16
Firm size (SIZE)	%	45.9	49.8	0	100
Specialization (SPFIRM)	%	27.2	44.5	0	100
Serialization (SEFIRM)	%	50.9	50.0	0	100
DPAMIS (DPMS)	%	15.1	35.8	0	100
R&D for defense (DRD)	%	68.1	46.6	0	100

This study discriminates the firm as to whether it invests into R&D for the defense part. 68.1% (681 observations) from all data set invests in R&D for the defense part. This study tests the effect of the defense R&D on technical efficiency of firms.

This study distinguishes firms in terms of different characteristics according to the specialized firm, serialized firm, the competitive environment among specialized or serialized firms, etc. To construct groups representing changes of competitive environment caused by the policies among specialized or serialized firms, this study divides the competitive condition by the policy changes presented in Table 10.1, after which it selects the specific firms by considering the industrial sector which is included in the competitive section. The sectors closely related to the commercial area are classified as competitive sectors and include: ships, wheeled vehicles, communication, electronics, command & control, and optics.

A basic summary of the values of some variables in data set is given in Table 10.3. The values of sales, labor, capital, and material indicate a considerable variation in size in the data set.

10.4 The Empirical Model

10.4.1 Functional Form

In this study, the stochastic frontier production function is employed. The frontier approach assumes that firms do not fully utilize the existing technology because of various non-prices and organizational factors. This implies the existence of a technical inefficiency effect that causes a firm to produce below its potential output level or a set of output on the production frontier.

Schmidt (1986), Greene (1997), Kalirajan and Shand (1999), Kumbhakar and Lovell (2000), and Heshmati (2003) presented overviews of the concept, modeling, estimation of models and methods for efficiency comparison at the firm level. They also surveyed some of the empirical applications of frontier functions. The frontier function allows for stochastic errors due to statistical noise or measurement errors, and hence decomposes the error term into two components, the random effect outside the control of the firm and the component that captures the inefficiency part of the firm production. In the estimation of the production function, a translog function form is used to avoid strong priority restrictions on the technology.

In this study, the model by Battese and Coelli (1995) is applied with an unbalanced panel data set because we can overcome the problem of not being able to separate firm specific effects that are not related to inefficiency with this model. This study conducted likelihood-ratio tests to select an appropriate production model among the Cobb–Douglas, Cobb–Douglas with time trend, and generalized translog function types. The null hypothesis that all coefficients in the translog function are insignificant was strongly rejected. If the frontier technology for firms is assumed to be a translog frontier technology, then it can be formulated as follows:

$$\begin{aligned} \ln Y_{it} = & \beta_0 + \sum_{j=1}^3 \beta_j \ln X_{jit} + \beta_t t + \frac{1}{2} \sum_{j=1}^3 \sum_{k=1}^3 \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} t^2 \\ & + \sum_{j=1}^3 \beta_{jt} \ln X_{jit} t + v_{it} - u_{it}, \end{aligned} \quad (10.1)$$

where the subscripts i and t represent the i th firm ($i = 1, 2, \dots, 155$) and the t th year ($t = 1, 2, \dots, 16$) of observations, respectively:

- Y represents the sales (in million Won)
- X_1 is the number of labors
- X_2 is the capital cost (in million Won). The study uses the tangible fixed assets of the defense factory. These assets of defense factory may include some assets of pure commercial part in case the firm has more than two factories
- X_3 is the material cost (in million Won)

The v_{it} s are random variables, which are associated with measurement errors in the output variable or the effects of unspecified explanatory variables in the model, which are assumed to be independent and identically distributed with $N(0, \sigma_v^2)$ -distribution, independent of the u_{it} s. The u_{it} s are non-negative unobservable random variables associated with the technical inefficiency of production, such that for a given technology and level of inputs, the observed output falls short of its potential output. In addition u_{it} is obtained by the truncation at zero of the $N(z_{it}\delta, \sigma_u^2)$ -distribution. z_{it} is a vector ($1 \times m$) of firm-specific variables identified as determinants of inefficiency in production which may vary over time, and δ is a vector ($m \times 1$) of unknown coefficients of the firm-specific inefficiency variables that are to be estimated together with the unknown parameters of the production function, the β 's.

Following Battese and Coelli (1995), technical inefficiency is defined as:

$$\begin{aligned}
u_{it} &= \delta_0 + \sum_{l=1}^4 \delta_l C_{lit} + \sum_{m=1}^6 \delta_m D_{mit} + W_{it} \\
&= \delta_0 + \delta_1 \text{DRT}_{it} + \delta_2 \text{ORT}_{it} + \delta_3 \text{AGE}_{it} + \delta_{d1} \text{SIZE}_{it} \\
&\quad + \delta_{d2} \text{SPFIRM}_{it} + \delta_{d3} \text{SEFIRM}_{it} + \delta_{d4} \text{DPMS}_{it} + \delta_{d5} \text{DRD}_{it} \\
&\quad + \delta_{d6} \text{COMP}_{it} + \delta_4 \text{DRTSIZE}_{it} + W_{it}, \tag{10.2}
\end{aligned}$$

where the C_s are the variables affecting the inefficiency of the production; number of coefficients of inefficiency term is $m = C + D$; and the random variable, W_{it} , is defined by the truncation of the normal distribution with zero mean and variance σ_u^2 . So, the truncation point becomes $-z_{it}\delta$, which satisfies the condition of $W_{it} \geq -z_{it}\delta$. These assumptions are consistent with u_{it} being a non-negative truncation of the $N(z_{it}\delta, \sigma_u^2)$ -distribution:

- C_1 (DRT): Defense ratio of the firm (sales from pure defense part/total sales)
- C_2 (ORT): Rate of operation of the defense part
- C_3 (AGE): Sum of years, which a firm has served as a defense firm
- C_4 (DRTSIZE): Interaction term, $\text{DRT} \times \text{Size}$

The D_m s are dummy variables having value one, if the observation satisfies the conditions given below:

- D_1 (SIZE): Firm size based on the total number of labors; the value is one, if it is over 300
- D_2 (SPFIRM): Specialized firm
- D_3 (SEFIRM): Serialized firm
- D_4 (DPMS): If a firm is under the cost monitoring system, Defense Procurement Agency Management Information System (DPAMIS)
- D_5 (DRD): If a firm has R&D organization for the defense part
- D_6 (COMP): Overall competitive environment (1999–2005)

The flexible functional form of the translog function is specified in (10.1), in which more general technologies can be accounted for than in the Cobb–Douglas model. The model for the inefficiency effects in (10.2) specifies that the technical inefficiencies are different for firms in different sectors, in different environments expressed as variables in the inefficient model. The rate of productivity growth can be decomposed into technical change and inefficiency change over time.

The elasticities of output with respect to inputs, E_j , are calculated as:

$$E_j = \frac{\partial \ln Y}{\partial \ln X_j} = \beta_j + \sum_{l \neq j} \beta_{jl} \ln X_{lit} + \beta_{jj} \ln X_j + \beta_{jt} t, \quad j, l = L, K, M. \tag{10.3}$$

These input elasticities vary according to both time and firms. Returns to scale (RTS) defined as the percentage change in output due to a proportional increase in the use of all inputs, can be calculated as the sum of input elasticities as

$$RTS = \sum_j E_j, \quad j = L, K, M. \quad (10.4)$$

The rate of technical change, E_t , is obtained as

$$E_t = \partial \ln Y_{it} / \partial t = \beta_t + \beta_{it} t + \sum_j \beta_{jt} \ln X_{jit}, \quad j = L, K, M. \quad (10.5)$$

The rate of technical change can be decomposed into pure and non-neutral technical changes. The pure (neutral) technical change is derived as:

$$PTC = \beta_t + \beta_{it} t. \quad (10.6)$$

The non-neutral technical change is derived as:

$$NTC = \sum_j \beta_{jt} \ln X_{jit}. \quad (10.7)$$

The likelihood function and its partial derivatives with respect to the parameters of the model are presented in Battese and Coelli (1993). The parameters of the stochastic frontier models are estimated using the FRONTIER version 4.1 developed by Coelli (1996). This software provides the maximum likelihood estimates of the parameters and it predicts the technical efficiencies for all the firms included in the study. The variance parameters in the frontier model are expressed as:

$$\sigma_s^2 = \sigma_v^2 + \sigma_u^2 \text{ and } r = \sigma_u^2 / \sigma_s^2, \quad (10.8)$$

where r is a parameter that has a value between 0 and 1. It measures the relative magnitude of the variance associated with the inefficiency effects. On the basis of the model specified in production model, one can test hypotheses of the parameters in the frontier function using the generalized likelihood ratio test statistic, which has an approximate Chi-Square distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypotheses. Critical values for the generalized likelihood ratio test are obtained from the table developed by Kodde and Palm (1986).

The technical efficiency of the i th firm in the t th year of observation, given the values of the output and inputs, is defined by the ratio of the stochastic frontier production to the observed one. Given the above model specification, the technical efficiency of the i th firm in the t th year is defined by:

$$TE_{it} = \exp(-u_{it}) = \exp(-z_{it}\delta - W_{it}), \quad (10.9)$$

indicating that the technical efficiency is not greater than one. The technical efficiency equals one only if a firm has an inefficiency effect equal to zero; otherwise it is less than one. The magnitude of u_i specifies the “efficiency gap”, which shows how far a given firm’s output is from its potential output level. The SFA model allows for a formal statistical testing and the construction of confidence intervals.

10.4.2 Decomposition of TFP

The sources of TFP growth have been decomposed into four components: technical progress (TP), changes in technical efficiency (TE), scale effects (SE), and change in allocative efficiency (AE). The decomposition method proposed by Kumbhakar (2000) is applied. A stochastic frontier production function is defined by

$$y_{it} = f(x_{it}, t) \exp(-u_{it}), \quad (10.10)$$

where y_{it} is the output of the i th firm ($i = 1, \dots, N$) in the t th time period ($t = 1, \dots, T$), $f(\cdot)$ is the production frontier, x is an input vector; t is a time trend index, and $u_{it} \geq 0$ is the output-oriented technical efficiency. Technical efficiency in (10.10) varies over time.

The production frontier $f(\cdot)$, is totally differentiated with respect to time as follows. For simplicity purposes, the subscripts ' it ' are omitted.

$$\frac{d \ln f(x, t)}{dt} = \frac{\partial \ln f(x, t)}{\partial t} + \sum_j \frac{\partial \ln f(x, t)}{\partial x_j} \frac{dx_j}{dt}. \quad (10.11)$$

The first and second terms on the right-hand side of (10.11) measures the change in frontier output caused by TP and by change in input use, respectively. From the output elasticity of input j , $\varepsilon_j = \partial \ln f / \partial \ln x_j$, the second term can be expressed as $\sum_j \varepsilon_j \dot{x}_j$, where a dot over a variable indicates its rate of change. Thus, (10.11) is described as

$$\frac{d \ln f(x, t)}{dt} = TP + \sum_j \varepsilon_j \dot{x}_j. \quad (10.12)$$

Totally differentiating the logarithm of y of (10.10) with respect to time and using (10.12), the change in production can be represented as:

$$\dot{y} = \frac{d \ln f(x, t)}{dt} - \frac{du}{dt} = TP + \sum_j \varepsilon_j \dot{x}_j - \frac{du}{dt}. \quad (10.13)$$

TP is positive (negative) if exogenous technical change shifts the production frontier upward (downward), for a given level of input(s). The second term of (10.13), $-du / dt$, shows the rate at which an inefficient producer catches up to the production frontier.

To examine the effect of TP and a change in efficiency on TFP growth, $\dot{TFP}$ ($\Delta \dot{TFP} / TFP$) is defined as output growth explained by input growth:

$$\dot{TFP} = \dot{y} - \sum_j S_j \dot{x}_j, \quad (10.14)$$

where S_j is the cost share of input ($S_j = w_j x_j / C$, $C = \sum_j w_j x_j$). Only the growth rates in inputs and outputs and the cost shares are required for the calculation of the TFP growth index.

By substituting (10.13) into (10.14), (10.14) is re-written as:

$$\begin{aligned} T\dot{F}P &= TP - \frac{du}{dt} + \sum_j (\varepsilon_j - S_j) \dot{x}_j \\ &= TP - \frac{du}{dt} + (RTS - 1) \sum_j \lambda_j \dot{x}_j + \sum_j (\lambda_j - S_j) \dot{x}_j, \end{aligned} \quad (10.15)$$

where $RTS (= \sum_j \varepsilon_j)$ denotes the measurement of returns to scale, and $\lambda_j = f_j x_j / \sum_l f_l x_l = \varepsilon_j / \sum_l \varepsilon_l = \varepsilon_j / RTS$. The second term of (10.15) tells the rate at which an inefficient firm catches up to the frontier. The third component in (10.15) denotes the effect of scale economies (SE). A firm can benefit from economies of scale through access to a larger market. The last component in (10.15) measures the effect of resource allocation efficiency (AE) subject to the deviations of factor input prices from the value of their marginal products. If technical inefficiency does not exist or is time-invariant, the above decomposition implies that technical inefficiency does not affect TFP growth, as in the Solow residual approach (Heshmati 2003; Kim and Han 2001).

10.5 Empirical Results

10.5.1 Estimates and Tests

Because the stochastic frontier production function model with inefficiency term involves a large number of parameters, tests of several null hypotheses are first considered to decide if a simpler model would be an adequate representation of data. The generalized likelihood ratio tests are presented in Table 10.4. First, this study tested whether the Cobb–Douglas or the translog stochastic frontier function would better represent the data on the Korean defense industry. The null hypothesis of Cobb–Douglas was rejected. Thus, the Cobb–Douglas function is not an adequate representation of the data.

The null hypothesis, $H_0: \gamma = \delta_1 = \dots = \delta_4 = \delta_{d1} = \dots = \delta_{d6} = 0$ states that the inefficiency effects are absent from the model, so the firms are fully efficient in the defense industry in their use of inputs. This null hypothesis was rejected at the 1% level of significance. Moreover the value and significance of the estimate for the

Table 10.4 Likelihood ratio tests for parameters of the stochastic frontier production model

Null hypothesis	Test statistics	Critical value
Cobb–Douglas no TC vs. neutral with TC	26.21	6.64
Cobb–Douglas with neutral TC vs. Translog with TC	47.28	23.21
$H_0: \gamma = \delta_1 = \dots = \delta_4 = \delta_{d1} = \dots = \delta_{d6} = 0$	280.37	33.82
$H_0: \delta_1 = \dots = \delta_4 = \delta_{d1} = \dots = \delta_{d6} = 0$	132.96	27.69

parameter, γ , support these likelihood ratio tests. The estimates for the variance parameter γ of the model in the inefficiency component with variables $C_1, \dots, C_4$, dummy variables $D_1, \dots, D_6$, and $C_1, \dots, C_4, D_1, \dots, D_6$, are 0.815, 0.831 and 0.832, respectively. This implies that a substantial proportion of the total variability is associated with the inefficiency of production. The last hypothesis, $H_0: \delta_1 = \dots = \delta_4 = \delta_{d1} = \dots = \delta_{d6} = 0$, (see Table 10.4) specifies that the coefficients of all ten explanatory variables in the inefficiency model are simultaneously equal to zero. Therefore, these variables are not useful in describing the inefficiencies of production. This hypothesis is strongly rejected at the 1% level of significance implying that the explanatory variables included in the explanation of the inefficiency effects that are associated with the production of the firm should be taken into consideration.

The maximum-likelihood estimates for the parameters in the translog stochastic frontier function estimated using FRONTIER Version 4.1 with an unbalanced panel data are presented in Table 10.5. The results show that there is an evidence that the stochastic frontier model is an appropriate model since γ is high and very significant. Hence, the inefficiency effects are important, implying the rejection of the null hypotheses (see the third and fourth rows in Table 10.4).

The signs of the coefficients of the stochastic frontier for labor, capital, material and time trend are all positive and the estimates for labor and material are significant at 1% level of significance. The positive and statistically significant coefficient of time trend suggests positive rate of technical change. However, due to the very small and insignificant coefficient of the time trend squared, one cannot definitely assume that the technical change is positive and at an increasing rate over time.

All coefficients of the inefficiency model terms except variable 'DPMS', 'DRD', and 'DRDSIZE' are statistically significant at 1% level of significance. All coefficients of the inefficiency model are negative. The negative estimates imply that the firms with greater value in these variables tend to be less inefficient. The coefficient 'ORT' and 'DRTSIZE' are negative, but very small. This shows that the 'ORT' variable of inefficient model significantly affects the efficiency, but the impact size of them is very small. From the 'DRTSIZE' estimate, one can find that the firms with greater defense ratio among large firms have greater technical efficiency. The variable 'AGE' has a negative sign in the inefficient model. This suggests that if the firm has been serving in the defense industry as a defense firm, then the firm shows higher technical efficiency.

The variable 'SIZE' shows a negative sign to technical inefficiency, which indicates that the large firms are more efficient than small and medium sized firms. Due to the high level of the coefficient for variable 'SIZE' on average, parametric and non-parametric tests to identify the significant difference in efficiency value between two size groups are required.

The signs of the dummy variables 'SPFIRM' and 'SEFIRM' in the inefficiency model are of a particular interest in this research. Specialized firms and serialized firms are selected from the designated defense firms. Specialized firms are guaranteed with the priority in R&D projects and equipment acquisition programs. In addition, specialized firms produce large scale equipment, and they are especially

Table 10.5 Maximum-likelihood estimates for parameters of the stochastic frontier model

Variable	Parameter	Estimate	Standard error	t-ratio
Production function				
Intercept	β_0	5.2504***	0.7857	6.6824
Ln(L)	β_L	0.3449***	0.1229	2.8075
Ln(K)	β_K	0.0930	0.0805	1.1549
Ln(M)	β_M	0.3726***	0.0819	4.5498
Year	β_t	0.0663**	0.0282	2.3509
Ln(L) ²	β_{LL}	0.1045***	0.0151	6.8986
Ln(K) ²	β_{KK}	-0.0205***	0.0059	-3.4485
Ln(M) ²	β_{MM}	0.0046	0.0079	0.5792
Ln(L)ln(K)	β_{LK}	-0.0184***	0.0077	-2.3926
ln(L)ln(M)	β_{LM}	-0.0293***	0.0079	-3.7133
ln(K)ln(M)	β_{KM}	0.0267***	0.0054	4.9632
Year ²	β_{tt}	0.0005	0.0014	0.3644
ln(L)*year	β_{Lt}	0.0099***	0.0030	3.3228
ln(K)*year	β_{Kt}	0.0008	0.0017	0.4536
ln(M)*year	β_{Mt}	-0.0072***	0.0022	-3.2852
Inefficiency model				
Intercept	δ_0	2.0371***	0.1348	15.1145
Defense Ratio (DRT)	δ_1	-0.0397***	0.0034	-11.5722
Rate of Operation (ORT)	δ_2	-0.0175***	0.0021	-8.4013
Serving Period (AGE)	δ_3	-0.0466***	0.0097	-4.7941
D(SIZE): 300 employees	δ_{d1}	-0.3468***	0.1072	-3.2350
D (SPFIRM)	δ_{d2}	-0.4312***	0.1037	-4.1593
D (SPFIRM)	δ_{d3}	-0.4180***	0.0789	-5.2991
D (DPMS)	δ_{d4}	-0.2123	0.2113	-1.0048
D (DRD): R&D for defense part	δ_{d5}	-0.2128**	0.0940	-2.2630
D (COMP): 1999~2005	δ_{d6}	-0.6505***	0.1103	-5.8974
DRTSIZE: Defense ratio * D (Size)	δ_4	-0.0045**	0.0019	-2.3566
Variance parameters				
σ^2		0.6255***	0.0631	9.9139
γ		0.8306***	0.0233	35.6974
Log-likelihood	654.30			

Note: ** and *** indicate significant at 5% and 1% level of significance

engaged in system assembling activities. Serialized firms produce component units as supporting firms for specialized firms. The coefficients of ‘SPFIRM’ and ‘SEFIRM’ in the inefficiency model are -0.4312 and -0.4180, respectively, which implies that specialized and serialized firms are more efficient compared to other firms which are neither specialized nor serialized.

The negative estimate for the variable ‘DRD’ is significant at 5% level. This implies that firms with R&D organization and employees for the defense part tend to be less inefficient, and its relationship is relatively smaller than the other estimates of the inefficiency model. When limited data set having R&D investment cost are included for the same type of analysis, R&D investment cost affects technical efficiency at 1% significance level. This means that the more the R&D investment

in the defense industry, the higher the efficiency level. This study conducts tests for identifying significant difference by dividing the firms into two groups: firms investing into defense R&D or not.

The overall competitive period is defined as post 1998, which was when the third policy revision was implemented. As described in Sect. 10.2, from the third revision time, the competitive environment changed dramatically for both incumbents in the defense industry and all potential firms which can enter the defense industry. The KMND lowered the barrier for the defense industry and canceled the amount of productions for competition. The estimated variable 'COMP' with a native sign and the largest size of coefficient suggests that there has been a considerable change in technical efficiency from the third policy revision.

10.5.2 The Input Elasticities

The elasticities are time and firm-specific. However, in order to save space, this study reports only their values evaluated at the mean by year (1990–2005), sector, size of the firm, overall competitive condition, policy change, specialization/serialization, competition changes in SOS firms and by firms which have R&D labors for defense part. Table 10.6 presents a summary of the statistics of the estimated elasticities with respect to inputs, technical change and return to scale.

The signs of the mean value of elasticities are all positive, which are consistent with the expectation. The mean of elasticities with respect to labor, capital and materials are 0.178, 0.073 and 0.681, respectively. The elasticity of output with respect to capital, E_K , is the smallest for the whole sample period. The elasticity of output with respect to the material, E_M , is quite large in magnitude compared to

Table 10.6 Mean input elasticities, technical changes and return to scale

	N	E_L	E_K	E_M	E_t	Pure TC	Non-neural TC	RTS
Mean by year:								
1990	79	0.111	0.065	0.733	0.017	0.065	-0.048	0.909
1991	83	0.106	0.068	0.732	0.016	0.066	-0.050	0.906
1992	82	0.123	0.066	0.721	0.018	0.067	-0.049	0.911
1993	81	0.134	0.066	0.714	0.019	0.067	-0.048	0.914
1994	77	0.156	0.060	0.705	0.022	0.068	-0.046	0.922
1995	79	0.170	0.058	0.697	0.023	0.069	-0.045	0.925
1996	78	0.175	0.061	0.692	0.023	0.070	-0.047	0.929
1997	78	0.184	0.064	0.686	0.023	0.070	-0.048	0.935
1998	79	0.217	0.057	0.673	0.026	0.071	-0.045	0.948
1999	73	0.221	0.074	0.659	0.025	0.072	-0.047	0.953
2000	68	0.194	0.076	0.668	0.022	0.072	-0.051	0.938
2001	71	0.189	0.082	0.664	0.021	0.073	-0.052	0.935
2002	70	0.204	0.091	0.649	0.021	0.074	-0.053	0.944

(continued)

Table 10.6 (continued)

	N	E_L	E_K	E_M	E_t	Pure TC	Non-neural TC	RTS
2003	76	0.214	0.093	0.639	0.022	0.075	-0.053	0.947
2004	77	0.234	0.098	0.625	0.023	0.075	-0.052	0.956
2005	70	0.246	0.100	0.617	0.023	0.076	-0.053	0.956
Mean by sector:								
Aviation, guidance	77	0.256	0.067	0.665	0.025	0.071	-0.046	0.987
Fires	147	0.194	0.056	0.693	0.023	0.071	-0.048	0.942
Ammunition	84	0.221	0.064	0.676	0.024	0.070	-0.046	0.961
Maneuver	169	0.148	0.068	0.704	0.018	0.071	-0.053	0.920
Communication, electronics	212	0.189	0.097	0.657	0.020	0.071	-0.051	0.943
Ship, submarine	94	0.193	0.071	0.685	0.021	0.071	-0.050	0.948
Chemistry	32	0.210	0.104	0.647	0.020	0.071	-0.050	0.961
Etc	406	0.151	0.071	0.686	0.022	0.070	-0.048	0.908
Mean by firm size:								
F1	661	0.160	0.089	0.668	0.021	0.071	-0.050	0.917
F2	560	0.199	0.055	0.697	0.022	0.070	-0.048	0.952
Mean by overall competitive environment change:								
C1	716	0.152	0.063	0.706	0.021	0.068	-0.047	0.922
C2	505	0.215	0.088	0.645	0.022	0.074	-0.052	0.948
Mean by changes of defense policy on specialization and serialization:								
P1	149	0.175	0.081	0.678	0.020	0.070	-0.050	0.935
P2	246	0.121	0.067	0.723	0.018	0.067	-0.049	0.910
P3	391	0.181	0.060	0.691	0.023	0.070	-0.046	0.932
P4	212	0.202	0.077	0.663	0.022	0.072	-0.050	0.942
P5	223	0.218	0.094	0.637	0.022	0.075	-0.053	0.949
Mean by specialized, serialized firms:								
S1	478	0.146	0.080	0.681	0.020	0.071	-0.051	0.907
S2	121	0.224	0.064	0.682	0.023	0.071	-0.048	0.969
S3	411	0.165	0.072	0.685	0.022	0.070	-0.049	0.921
S4	211	0.252	0.066	0.675	0.023	0.070	-0.047	0.992
Mean by competition change in specialization and serialization firms:								
SC1	478	0.146	0.080	0.681	0.020	0.071	-0.051	0.907
SC2	420	0.203	0.070	0.672	0.023	0.071	-0.048	0.946
SC3	323	0.193	0.067	0.693	0.021	0.069	-0.048	0.953
Mean by firm which has R&D employees for defense part:								
D1	390	0.126	0.073	0.697	0.020	0.070	-0.050	0.895
D2	831	0.203	0.073	0.674	0.022	0.071	-0.049	0.950
Overall means and standard deviations:								
Means	1221	0.178	0.073	0.681	0.021	0.070	-0.049	0.933
Std dev	1221	0.012	0.049	0.060	0.012	0.003	0.012	0.072

Glossary of variables

Firm size: *F1* under 300, *F2* over 300; Overall competition: *C1* 1990–1998; *C2* 1999–2005; Policy change on Specialization & serialization: *P1* Special Act on Defense Industry in 1983 (1990), *P2* First revision in 1990 (1991–1993), *P3* Second revision in 1993 (1994–1998), *P4* Third revision in 1998 (1999–2001), *P5* Fourth revision in 2001 (2002–2005); Specialization, serialization: *S1* No SOS, *S2* Specialization, *S3* Serialization, *S4* Both; Competition in specialization and serialization: *SC1* No SOS, *SC2* No competition, *SC3* Competition; R&D investment for a defense part: *D1* No, *D2* Yes

E_L and E_K . The returns to scale represent decreasing returns to scale with a mean value of 0.933 and a small standard deviation, meaning that more input generates smaller output. The mean value of returns to scales of F2 (0.952) is higher than that of F1 (0.917). These results imply that F2 has more scale effect on production given input values. The return to scale of the overall competitive period (C2, 0.948) is less than the value of the non-competitive period (C1, 0.922).

10.5.3 Technical Changes

This study looks at the elasticities of output with respect to time – interpreted as the rate of exogenous technical change, E_t , as defined in (10.5). These elasticities are both firm and time-specific.

Table 10.6 outlines the estimates of technical change and its decomposition into pure and non-neutral technical change components. The rate of technical change varies over time and sector. The result indicates that the mean rate of technical change is 0.021 with a relatively large standard deviation of 0.012, which implies, that on average, one year later, for a given amount of inputs, 2.1% more output can be produced.

Over time, an obvious general trend was observed in the rate of technical change. The technical change is found to be positive during the whole sample period with the maximum value (0.026) in 1998. It declined from 1998 to 2002, then slightly increased until 2005 with a value of 0.023. The mean of technical changes varies over industry sector with the lowest value of 0.018 in ‘Maneuver’, and with the highest value of 0.025 in ‘Aviation and Guidance’.

Technical changes grouped by the size of the firm show that the mean of technical changes for F2 (0.022) is greater than the mean of F1 (0.021). The analysis of variance (ANOVA) test, Wilcoxon Rank-Sum test and Kruskal–Wallis test were conducted in order to test the null hypothesis that the mean technical change of F1 and F2 are the same. The ANOVA is a parametric test conducted on the differences between the means. It assumes that the underlying distributions are normal (Freund et al. 1999). As the ANOVA test also requires that the population variances to be equal, the results derived from the ANOVA test alone may not be valid. Therefore, the non-parametric tests Wilcoxon Rank-Sum test and Kruskal–Wallis test were also carried out. These non-parametric tests do not require any assumptions with respect to the normality or variances of the populations. The results are reported in Table 10.7. At the 1% level of significance, the hypothesis that the mean technical change by the size of the firm is the same cannot be rejected. There was no significant difference in firm size in terms of technical change.

The rate of technical change across the group by specialization and serialization is not significantly different. We can assume that means of technical changes before the competitive period (C1) and during the competitive period (C2) are different according to the result of the tests. The hypothesis that the mean of technical change of C1 is the same as C2 is rejected (see Table 10.7). The mean technical

Table 10.7 Summary of the tests of the hypotheses on technical change

Hypothesis	ANOVA	Wilcoxon-rank sum	Kruskal–Wallis	Decision
$H_0: \mu_{TC} F1 = \mu_{TC} F2$	3.54*	2.23**	4.99*	Cannot Reject H_0
$H_0: \mu_{TC} C1 = \mu_{TC} C2$	6.41**	2.51**	6.33**	Reject H_0
$H_0: \mu_{TC} SC2 = \mu_{TC} SC3$	5.08**	-1.81*	3.28*	Cannot Reject H_0
$H_0: \mu_{TC} D1 = \mu_{TC} D2$	11.45***	-2.65***	7.06***	Reject H_0

Note: *, ** and *** indicate significant at 10%, 5% and 1% level of significance.

Firm size by total employees: *F1* under 300, *F2* over 300; Overall competition: *C1* 1990–1998, *C2* 1999–2005; Competition in specialization and serialization: *SC2* No competition, *SC3* Competition; R&D investment for a defense part: *D1* No, *D2*: Yes

change in the competitive period shows a higher value than that in the non-competitive period, but the difference rate is very low (0.1%).

Of all the SOS firms, the mean technical change of firms which are under the competitive condition (SC3) is 0.021, while the firms that are not under the competitive environment (SC2) is 0.023. Contrary to the result of C1 and C2, the relationship between SC2 and SC3 suggests that change into competitive environment is not fruitful for SOS firms in terms of the technical change. The significant difference between SC2 and SC3 is supported by the tests given in Table 10.7. The technical change of firms with R&D employees (D2) for the defense part is higher than that of the firms that have no R&D employees (D1) for the defense part, D1 (0.020) and D2 (0.022).

The decomposition of technical change shows that pure technical change is the primary component that has directed technical change over the entire time period. The pure component of technical change is found to be positive (0.070) while the non-neutral component of technical change is negative (−0.049).

10.5.4 Technical Efficiency

The summary statistics of the mean technical efficiencies of several groups are reported in Table 10.8. The mean technical efficiency is 0.767. It indicates that, on average, it is possible that for given level of labor, capital and material, the firms can produce 23.3% more output by using the best practice production technology.

Some variations were found in technical efficiency over time. The sample mean levels of technical efficiency were high in 2004 (0.840) and in 2005 (0.837). The technical efficiency slightly declined from the beginning of the sample period and kept lower values than the overall mean technical efficiency, until 1998. However, it leaped to above the mean technical efficiency in 1999 (0.768) and maintained relatively high technical efficiencies until the end of the analysis period. It means that the technical inefficiencies decreased rapidly after 1998.

Table 10.8 Estimates of mean technical efficiency by groups

	N	Mean	Std. error	Minimum	Maximum
Mean by year:					
1990	79	0.744	0.160	0.239	0.918
1991	83	0.741	0.178	0.229	0.941
1992	82	0.753	0.170	0.194	0.925
1993	81	0.723	0.185	0.031	0.924
1994	77	0.708	0.195	0.177	0.924
1995	79	0.734	0.208	0.054	0.956
1996	78	0.715	0.204	0.135	0.932
1997	78	0.746	0.172	0.174	0.932
1998	79	0.725	0.207	0.074	0.947
1999	73	0.768	0.185	0.119	0.937
2000	68	0.800	0.125	0.261	0.940
2001	71	0.823	0.115	0.436	0.934
2002	70	0.831	0.101	0.342	0.932
2003	76	0.829	0.121	0.275	0.947
2004	77	0.840	0.087	0.560	0.943
2005	70	0.837	0.096	0.547	0.956
Mean by sector:					
Aviation, guidance	77	0.843	0.088	0.547	0.956
Fires	147	0.738	0.196	0.136	0.942
Ammunition	84	0.835	0.102	0.550	0.930
Maneuver	169	0.730	0.196	0.054	0.956
Communication, electronics	212	0.775	0.154	0.135	0.942
Ship, submarine	94	0.777	0.141	0.216	0.912
Chemistry	32	0.840	0.097	0.467	0.919
Etc	406	0.755	0.178	0.031	0.947
Mean by firm size (number of employees > 300):					
F1	661	0.767	0.173	0.031	0.947
F2	560	0.769	0.165	0.136	0.956
Mean by of firm size among specialized firms:					
F1	75	0.852	0.084	0.467	0.922
F2	257	0.818	0.132	0.141	0.956
Mean by overall competitive environment change:					
C1	716	0.732	0.187	0.031	0.956
C2	505	0.819	0.124	0.119	0.956
Mean by changes of defense policy on specialization and serialization:					
P1	149	0.788	0.141	0.239	0.956
P2	246	0.739	0.178	0.031	0.941
P3	391	0.726	0.197	0.054	0.956
P4	212	0.797	0.147	0.119	0.940
P5	223	0.833	0.104	0.275	0.947
Mean by specialization, serialization firms and both:					
S1	478	0.728	0.197	0.031	0.947
S2	121	0.789	0.151	0.196	0.940
S3	411	0.769	0.151	0.177	0.942
S4	211	0.846	0.100	0.141	0.956
Mean by competition change in specialization and serialization firms:					
SC1	478	0.728	0.197	0.031	0.947
SC2	420	0.800	0.137	0.177	0.956
SC3	323	0.786	0.149	0.141	0.956
Mean by firms which have R&D employees for the defense part:					
D1	390	0.699	0.209	0.031	0.947
D2	831	0.800	0.135	0.074	0.956
Means	1,221	0.767	0.169	0.031	0.956

It should be noted that the time when the technical efficiency changed over the mean value in 1998 coincides with the time when the third revision of the policy was implemented. Further, it is also in accord with the period when the Korean financial crisis had been maintained. The Korean financial crisis officially started in November 1997. It is not certain whether this conversion of technical efficiency was due to the revision of the defense policy or due to the financial crisis. Based on this, however, where several tests were conducted to compare the distributions and means, we may be able to make some deductions on the effect of competition policy changes.

The estimate of technical efficiency varies substantially across industry. The technical efficiency is highest in ‘Aviation and Guidance’ with mean value of 0.843. There are five sectors having mean technical efficiency greater than the overall mean efficiency, but sector ‘Maneuver’ ranks the top of the list of sectors that are technically inefficient (0.730). It was found that firms in efficient sectors are relatively smaller than those in other sectors.

Now, the study looks at the technical efficiency by the size of the firm which is the most interesting hypothesis in this study. Firm size is classified by “Framework Act on Small and Medium Enterprises”. Firm size is large if the total number of labors is greater than 300. The same definition has been used in the annual report of the defense industry. In the inefficiency component of the stochastic frontier model, the same definition as that described above is adopted. The variable ‘SIZE’ shows a negative sign in the inefficiency model, indicating that large firms are positively related with the technical efficiency. The mean of technical efficiency of F1 and F2 are 0.767 and 0.769, respectively. The difference is 0.011. This test can be supported by the coefficient of the variable ‘Employees’ in the inefficiency model which is conducted as a supplementary model, resulting to a zero effect at a high significant level. This indicates the there is no obvious evidence of relationship between the efficiency and the number of workers.

The results of the tests for the technical efficiency by the size of the firm are reported in Table 10.9. The parametric and non-parametric tests of firm size hypotheses cannot reject the null hypotheses. Hence, one cannot declare that technical efficiencies of F2 are higher than those of F1. Another point of reference is

Table 10.9 Summary of the tests of firm size hypotheses

$H_0: \mu_{TE} F1(< 300) = \mu_{TE} F2(\geq 300)$: mean (F1: 0.767, F2: 0.769), N (F1:661, F2: 560)								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal– Wallis	Pr > F	Kolmogorov– Smirnov	Pr > KSa	Decision
0.07	0.785	–1.150	0.225	1.323	0.250	0.256	0.798	Cannot reject H_0
$H_0: \mu_{TE} F1(< 1,000) = \mu_{TE} F2(\geq 1,000)$: mean (F1: 0.766, F2: 0.771), N (F1:814, F2: 407)								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal– Wallis	Pr > F	Kolmogorov– smirnov	Pr > KSa	Decision
0.26	0.609	0.619	0.536	0.383	0.536	1.093	0.183	Cannot reject H_0

set to divide the firms into F1 or F2 based on the number of labors of 1,000. The same tests were conducted to investigate whether there was a significant difference in technical efficiency among the two groups, F1 and F2. In the end, no significant difference was found between the two groups.

The whole period can be divided into two periods (C1, C2) considering the time the third policy was implemented in 1998. The reason for selecting these points and its limitations are described in Sects. 10.2 and 10.3. The estimate of variable 'COMP' in inefficiency component is -0.650 , with a t -ratio of 5.897, indicating a highly positive relationship between the technical efficiency and the time period 1999–2005. This estimate is supported by the trend of the technical efficiency over time, which is presented in Table 10.8. To confirm the effect of the change in competitive condition on technical efficiency, a more detailed classification and statistical tests are required, because the time that the third revision was executed is in parallel with the period of the financial crisis, and the period after the fourth revision overlapped with the period in which all firms adapted themselves to new economic circumstances.

To see whether the change of competitive environment led firms to become technically more efficient, SOS firms (743 observations) were divided into two groups; SOS firms that have been operated under non-competitive condition (SC2) and SOS firms that have serviced under competitive environment (SC3). The competitive condition was derived from the policy changes on defense industry, and from the fluctuation of the number of products. The result is contradicts our expectations, i.e. competitive conditions impacted positively to technical efficiency. The SOS firms which have been subject to more competitive environment were less technically efficient than the other firms that had not been in competitive condition. But the test results show that the mean technical efficiency difference between the two groups is not significant (see Table 10.10). Due to these two opposite results, we cannot conclude that the main source of improvement in technical efficiency is the change into competitive environment by the KMND.

The mean of technical efficiency of the firms having R&D organization and researchers (D2) is 0.800, which is larger than that of D1 (0.699). The estimate of variable 'DRD' is -0.183 , which is significant at 1% level, indicating that D1 firms are closely related with technical inefficiency. Higher mean of technical efficiency value of D2 can be expected from the results in the inefficiency component. Of all the firms that have R&D researchers in their defense parts (831 from 1,221 observations), 471 observations are from large firms (F2), which comprise of 56.7%. The technical efficiency gap is significant and it is supported by tests rejecting the null hypothesis at the 1% significant level (see Table 10.10).

The ratio of the defense part, defined as the amount of sales from the defense part divided by total sales, was estimated and it shows a positive relationship with the technical efficiency. The size of estimate, however, was small (-0.039), but still significant at 1% level. As the variable 'DRT' is not a (group) dummy variable, it is difficult to test the differences among the groups. When the model with a square term of variable 'DRT' was tested, a positive sign was estimated with a very small size of the coefficient. It indicates that the ratio of defense part is positively related

Table 10.10 Summary of the tests of competitive environment change and defense R&D hypotheses

$H_0: \mu_{TE} C1(noncompetitive) = \mu_{TE} C2(competitive)$; mean (0.732, 0.819), N (716, 505)								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal-Wallis	Pr > F	Kolmogorov-Smirnov	Pr > KSa	Decision
82.05	0.000***	9.285	0.000***	86.21	0.000***	4.41	0.000***	Reject H_0
$H_0: \mu_{TE} SC2(noncompetitive) = \mu_{TE} SC3(competitive)$; Mean (0.800, 0.786), N (420, 323)								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal-Wallis	Pr > F	Kolmogorov-Smirnov	Pr > KSa	Decision
1.93	0.165	-1.75	0.080*	3.06	0.080*	1.23	0.096*	Cannot be rejected
$H_0: \mu_{TE} D1(No\ Defense\ R\&D) = \mu_{TE} D2(Defense\ R\&D)$; mean (0.699, 0.800), N (390, 831)								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal-Wallis	Pr > F	Kolmogorov-Smirnov	Pr > KSa	Decision
11.45	0.000***	-2.66	0.008***	7.06	0.008***	2.42	0.000***	Reject H_0

Note: * and *** indicate significant at 10% and 1% level of significance

with the technical efficiency path, and technical efficiency has a concave shape when the defense ratio is increased.

The firms that are implemented with DPAMIS, one of monitoring or auditing systems for cost in defense firms, are expected to show higher technical efficiency, because this system could control excessive change of cost in the defense factory. Even in the case of DPAMIS which was started from 1999, the following test was developed for the data set of 2002–2005, assuming that this system was implemented in 2002 effectively. The parametric and non-parametric test results are summarized in Table 10.11. The technical efficiency gap by monitoring system is significant at the 1% significance level. For in-depth tests, the data from 1990 to 2001 was excluded. The number of observations under DPAMIS remained unchanged (184), but the number of observations which are not implementing the systems reduced from 321 to 109. The difference in technical efficiency between the two groups is not valid at the 10% significance level. This result is supported by the estimate in the inefficiency term of the frontier function as shown in Table 10.5. Thus, the effect of cost monitoring regulation is not clear. This result has a limitation in that the data of DPAMIS exist for the short period.

The frequency distribution of technical efficiency for the entire sample by year, size, sector, and competitive condition change are reported in Table 10.14. The efficiencies are highly concentrated in the interval 85.1–90% (334 observations, 27.35% of the whole sample). There is no observation which is found to be fully (100%) efficient.

10.5.5 Decomposition of TFP

Tables 10.12 and 10.13 report the change in TP, SE, AE, and average for selected time periods. The estimated results of TFP growth and its decomposition into four components by firm size, R&D investment activity, and SOS are presented in Tables 10.15–10.17.

The average rate of TP was estimated at 0.021. The change in TP, pure technical change, and non-neutral technical change by year are given and explained in Table 10.6. The scale components, which measure the effects of input changes on output growth, are zero if RTS is constant, or are greater (less) than zero if RTS is increasing (decreasing). Average SE is 0.005 for the whole industry, positive but small value, and negative in the ‘Ship and Submarine’ and ‘Chemistry’. SE is the highest in ‘Maneuver’ with the value of 0.017. The fluctuation range of SE is very high in the early stage, and no consistent increasing or decreasing pattern in SE is found. The estimated scale components in TFP growth for large sized firms in Table 10.15 are very small and not sensitive, implying that large firms had already reached a certain size where scale economies no longer existed.

Allocative inefficiency occurs when factor prices are not equal to their marginal product. For the total sample, the average AE was estimated at 0.012. On average, sector ‘Aviation and Guidance’ and ‘Ammunition’ have negative AE with the value

Table 10.11 Summary of tests of regulation hypotheses

$H_0: \mu_{TE} DP1(\text{no DPAMIS}) = \mu_{TE} DP2(\text{DPAMIS}); \text{Mean (DP1: 0.755, DP2: 0.841), N (DP1:1037, DP2: 184)}$								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal-Wallis	Pr > F	Kolmogorov-Smirnov	Pr > KSa	Decision
42.15	0.000***	7.16	0.000***	51.31	0.000***	3.47	0.000***	Reject H_0
$H_0: \mu_{TE} DP1(\text{no DPAMIS, 2002~}) = \mu_{TE} DP2(\text{DPAMIS, 2002~}); \text{mean (DP1: 0.822, DP2: 0.841), N (DP1:109, DP2: 184)}$								
ANOVA	Pr > F	Wilcoxon rank-sum	Pr > Z	Kruskal-Wallis	Pr > F	Kolmogorov-Smirnov	Pr > KSa	Decision
2.40	0.123	-1.64	0.101	2.71	0.100	1.17	0.128	Cannot be rejected

Note: *** indicates significant at 1% level of significance

Table 10.12 Technical progress (TP) and scale effect (SE) by sector

		Mean	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8
TP	1990–1991	0.016	0.024	0.022	0.022	0.014	0.011	0.011	0.019	0.016
	1991–1992	0.018	0.022	0.021	0.021	0.012	0.019	0.012	0.021	0.019
	1992–1993	0.019	0.023	0.016	0.023	0.016	0.018	0.019	0.023	0.020
	1993–1994	0.022	0.021	0.025	0.024	0.016	0.021	0.015	0.024	0.024
	1994–1995	0.023	0.030	0.026	0.023	0.020	0.024	0.018	0.021	0.024
	1995–1996	0.023	0.024	0.023	0.023	0.019	0.024	0.022	0.019	0.024
	1996–1997	0.023	0.021	0.024	0.022	0.020	0.019	0.026	0.019	0.025
	1997–1998	0.026	0.020	0.033	0.028	0.031	0.025	0.026	0.022	0.024
	1998–1999	0.025	0.026	0.027	0.027	0.024	0.023	0.027	0.019	0.024
	1999–2000	0.022	0.025	0.028	0.024	0.015	0.020	0.021	0.020	0.021
	2000–2001	0.021	0.028	0.024	0.026	0.012	0.021	0.021	0.021	0.020
	2001–2002	0.021	0.027	0.019	0.028	0.015	0.018	0.021	0.021	0.023
	2002–2003	0.022	0.023	0.015	0.028	0.019	0.019	0.028	0.021	0.025
	2003–2004	0.023	0.023	0.020	0.029	0.018	0.023	0.028	0.017	0.026
	2004–2005	0.023	0.027	0.020	0.029	0.021	0.023	0.026	0.020	0.025
	1990–2005	0.021	0.025	0.023	0.024	0.018	0.020	0.021	0.020	0.022
SE	1990–1991	0.031	0.037	0.142	0.188	-0.025	0.006	-0.173	-0.007	0.023
	1991–1992	-0.011	0.015	-0.114	-0.016	-0.051	0.020	0.000	0.004	0.016
	1992–1993	0.012	-0.008	-0.139	0.035	0.065	-0.030	0.112	0.006	0.033
	1993–1994	0.024	0.006	0.075	-0.052	-0.006	-0.005	-0.149	-0.005	0.083
	1994–1995	0.006	-0.010	0.004	-0.014	-0.005	0.030	0.030	-0.023	0.005
	1995–1996	-0.011	0.017	0.085	-0.034	-0.011	-0.068	0.033	-0.007	-0.025
	1996–1997	0.014	0.003	0.020	-0.003	0.013	0.011	-0.020	-0.006	0.028
	1997–1998	-0.015	-0.026	-0.010	0.020	0.051	0.036	-0.034	0.003	-0.077
	1998–1999	-0.003	0.000	0.020	-0.002	-0.037	-0.012	-0.047	-0.010	0.021
	1999–2000	-0.009	0.028	-0.005	0.000	-0.074	0.016	0.000	0.003	-0.017
	2000–2001	0.011	0.114	-0.045	0.015	-0.016	0.004	-0.008	0.008	0.018
	2001–2002	0.026	0.004	0.013	0.006	0.128	0.032	-0.006	0.002	-0.006
	2002–2003	0.000	0.070	-0.036	-0.002	-0.022	-0.021	0.035	0.003	0.010
	2003–2004	-0.002	-0.031	0.022	-0.003	0.033	0.026	-0.050	0.004	-0.027
	2004–2005	0.006	0.015	0.007	0.028	-0.008	0.012	0.018	0.004	0.002
	1990–2005	0.005	0.017	0.003	0.013	0.005	0.005	-0.017	-0.001	0.008

Sector: Sector1: Aviation, Guidance; Sector2: Fires; Sector3: Ammunition; Sector4: Maneuver; Sector5: Communication, electronics; Sector6: Ship, submarine; Sector7: Chemistry; Sector8: Etc

of -0.012. Mean level of AE fluctuation is greater than that of SE. AE was highest in 'Ship and Submarine', with an estimated mean value of 0.048. The difference in AE among industries indicates that the degree of market distortion varied across the industry. Interestingly, AE fell into a negative except for the two sectors, and started to discover its inefficiency.

The TFP in the defense industry has grown at an annual rate of 3.9%. The TFP growth decreased during 1990–1994, and in 1998, and increased from 1998–1999. For the industry estimates during the sample period, the sector 'Communication' has the highest growth value while it has not grown continuously. During the period 1997–1998, a large downturn in TFP was observed in the industry. All sectors show a positive TFP growth. The overall mean rate of TFP growth of S&S

Table 10.13 Allocative efficiency (AE) and TFP growth (TFP) by sector

	Mean	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8	
AE	1990–1991	-0.058	-0.374	-0.395	-0.461	-0.312	-0.026	0.948	-0.058	0.083
	1991–1992	0.065	0.090	0.330	0.098	0.228	-0.107	-0.026	-0.038	0.014
	1992–1993	-0.035	-0.008	0.382	-0.059	-0.255	0.066	-0.676	-0.029	-0.006
	1993–1994	-0.078	0.075	-0.197	0.071	0.106	0.015	0.445	-0.047	-0.300
	1994–1995	-0.016	-0.161	0.044	0.018	-0.010	-0.103	-0.203	0.130	0.038
	1995–1996	0.078	0.179	-0.096	0.155	0.061	0.200	-0.092	0.076	0.089
	1996–1997	-0.031	0.036	-0.094	0.036	-0.105	0.056	0.098	0.044	-0.086
	1997–1998	-0.051	0.020	-0.262	-0.220	-0.287	-0.146	-0.031	-0.088	0.216
	1998–1999	0.072	-0.009	0.040	0.045	0.348	0.030	-0.040	0.123	0.012
	1999–2000	0.099	-0.049	-0.038	0.099	0.512	0.026	0.103	-0.021	0.108
	2000–2001	-0.010	-0.412	0.113	-0.029	0.044	0.019	-0.043	-0.021	0.056
	2001–2002	0.065	0.065	0.275	0.001	-0.071	0.101	0.179	0.032	-0.011
	2002–2003	0.046	0.235	0.207	0.005	-0.011	0.144	-0.176	0.009	-0.027
	2003–2004	0.060	0.105	-0.116	-0.026	0.036	0.083	0.163	0.077	0.093
	2004–2005	0.014	-0.065	0.024	0.066	0.012	-0.051	0.110	-0.034	0.056
	1990–2005	0.012	-0.021	0.010	-0.021	0.011	0.017	0.048	0.010	0.017
TFP growth	1990–1991	-0.062	-0.204	-0.383	-0.313	-0.452	-0.137	0.835	-0.126	0.123
	1991–1992	0.103	0.197	0.423	0.140	0.314	0.056	-0.038	-0.065	-0.031
	1992–1993	-0.071	-0.014	0.252	-0.017	-0.342	0.041	-0.756	0.103	-0.027
	1993–1994	-0.048	0.115	-0.187	0.022	0.137	0.028	0.452	-0.132	-0.237
	1994–1995	0.032	-0.091	0.125	-0.040	-0.156	-0.073	-0.081	0.169	0.160
	1995–1996	0.094	0.188	-0.224	0.202	0.235	0.208	-0.062	0.096	0.082
	1996–1997	0.055	0.055	0.102	0.056	-0.103	0.028	0.128	0.172	0.086
	1997–1998	-0.143	0.006	-0.422	-0.172	-0.459	-0.122	-0.379	-0.075	0.112
	1998–1999	0.115	0.009	0.226	0.081	0.354	0.000	0.107	0.153	0.039
	1999–2000	0.161	0.121	-0.143	0.143	0.706	0.121	0.181	-0.035	0.166
	2000–2001	0.023	-0.320	0.058	-0.010	0.136	0.058	-0.032	0.021	0.088
	2001–2002	0.119	0.074	0.335	0.017	-0.051	0.225	0.181	0.020	0.065
	2002–2003	0.083	0.449	0.222	0.036	0.072	0.168	-0.301	0.082	0.009
	2003–2004	0.146	0.092	-0.095	0.001	0.092	0.304	0.350	0.117	0.142
	2004–2005	0.045	-0.078	0.056	0.111	0.040	-0.005	0.108	-0.007	0.092
	1990–2005	0.039	0.036	0.015	0.012	0.022	0.061	0.046	0.033	0.051

Table 10.14 Frequency distribution of technical efficiency

00.0–60.0			60.1–65.0			65.1–70.0			70.1–75.0			75.1–80.0			80.1–85.0			85.1–90.0			90.1–95.0			95.1–99.9			Sample	
n	%		N	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%		
1990	14	1.15	6	0.49	7	0.57	7	0.57	7	0.57	6	0.49	10	0.82	19	1.56	10	0.82	0	0.00	79	6.47						
1991	15	1.23	3	0.25	7	0.57	7	0.57	8	0.66	14	1.15	19	1.56	10	0.82	0	0.00	83	6.80								
1992	15	1.23	6	0.49	3	0.25	5	0.41	8	0.66	15	1.23	20	1.64	10	0.82	0	0.00	82	6.72								
1993	16	1.31	9	0.74	3	0.25	1	0.08	14	1.15	12	0.98	23	1.88	3	0.25	0	0.00	81	6.63								
1994	19	1.56	5	0.41	6	0.49	5	0.41	6	0.49	14	1.15	13	1.06	9	0.74	0	0.00	77	6.31								
1995	14	1.15	6	0.49	4	0.33	5	0.41	9	0.74	13	1.06	15	1.23	12	0.98	1	0.08	79	6.47								
1996	17	1.39	5	0.41	4	0.33	3	0.25	13	1.06	13	1.06	13	1.06	10	0.82	0	0.00	78	6.39								
1997	12	0.98	4	0.33	6	0.49	7	0.57	9	0.74	16	1.31	15	1.23	9	0.74	0	0.00	78	6.39								
1998	14	1.15	7	0.57	3	0.25	7	0.57	8	0.66	13	1.06	20	1.64	7	0.57	0	0.00	79	6.47								
1999	12	0.98	3	0.25	2	0.16	2	0.16	10	0.82	8	0.66	25	2.05	11	0.90	0	0.00	73	5.98								
2000	4	0.33	2	0.16	5	0.41	5	0.41	8	0.66	12	0.98	21	1.72	11	0.90	0	0.00	68	5.57								
2001	5	0.41	3	0.25	3	0.25	4	0.33	6	0.49	6	0.49	27	2.21	17	1.39	0	0.00	71	5.81								
2002	3	0.25	2	0.16	3	0.25	2	0.16	5	0.41	15	1.23	26	2.13	14	1.15	0	0.00	70	5.73								
2003	4	0.33	1	0.08	2	0.16	5	0.41	8	0.66	9	0.74	29	2.38	18	1.47	0	0.00	76	6.22								
2004	1	0.08	3	0.25	4	0.33	2	0.16	8	0.66	15	1.23	27	2.21	17	1.39	0	0.00	77	6.31								
2005	4	0.33	0	0.00	5	0.41	1	0.08	7	0.57	10	0.82	22	1.80	20	1.64	1	0.08	70	5.73								
F1	93	7.62	40	3.28	47	3.85	37	3.03	60	4.91	82	6.72	177	14.50	125	10.24	0	0.00	661	54.14								
F2	76	6.22	25	2.05	20	1.64	31	2.54	73	5.98	113	9.25	157	12.86	63	5.16	2	0.16	560	45.86								
S1	1	0.08	4	0.33	3	0.25	2	0.16	8	0.66	10	0.82	31	2.54	17	1.39	1	0.08	77	6.31								
S2	29	2.38	7	0.57	3	0.25	7	0.57	12	0.98	38	3.11	45	3.69	6	0.49	0	0.00	147	12.04								
S3	1	0.08	7	0.57	8	0.66	4	0.33	2	0.16	6	0.49	25	2.05	31	2.54	0	0.00	84	6.88								
S4	34	2.78	6	0.49	7	0.57	14	1.15	17	1.39	34	2.78	48	3.93	8	0.66	1	0.08	169	13.84								
S5	30	2.46	11	0.90	16	1.31	12	0.98	21	1.72	29	2.38	50	4.10	43	3.52	0	0.00	212	17.36								
S6	8	0.66	6	0.49	4	0.33	8	0.66	9	0.74	28	2.29	25	2.05	6	0.49	0	0.00	94	7.70								
S7	1	0.08	0	0.00	1	0.08	3	0.25	3	0.25	2	0.16	14	1.15	8	0.66	0	0.00	32	2.62								
S8	65	5.32	24	1.97	25	2.05	18	1.47	61	5.00	48	3.93	96	7.86	69	5.65	0	0.00	406	33.25								
C1	136	11.14	51	4.18	43	3.52	47	3.85	81	6.63	120	9.83	157	12.86	80	6.55	1	0.08	716	58.64								
C2	33	2.70	14	1.15	24	1.97	21	1.72	52	4.26	75	6.14	177	14.50	108	8.85	1	0.08	505	41.36								
Sum	169	13.84	65	5.32	67	5.49	68	5.57	133	10.89	195	15.97	334	27.35	188	15.40	2	0.16	1,221	100								

Table 10.15 TFP growth and its components by firm size

Year	Small and medium					Large				
	TFP growth	TP	TE	SE	AE	TFP growth	TP	TE	SE	AE
1990–1991	0.156	0.014	-0.003	-0.017	0.159	-0.318	0.018	-0.111	0.087	-0.314
1991–1992	0.033	0.018	0.011	0.009	-0.006	0.190	0.018	0.055	-0.036	0.152
1992–1993	-0.041	0.018	-0.086	0.017	0.009	-0.107	0.021	-0.045	0.006	-0.088
1993–1994	-0.100	0.021	-0.025	0.042	-0.139	0.013	0.022	-0.004	0.002	-0.006
1994–1995	-0.021	0.024	-0.026	0.006	-0.025	0.091	0.023	0.068	0.007	-0.005
1995–1996	0.173	0.024	0.068	-0.025	0.107	0.015	0.022	-0.059	0.003	0.049
1996–1997	0.017	0.024	0.036	0.017	-0.060	0.091	0.022	0.062	0.010	-0.003
1997–1998	-0.129	0.027	-0.086	-0.011	-0.060	-0.156	0.026	-0.120	-0.018	-0.044
1998–1999	0.151	0.025	0.010	-0.010	0.126	0.079	0.024	0.035	0.003	0.018
1999–2000	0.310	0.020	0.086	-0.020	0.225	-0.016	0.024	0.006	0.005	-0.051
2000–2001	0.016	0.019	-0.002	0.024	-0.025	0.031	0.023	0.004	-0.004	0.008
2001–2002	0.089	0.020	-0.011	0.048	0.032	0.156	0.022	0.029	-0.001	0.105
2002–2003	0.132	0.021	0.040	0.005	0.066	0.019	0.023	-0.017	-0.007	0.019
2003–2004	0.182	0.022	0.104	-0.003	0.059	0.094	0.025	0.009	0.000	0.061
2004–2005	-0.003	0.023	-0.007	0.007	-0.026	0.112	0.023	0.013	0.005	0.070
Mean	0.060	0.021	0.006	0.006	0.026	0.016	0.022	-0.007	0.004	-0.004

Table 10.16 TFP growth and its components by R&D investment in defense part

Year	R&D investment					No R&D investment				
	TFP growth	TP	TE	SE	AE	TFP growth	TP	TE	SE	AE
1990–1991	−0.007	0.013	−0.113	0.044	0.046	−0.102	0.018	−0.009	0.022	−0.134
1991–1992	0.198	0.016	0.041	−0.046	0.187	0.034	0.019	0.023	0.015	−0.024
1992–1993	−0.136	0.017	−0.106	0.046	−0.096	−0.029	0.020	−0.043	−0.010	0.004
1993–1994	−0.213	0.023	−0.063	0.052	−0.226	0.041	0.021	0.010	0.008	0.002
1994–1995	−0.009	0.023	−0.023	0.026	−0.035	0.054	0.024	0.040	−0.004	−0.006
1995–1996	0.146	0.024	0.086	0.003	0.035	0.068	0.022	−0.036	−0.018	0.099
1996–1997	−0.119	0.023	−0.056	0.034	−0.120	0.132	0.023	0.096	0.005	0.009
1997–1998	−0.040	0.025	−0.065	−0.073	0.074	−0.191	0.027	−0.121	0.012	−0.109
1998–1999	0.088	0.022	−0.002	0.006	0.065	0.126	0.026	0.033	−0.007	0.074
1999–2000	−0.030	0.020	−0.099	0.006	0.042	0.217	0.023	0.093	−0.014	0.116
2000–2001	−0.056	0.019	−0.063	0.037	−0.049	0.053	0.022	0.025	0.002	0.004
2001–2002	0.201	0.019	0.012	0.016	0.156	0.097	0.022	0.006	0.029	0.040
2002–2003	0.000	0.021	−0.028	0.028	−0.020	0.106	0.022	0.027	−0.008	0.064
2003–2004	0.183	0.022	0.103	0.000	0.057	0.135	0.023	0.054	−0.003	0.061
2004–2005	0.076	0.022	0.005	−0.002	0.051	0.037	0.024	0.000	0.009	0.004
Mean	0.012	0.020	−0.028	0.011	0.008	0.052	0.022	0.012	0.003	0.014

Table 10.17 TFP growth and its components by SOS

Year	Neither specialization nor serialization						Specialization or serialization			
	TFP growth	TP	TE	SE	AE	TFP growth	TP	TE	SE	AE
1990–1991	–0.097	0.012	–0.119	0.085	–0.080	–0.043	0.019	–0.017	0.002	–0.047
1991–1992	0.296	0.014	0.065	–0.052	0.270	–0.017	0.020	0.010	0.015	–0.063
1992–1993	–0.152	0.015	–0.136	0.032	–0.065	–0.027	0.021	–0.031	0.001	–0.019
1993–1994	–0.112	0.020	–0.014	0.035	–0.153	–0.016	0.023	–0.016	0.018	–0.039
1994–1995	–0.154	0.023	–0.105	0.024	–0.095	0.129	0.024	0.083	–0.003	0.025
1995–1996	0.094	0.022	0.050	0.006	0.017	0.094	0.023	–0.020	–0.020	0.110
1996–1997	–0.075	0.024	–0.008	0.031	–0.120	0.120	0.022	0.078	0.005	0.014
1997–1998	–0.256	0.029	–0.182	–0.004	–0.100	–0.081	0.025	–0.061	–0.02	–0.024
1998–1999	0.192	0.025	0.036	–0.043	0.175	0.081	0.024	0.017	0.014	0.026
1999–2000	0.305	0.020	0.025	–0.022	0.282	0.077	0.023	0.063	–0.002	–0.008
2000–2001	–0.038	0.019	0.011	0.026	–0.095	0.063	0.023	–0.006	0.002	0.045
2001–2002	0.118	0.019	–0.025	0.075	0.049	0.120	0.023	0.030	–0.007	0.076
2002–2003	0.156	0.020	0.061	–0.001	0.077	0.031	0.024	–0.017	0.001	0.024
2003–2004	0.144	0.023	0.098	0.007	0.015	0.148	0.023	0.034	–0.011	0.101
2004–2005	0.004	0.024	–0.003	0.009	–0.026	0.084	0.023	0.005	0.004	0.051
Mean	0.028	0.020	–0.015	0.014	0.008	0.047	0.023	0.009	0.000	0.015

firms (0.069) is about two times higher than the overall TFP growth rate, and rate of the specialized firms is the lowest (0.023). The TFP growth is the sum of changes in technical efficiency, changes in allocative efficiency, changes in scale components, and the technical change which is the shift in the production frontier function over time. The main factor dominating TFP growth is TP, which means that the productivity growth was mainly obtained by TP, followed by AE.

10.6 Conclusions

10.6.1 *Summary of the Study*

Since the government is the unique demand for the defense firms, it is necessary for the government to examine the efficiencies of the defense firms prior to policy execution and regulation enforcement. In this perspective, the government takes a primary role in inducing innovation. This study analyzed technical efficiencies and technical changes of the defense industry from 1990 to 2005 by examining a firm-level unbalanced panel data. A stochastic frontier production model in the form of translog was used. The main results and important conclusions derived from this study are summarized in the following paragraphs.

The elasticity of output with respect to labor has increased over time with a mean value of 0.178. It was found that F1, on average, uses more labor than F2 but produces the same amount of output. S&S (S4) firms use less labor than the firms that are not included in the S&S firms. The capital elasticity of output shows the smallest value with a mean value of 0.073. The material elasticity of output is quite large in magnitude with a mean value of 0.681. The elasticity of output with respect to labor shows a nearly symmetric pattern of the material elasticity of output over time. The decreasing return to scale was estimated during the whole sample period. The mean value of returns to scale of F2 is greater than F1. The return to scale of the competitive period is greater than of the non-competitive period.

The technical changes are both firm and time specific. The technical changes can be decomposed into pure and non-neutral technical change components. The mean of technical change for the entire sample was found to be 0.021 with a relatively large variation. The rate of technical change varied over time and industry. Over time, an obvious trend was observed in the rate of technical change. The technical change was found to be positive during the whole sample period reaching the maximum in 1998. It declined from 1998 to 2002 and then slightly increased from 2003 to 2005.

The technical change varied over industry sector with the lowest value in 'Maneuver' and the highest value in 'Aviation and Guidance'. As the parametric and non-parametric tests did not reject the null hypotheses of equality of rate of technical change, the mean technical change in terms of the size of the firm was the same. There is no significant difference in technical change among groups of firms divided by specialization or serialization (S1–S4).

The mean technical change of firms which are in the competitive condition was higher than of the firms operating in the non-competitive environment. However, the competition effect on technical change for SC2 and SC3 was not significant. This implies that conversion into a competitive environment is not fruitful for SOS firms in terms of technical change. Decomposition of technical change shows that pure technical change is the primary component that has directed the technical change over the entire time period.

The mean of the technical efficiency for the entire sample was found to be 0.767 with a standard error of 0.169. In this study, the trend of efficiencies across year, sector, and policy were investigated. By conducting the parametric and non-parametric tests, this study examined the effect of firm size, change of competitive conditions, and policies on defense industry. This study found that technical efficiency slightly declined from the beginning of the sample period and remained at lower values until 1998; however, it leaped beyond the mean technical efficiency in 1999 and remained at relatively higher values until the end of the analysis period. The width of the confidence intervals decreased since 1998, when the mean technical efficiency started to exceed the overall mean efficiency. The estimate of technical change varied substantially across industries. While 'Aviation and Guidance' was the most technically efficient sector, 'Maneuver' was the most technically inefficient one.

The effect of the size of the firm on technical efficiency was tested. The variable 'SIZE' showed a negative sign in the inefficiency model, which indicates that the large firms are positively related with higher level of technical efficiency. The mean of technical efficiency of F1 and F2 are 0.767 and 0.769, respectively. The difference between the two groups by the size of the firm, based on total employees over 300, was not rejected by the tests. After setting up a new standard based on 1,000 labors, this study, however, could not find any significant difference between the two groups. In short, F2 showed higher technical efficiency than the other but their difference was statistically insignificant.

Concerning the competition effect on technical efficiency, the effect of change in competitive environment changes was supported by the estimate of the inefficient component and the parametric and non-parametric tests which resulted in reduction of technical inefficiency in competitive condition. However, when this study compared the efficiency between the SOS firms operating under non-competitive condition (SC2) and under competitive environment (SC3), the result was contrary to the expectation that the competition has a positive effect on technical efficiency. The SOS firms which have been subject to more competitive environment were less technically efficient. This study was not able to find the effectiveness of the competitive policies for the SOS firms.

Firms that have their R&D organizations and researchers are closely related with a higher level of technical efficiency. The rate of defense part is positively related to efficiency, but its significance level is very low. In addition, technical efficiency level shows to be a concave shape when defense ratio is increased.

The TFP in the defense industry has grown at an annual rate of 0.039. The 'Communication' sector has the highest growth value. The sources of TFP growth were decomposed into changes in TP, TE, SE, and AE. While the average

SE was 0.005 for the whole industry and had a small value, there were negative values in the 'Ship and Submarine' and 'Chemistry'. Allocative efficiency change for the total sample was estimated as 0.012. Empirical results show that productivity growth was mainly driven by technical progress. Thus, the defense industry policies should encourage investments to introduce newly developed production technologies.

10.6.2 Policy Implications

This study provides several policy implications from the viewpoint of productivity and efficiency. The results of the study provide the effects of competition policies on technical efficiency and technical progress and this can provide an effective guideline to establishing the competition policies. The main factors that have influenced the Korean defense industry as well as the vulnerable points that should be promoted are identified by the analysis of TFP growth and its decomposition into four components. The effect of the firm size and the cost monitoring system on technical efficiency are verified. The proper size of the firm in each sector can be decided and the regulation policies can be established based on these results.

Research results on competition policy for the Korean defense industry can be summarized as expansion of competitiveness, relaxation of restrictions on entry into defense market, and execution of different competition policies by sector.

First, researchers, in general, agree that competitive environment is more effective than the non-competitive environment in inducing the firms to put their managerial priority on innovation and technology development.

Second, lower entry barriers to the defense market should be guaranteed for the small and medium businesses, especially for the firms that produce serialized units or components. To promote an active participation of the small and medium businesses, the policies should be set to protect these firms from the large firms.

Third, characteristics of each sector should be considered in policy making. Researchers argue that while the sectors – 'Fires', 'Ammunition', 'Aviation' and 'Ship' – requiring large scale facilities and lacking the interrelationship between the commercial and defense industries should be maintained as full responsibility system, the sectors – 'Communication', 'Electronics', 'Optic', and 'Command and Control' – expecting stable and huge amount of demand, and having high interrelationship between commercial and defense industries are likely to be converted into a more competitive environment.

The KMND has decided to introduce open competition to all defense industry sectors starting in 2009. The anticipated problems from the unexpected introduction of the competitive system have been widely discussed within the defense research communities. Because the Korean defense industry system for new product developments depends on productions through introduction of overseas technology than on indigenous technology development, F1 firms lacking financing capabilities have more possibility of facing liquidation. Nevertheless, the introduction

of competition can give strong motivation for the firms to develop defense technologies, and unless the government ensures a steady and long demand for the defense products, defense firms would not participate in the domestic defense market. If serialized units are produced in a more competitive environment, we can expect the price of the serialized units to go down with the possibility of quality deterioration, supply discontinuance, and bankruptcies of small sized firms and venture businesses. In addition, it is more likely that foreign companies will occupy the serialized unit market, which leads to reduction of Korea's self-sufficiency.

The KMND has carried out different competitive policies since 1983, specifically aimed at firms which are designated as specialized or serialized firms. The third revision in 1998 was selected as critical point at which competitive environment was dramatically expanded. The analysis examined the technical efficiencies of the defense industry's pre- and post-competitive period. The test to see whether the change of competitive environment led firms to be technically efficient for the SOS firms have been operated under noncompetitive condition (SC2) and under competitive condition (SC3). This test shows that that SC3 firms were less technically efficient. Mean technical efficiency of the 'Aviation and Guidance' sector and the 'Communication and Electronics', however, increased.

In this case, we can expect the possibility of a drop in technical efficiency in the six sectors except 'Aviation and Guidance' and 'Communication and Electronics'. Thus, it is necessary to formulate the competition policies gradually or to make decisions on competition after identifying the results of each competition stage for the sectors which require large scale investment in equipments and have some possibility of overlapped investment. From the technical efficiency point of view, the 'Aviation and Guidance' sector has shown the highest value from the beginning of the sample period. Thus, we can expect this sector to be less affected by the open competition.

The assertion that a protective defense policy for F1 firms is necessary for inducing a competitive environment is supported by the empirical results of this study. Among the specialized or serialized firms, F2 shows a less declination in technical efficiency than F1, when the competition is keen. If we look at the efficiency changes of F1 and F2 in industry sector 'Etc', efficiency level of F2 increased by 3.3% from 0.735 to 0.767, while that of F1 fell by 5.1% from 0.794 to 0.743. These results indicate that protective policy for F1 should be carefully prepared before the government raises the competitive pressure.

Now, this research looks at the SSP from the viewpoint of technical progress and technical efficiency. Even though the abolition of SSP has been suggested by some researchers, the KMND has not formed any concrete plan for doing so. The main finding of the decomposition analysis is that the factors that influence TFP growth are largely due to changes in TP and AE, followed by SE. The mean TFP growth rate of SOS and non-SOS are 0.028 and 0.047, respectively. In particular, the mean TFP growth rate of S&S is the highest with the value of 0.069. The SOS firms have greatly contributed to the growth of the Korean defense industry. The TFP growth by SOS, however, is mainly achieved not by TC, but by TE and SE (see Table 10.17). The industry policies that can promote the technical change of SOS are necessary to increase industry's competitiveness.

According to the results of the analyses, the technical change and efficiency levels of D2 are greater than those of D1. The mean differences of technical change and technical efficiency between D2 and D1 are 2% and 10%, respectively. R&D activity by D2 has not influenced the improvement of TC than TE. This means that R&D investment has not led the defense firms to make progress in defense technologies, but induced firms to increase their technical efficiencies, which implies that the defense firms have improved their accessibility to technologies developed by the defense industry. Considering the estimated results that the TFP growth of the defense industry has been mainly improved by TC, and that the R&D investment has not increased TC significantly, it can be concluded that improving technology is essential for the evolution of the defense industry.

For the improvement of technological change, expansion of R&D investment by the KMND and defense firms, and policies regarding these investments should be made. In order to achieve the objectives and overcome the limitations in R&D systems, the policies can be proposed as follows. The government should create sufficient demand based on new technologies. Domestic defense firms should be allowed to have an opportunity to work with foreign defense firms (for technological development) when the government adopts projects that introduce new foreign technology. Policies to develop indigenous defense technologies should be promoted through revision of the profit incentive, compensation policy for the failed projects, expansion of dual-use technology projects, and small business innovation research (SBIR) programs for the small and medium sized defense firms. R&D policy should be carefully designed along with the incentive policy.

Concerning the effect of firm size on TC and TE, this effect was insignificant in the industry. There was no SE difference in TFP decomposition results between the two groups, F1 and F2. Mean TFP growth rate of F1 and F2 are 0.06 and 0.016, respectively. This gap is mainly due to the difference between the TE and AE. The decreasing RTS was estimated during the whole sample period. The size of the scale effect increased in the 1990s, but this growth level is very low. The estimated RTS of the sectors 'Aviation and Guidance', 'Ammunition', 'Chemistry' and 'Ship and Submarine' are 0.987, 0.961, 0.961, and 0.948, respectively. RTS results were relatively high in sectors that require larger scale facilities and firm size. It is suggested that different policies on firm size be designed considering the effects by sector.

In this study, the DPAMIS was considered as a cost monitoring system that regulates and supervises cost in the defense factory, and tests were conducted to see the effect of this regulation system on technical efficiency. Even though the time period was short to analyze the effect of regulation, it was concluded that the effect of cost monitoring regulation on technical efficiency was not clear. The possibility of cost-shifting incentive by mixed type firms was also rejected through several tests. However, it should be noted that the non-effective cost monitoring system caused this result by not allowing firms to transfer input factors into the defense parts, and by the defense firms operating under the fair cost policies without any regulation system. Therefore, regulation policy, allowing firms' cost control as well as considering the circumstances that each firm faces, should be promoted while maintaining the appropriate strength of the regulation.

Appendix

See Tables 10.14–10.17.

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Chapter 11

Performance Measurement of Agricultural Cooperatives in Thailand: An Accounting-Based Data Envelopment Analysis

W. Krasachat and K. Chimkul

11.1 Introduction

Despite the emergence of industrialisation, the agricultural sector still plays a prominent role both in the Thai economy and social development. As indicated by the National Statistical Office (2006), around 57% of the total population relies on the agricultural sector in Thailand, while the contribution of the agricultural sector to gross domestic product has gradually decreased (Office of the National Economic and Social Development Board 2005). This implies that the more the Thai economy progresses, the more the productivity inequality between the conventional and modern sectors increases. It has long been a critical question for policy makers to choose the appropriate direction of development planning to improve the above situations through many measures and interventions on the sector in Thailand.

Agricultural cooperatives are one of the most important economic and social units in the Thai agricultural sector. As indicated by the Department of Cooperative Auditing (2005), in 2004, there were 4,461 agricultural cooperatives and 5.37 million members, or around 14% of the total population in this sector. Despite the long history of development, Thailand's agricultural cooperatives are viewed as a special-purpose vehicle for obtaining a sensible source of credit and purchasing goods or selling their products at a reasonable price through the existing market system. In addition, the cooperatives have been seen as a social and political support unit instead of a performance-oriented business unit. Some types of cooperatives have experienced a declining performance growth when their industry is extensively competitive. A large number of Thai cooperatives are small sized and they are disintegrated in the supply chain. Because of these factors, their competitiveness is eroding to the extent that it will be difficult for them to thrive or sustain themselves over the next decade.

W. Krasachat, K. Chimkul

Department of Agricultural Business Administration, King Mongkut's Institute of Technology
Ladkrabang, Bangkok, Thailand

The primary purpose of this study is to measure and investigate factors influencing Thai agricultural cooperatives' technical efficiency including its pure technical and scale efficiencies in 2004. The study was an application of a data envelopment analysis approach in order to estimate technical efficiency, based on the financial statements of agricultural cooperatives in Thailand, and also to investigate the determinants of the efficiencies among different management policies and operation environments. The empirical results of technical efficiency and influencing factors are necessary for policy makers and cooperatives' stakeholders to enable them to choose the appropriate direction of development planning to improve the performance of agricultural cooperatives and the Thai economy.

This paper is organized into five sections. Following this introduction, the analytical framework is explained. Next, data are described. The last two sections cover the empirical findings of this study, and conclusions and policy implications.

11.2 Analytical Framework

Coelli (1995), among many others, indicated that the DEA approach has two main advantages in estimating efficiency scores. First, it does not require the assumption of a functional form to specify the relationship between inputs and outputs. This implies that one can avoid unnecessary restrictions about functional form that can affect the analysis and distort efficiency measures, as mentioned in Fraser and Cordina (1999). Second, it does not require the distributional assumption of the inefficiency term.

According to Coelli et al. (2005), the constant returns to scale (CRS) DEA model is only appropriate when the firm is operating at an optimal scale. Some factors such as imperfect competition, constraints on finance, etc. may cause the firm not to be operating at an optimal level in practice. To allow for this possibility, Banker et al. (1984) introduced the variable returns to scale (VRS) DEA model. Due to the consequence of the heavy intervention by the government in both agricultural cooperatives and Thai agriculture as a whole, the cooperatives may well have been prevented from operating at the optimal level in firm operations. Therefore, technical efficiency in this study is calculated using the input-oriented variable returns to scale (VRS) DEA model. Following Fare et al. (1985), Coelli et al. (2005) and Sharma et al. (1999), the VRS model is discussed below.

Let us assume that there is data available on K inputs and outputs in each of the N decision units (i.e., firms). Input and output vectors are represented by the vectors x_i and y_i , respectively for the i -th firm. The data for all firms may be denoted by the $K \times N$ input matrix (X) and $M \times N$ output matrix (Y). The envelopment form of the input-oriented VRS DEA model is specified as:

$$\begin{aligned}
& \min_{\theta, \lambda} \theta, \\
& s_t - y_i + Y\lambda \geq 0, \\
& \theta x_i - X\lambda \geq 0, \\
& N1'\lambda = 1 \\
& \lambda \geq 0,
\end{aligned} \tag{11.1}$$

where θ is the input technical efficiency (TE) score having a value $0 \leq \theta \leq 1$. If the θ value is equal to one, indicating the firm is on the frontier, the vector λ is an $N \times 1$ vector of weights which defines the linear combination of the peers of the i -th firm. Thus, the linear programming problem needs to be solved N times and a value of θ is provided for each firm in the sample.

Because the VRS DEA is more flexible and envelops the data in a tighter way than the CRS DEA, the VRS TE score is equal to or greater than the CRS or 'overall' TE score. The relationship can be used to measure scale efficiency (SE) of the i -th firm as:

$$SE_i = \frac{TE_{i,CRS}}{TE_{i,VRS}} \tag{11.2}$$

where $SE = 1$ implies scale efficiency or CRS and $SE < 1$ indicates scale inefficiency. However, scale inefficiency can be due to the existence of either increasing or decreasing returns to scale. This may be determined by calculating an additional DEA problem with non-increasing returns to scale (NIRS) imposed. This can be conducted by changing the DEA model in (11.1) by replacing the $N1'\lambda = 1$ restriction with $N1'\lambda \leq 1$. The NIRS DEA model is specified as:

$$\begin{aligned}
& \min_{\theta, \lambda} \theta, \\
& s_t - y_i + Y\lambda \geq 0, \\
& \theta x_i - X\lambda \geq 0, \\
& N1'\lambda \leq 1 \\
& \lambda \geq 0,
\end{aligned} \tag{11.3}$$

If the NIRS TE score is unequal to the VRS TE score, it indicates that increasing returns to scale exists for that firm. If they are equal, then decreasing returns to scale apply.

Note that efficiency scores in this study are estimated using the computer program, DEAP Version 2.1 described in Coelli (1996).

In order to examine the effect of cooperative-specific factors on cooperative efficiency, a regression model is estimated where the level of inefficiency from DEA is expressed as a function of these factors. However, as indicated in Dhungana et al.

(2000), the inefficiency scores from DEA are limited to values between 0 and 1. That is, cooperatives which achieved Pareto efficiency always have an inefficiency score of 0. Thus, the dependent variable in the regression equation cannot be expected to have a normal distribution. This suggests that the ordinary least squares regression is not appropriate. Because of this, Tobit estimation, as mentioned in Long (1997), is used in this study.

11.3 Data

11.3.1 *Selected Output and Input Variables*

Due to the Thai cooperative regulations, every cooperative has its annual financial statements audited by the Department of Cooperative Auditing or an external auditor certified by the Department of Cooperative Auditing. At the end of 2005, 4,257 agricultural cooperatives submitted their annual financial statements to the Department of Cooperative Auditing. However, due to incomplete financial figures, only 2,546 agricultural cooperatives (or around 60% of total agricultural cooperatives) are used in this study.

According to Thailand's cooperative regulations, agricultural cooperatives are not only permitted to operate as part of a banking business unit, but also function as manufacturers, merchandisers and service providers for their members. Regarding the banking business, the agricultural cooperatives can merely take deposits from their members and advance loans to them. In addition, the cooperatives function as an intermediary or financial institution between those members that are savers and those that are lenders. This implies that Thailand's agricultural cooperatives play both roles of production and of intermediaries. Therefore, the specification of the analytical model based only on a production role or intermediary role alone is not appropriate. A mixed model of production and intermediary roles is essential in this study.

In the production approach, the agricultural cooperative is described as the production of output marketing for, and input supplying to its members by using production factors which are used as inputs to produce desired outputs. Meanwhile, the intermediation approach views agricultural cooperatives as intermediaries that convert financial assets from surplus units into deficit units.

Nevertheless, this study is not confined to one of these approaches to define output and input variables. Instead the two approaches are integrated and adjusted as an accounting-based approach to analyse the efficiency of Thai agricultural cooperatives.

In the application of the production approach, the accounting-based approach assumes that agricultural cooperatives generate their total revenue from two main income sources (i.e., marketing-supplying and depositing-lending activities) sufficient to cover direct business costs and administrative expenses. Therefore, this study has only one output variable, the total revenue (Table 11.1).

To generate the above output (i.e., total revenue), the production and intermediation approaches are mixed to determine input variables. As an intermediary unit, agricultural cooperatives lend and invest in other assets by using funds from deposits, other borrowings and equity. By undertaking these activities, total debts and equity are used as an input of total capital. As a unit of production, agricultural cooperatives allocate direct business costs (i.e., costs of goods sold and borrowing costs) and administrative expenses to be an input to service their members. Thus, there are four inputs: total debts, equity, direct business costs and administrative expenses in this study (Table 11.1).

11.3.2 Cooperative-Specific Factor Variables

In the transformation process of inputs into outputs, it is assumed that there are three sets of influencing variables determining the extent of agricultural cooperative's efficiency. These include a set of environment variables and two sets of control variables (i.e., cooperative structure and management policy). To define relationships between the agricultural cooperatives' efficiency scores and the above three sets of related variables, Tobit regression is used in this study as mentioned above.

The environment variable is a geographical variable used to calculate the impacts of the environment of cooperative location on cooperative's efficiency. It consists of six regional dummy variables: NORTH, NORTHEAST, CENTRAL, WEST, EAST and SOUTH. Each of these locations reflects different systematic risk encountered by the agricultural cooperatives.

The first set of control variables, cooperative structure variables, consists of six cooperative-type dummy variables, a cooperative age variable and a cooperative's asset size variable. The cooperative-type dummy variables include GENERAL, RUBBER, MARKETING (for Bank for Agriculture and agricultural cooperatives' clients), DAIRY, LIVESTOCK and WATER. The AGE and ASSET variables refer to the number of a cooperative's operating years and the amount of assets in its balance sheet, respectively. It is expected that the efficiency of cooperatives could be impacted by their structure.

Table 11.1 Variable definitions and measurement (Thai baht)

Variables	Definitions
Output:	
Total revenues(y)	Sales, interest and dividend incomes, and other incomes
Inputs:	
Direct business costs(x_1)	Costs of goods sold and borrowing costs
Administrative expenses(x_2)	Salaries, depreciation, and other expenses
Total debts(x_3)	Deposits, borrowings, and other debts
Equity(x_4)	Shareholders' equity

In the case of the second set of control variables, management variables comprise two key management policy ratios: the ratio of debt to equity and the ratio of loans (to members) to total assets. The two ratios reflect management policies set to transform cooperatives' total capital into incomes. The ratio of debt to equity represents the management's attitudes on financial leverage. Meanwhile, the management's reliance on the credit business is measured by the ratio of loans to total assets. On the other hand, the two ratios reflect the extent to which the management uses conservative financial policies.

The sign of the coefficients of the above variables indicates the direction of the influence while the ratio of the estimates to their standard errors indicates the strength of the relationship as indicated by Coelli et al. (2005). Through this, the impacts of types of environment, organizational structure and management policies on technical efficiency, "pure" technical efficiency and scale efficiency can be quantified.

The cooperative-specific factor variables for explaining the efficiencies of agricultural cooperatives in Thailand and summary statistics of the data sample are shown in Tables 11.2 and 11.3.

Table 11.2 Variable definitions and measurement for Tobit regression model

Variables	Definitions
CENTRAL	Dummy variable with a value of one if cooperative has operated in the Central Region and zero otherwise
EAST	Dummy variable with a value of one if cooperative has operated in the Eastern Region and zero otherwise
NORTH	Dummy variable with a value of one if cooperative has operated in the Northern Region and zero otherwise
NORTHEAST	Dummy variable with a value of one if cooperative has operated in the Northeastern Region and zero otherwise
SOUTH	Dummy variable with a value of one if cooperative has operated in the Southern Region and zero otherwise
WEST	Dummy variable with a value of one if cooperative has operated in the Western Region and zero otherwise
MARKETING	Dummy variable with a value of one for marketing cooperative and zero otherwise
DAIRY	Dummy variable with a value of one for dairy cooperative and zero otherwise
LIVESTOCK	Dummy variable with a value of one for livestock cooperative and zero otherwise
RUBBER	Dummy variable with a value of one for rubber cooperative and zero otherwise
WATER	Dummy variable with a value of one for water user cooperative and zero otherwise
GENERAL	Dummy variable with a value of one for general agricultural cooperative and zero otherwise
ASSET	Amount of assets (THB)
MEMBER	Number of cooperative's members
AGE	Cooperative's age (years)
AGE2	Cooperative's age squared
DE	Ratio of total debts to equity (%)
LOAN	Ratio of loans to assets (%)

Table 11.3 Summary statistics of data sample

Variables	Mean	Maximum	Minimum	Standard Deviation
y	23,709,965	2,397,913,497	9	87,779,752
x_1	20,757,873	2,070,137,699	14	80,965,583
x_2	2,221,525	267,898,934	20	7,522,071
x_3	19,974,590	816,132,998	7	50,423,017
x_4	11,704,169	816,481,047	2,186	30,368,461
CENTRAL	0.06	1	0	0.23
EAST	0.06	1	0	0.23
NORTH	0.22	1	0	0.42
NORTHEAST	0.35	1	0	0.48
SOUTH	0.23	1	0	0.42
WEST	0.06	1	0	0.23
MARKETING	0.03	1	0	0
DAIRY	0.04	1	0	0.19
LIVESTOCK	0.02	1	0	0.15
RUBBER	0.18	1	0	0.38
WATER	0.18	1	0	0.38
GENERAL	0.46	1	0	0.50
ASSET	31,521,520	1,632,614,045	2,496	77,358,322
MEMBER	2,044	155,928	0	9,371
AGE	15.72	64	1	9.90
AGE2	345.22	4,096.00	1.00	384.73
DE	2.22	313.14	0	7.64
LOAN	0.43	4.62 ^a	0	0.34

^aThe cooperatives with a loan to asset ratio of greater than 1 suffer from a negative equity

11.4 Empirical Results

Note that the objective of this study is to investigate the common factors affecting all Thailand's agricultural cooperatives in order to pursue a set of national policies and an aggregate figure for the cooperatives' efficiency level. Therefore, the specification of a model for the whole sample is preferred. However, in order to provide more robust results regarding regional differences, this study applied separate DEA analysis to regionally grouped data. The empirical results are quite robust as confirmed by a small variation of the standard deviation of the efficiency scores across regional and the whole sample models. Because these are beyond the scope of this study, only the Whole sample empirical results are reported and discussed.

Technical and scale efficiency scores of Thai agricultural cooperatives were calculated using (11.1) and (11.2) at the sample means. Table 11.4 indicates that the mean values of overall technical, scale and pure technical efficiency are 0.725, 0.894 and 0.808, respectively. Note that the overall technical efficiency of an

Table 11.4 Technical and scale efficiency scores of Thai agricultural cooperatives

Efficiency range	Overall technical efficiency		Pure technical efficiency		Scale efficiency	
<0.10	13	0.5%	2	0.1%	10	0.4%
0.11–0.20	14	0.5%	4	0.2%	5	0.2%
0.21–0.30	47	1.8%	26	1.0%	5	0.2%
0.31–0.40	85	3.3%	57	2.2%	5	0.2%
0.41–50	217	8.5%	110	4.3%	19	0.7%
0.51–60	342	13.4%	181	7.1%	58	2.3%
0.61–70	394	15.5%	266	10.4%	161	6.3%
0.71–80	377	14.8%	307	12.1%	201	7.9%
0.81–90	360	14.1%	561	22.0%	477	18.7%
0.91–1.00	697	27.4%	1,032	40.6%	1,605	63.1%
Total	2,546	100%	2,546	100%	2,546	100%
Mean	0.725		0.808		0.894	

agricultural cooperative is the product of its scale efficiency and its pure technical efficiency. These empirical results suggest two important findings. First, there are significant possibilities to increase efficiency levels in Thai agricultural cooperatives. The average overall technical inefficiency could be reduced by 28%, on average, by operating at optimal scales and by eliminating pure technical inefficiencies via the adoption of the best practices of efficient agricultural cooperatives. Second, the results also indicate that pure technical inefficiency for the Thai agricultural cooperatives makes a greater contribution to overall inefficiency.

The scale efficiency results are summarised in Fig. 11.1. The DEA results suggest that, of the 2,546 observations, only 7% operated at their optimal scale, 71% operated above their optimal scale and 22% operated below their optimal scale. This indicates that the largest increase in overall technical efficiency could be achieved by eliminating the problem of decreasing returns to scale, which would in turn lead to an increase in overall technical efficiency to a lesser extent. This implies, from an agricultural policy viewpoint, that if operational efficiency of the Thai agricultural cooperatives is to be improved, decreasing firm size would be better than increasing the size of farms.

Although the analytical results in general indicate that there exist advantages in decreasing firm size, it would be better to use them to focus on efficiency improvement at the level of individual agricultural cooperatives. Jaforullah and Whiteman (1999) indicated that there is a positive relationship between the availability of extension services and firm technical efficiency. An increase in the rate of diffusion of technology and of optimal firm management practices, encouraged by extension services and training programs, should increase the technical efficiencies of the inefficient agricultural cooperatives in Thailand.

Tobit regression models are estimated to investigate the impacts of the cooperative-specific environment, structure and management factors on technical inefficiency

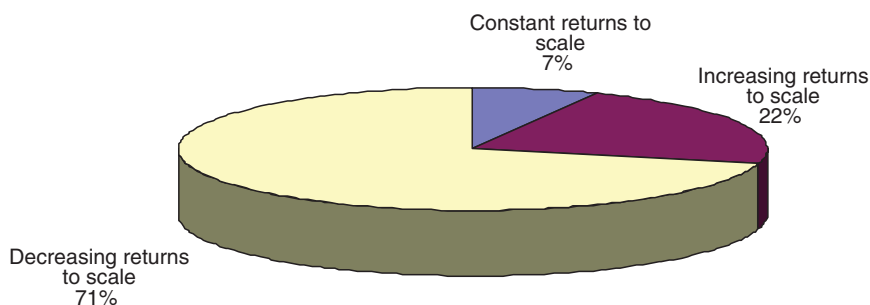


Fig. 11.1 The scale efficiency of Thai agricultural cooperatives

and its components. Inefficiency measures are first obtained by subtracting the level of efficiency calculated in the first stage from 1. Then, each inefficiency measure is regressed on the environment, structure and management factors. Due to the use of cross-section data, the presence of heteroscedasticity is likely. The LM test (Davidson and MacKinnon 1993) was used for the heteroscedasticity test. The empirical results indicate that the problem of heteroscedasticity existed. Therefore, the GLM standard errors (McCullough and Nelder 1989) procedure was used to correct the problem. The performance of the finalised model was satisfied, although the coefficients of determination, R-squared are quite small (Tables 11.5–11.7).

The empirical results indicate that the cooperatives locations in the Northern, Southern and Western Regions have a negative effect on overall and pure technical inefficiencies. This implies that the agricultural cooperatives located in the Northern, Southern and Western Regions achieved higher overall and pure technical efficiency. In addition, there is confirmation that the differences in cooperative locations have had a different impact on agricultural cooperatives' operational efficiency.

The empirical results also indicate that the marketing, dairy, rubber and general agricultural cooperatives have a negative effect on the overall and pure technical inefficiencies, while the dairy, livestock, rubber and water agricultural cooperatives have a negative effect on scale inefficiency. This implies that the marketing, dairy, rubber and general agricultural cooperatives achieved higher overall and pure technical efficiencies, while the dairy, livestock, rubber and water agricultural cooperatives achieved higher scale efficiency.

In addition, the cooperatives' age has a negative, except quadratic, effect on scale inefficiency. This suggests that older cooperatives achieved more scale efficiency compared to their newer counterparts, probably due to the fact that older cooperatives are more experienced, and hence more knowledgeable in management practices as compared to their newer counterparts.

Table 11.5 Estimation results of overall the technical inefficiency model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.309525	0.027155	11.39826	0.0000
CENTRAL	-0.016317	0.026911	-0.606330	0.5443
EAST	-0.015698	0.026861	-0.584425	0.5589
NORTH	-0.070534	0.024483	-2.881012	0.0040
NORTHEAST	0.007404	0.024220	0.305706	0.7598
SOUTH	-0.053704	0.025332	-2.119997	0.0340
WEST	-0.062003	0.027037	-2.293265	0.0218
MARKETING	-0.116153	0.034575	-3.359405	0.0008
DAIRY	-0.213793	0.020854	-10.25199	0.0000
LIVESTOCK	-0.043527	0.023845	-1.825360	0.0679
RUBBER	-0.206826	0.016703	-12.38280	0.0000
WATER	-0.018999	0.013551	-1.402082	0.1609
GENERAL	-0.044643	0.011695	-3.817220	0.0001
ASSET	2.47E-11	5.16E-11	0.477455	0.6330
MEMBER	-6.31E-07	5.80E-07	-1.088127	0.2765
AGE	-0.000750	0.001442	-0.520293	0.6029
AGE2	4.17E-05	3.86E-05	1.080279	0.2800
DE	-0.002538	0.000742	-3.421909	0.0006
LOAN	0.165866	0.012433	13.34051	0.0000
R-squared	0.377653	Log likelihood		937.5957

Table 11.6 Estimation results of the pure technical inefficiency model

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.252174	0.025220	9.999001	0.0000
CENTRAL	-0.020736	0.024976	-0.830239	0.4064
EAST	-0.028703	0.024966	-1.149646	0.2503
NORTH	-0.073301	0.022706	-3.228291	0.0012
NORTHEAST	-0.008745	0.022461	-0.389369	0.6970
SOUTH	-0.054528	0.023501	-2.320287	0.0203
WEST	-0.072494	0.025144	-2.883080	0.0039
MARKETING	-0.135914	0.032086	-4.235855	0.0000
DAIRY	-0.173079	0.019425	-8.909927	0.0000
LIVESTOCK	-0.029025	0.022178	-1.308742	0.1906
RUBBER	-0.173969	0.015563	-11.17827	0.0000
WATER	0.003901	0.012595	0.309696	0.7568
GENERAL	-0.048565	0.010887	-4.461005	0.0000
ASSET	-6.90E-10	5.83E-11	-11.83157	0.0000
MEMBER	-1.04E-08	5.41E-07	-0.019276	0.9846
AGE	0.001992	0.001341	1.485287	0.1375
AGE2	-8.20E-05	3.59E-05	-2.284096	0.0224
DE	-0.001642	0.000718	-2.287385	0.0222
LOAN	0.140694	0.011555	12.17650	0.0000
R-squared	0.338984	Log likelihood		1,012.638

Table 11.7 Estimation results of the scale inefficiency model

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.084575	0.019687	4.296034	0.0000
CENTRAL	-0.003585	0.019497	-0.183854	0.8541
EAST	0.004618	0.019464	0.237258	0.8125
NORTH	-0.018122	0.017734	-1.021880	0.3068
NORTHEAST	0.007759	0.017541	0.442342	0.6582
SOUTH	-0.015539	0.018359	-0.846397	0.3973
WEST	-0.022219	0.019620	-1.132456	0.2574
MARKETING	0.002042	0.025052	0.081502	0.9350
DAIRY	-0.064827	0.015142	-4.281190	0.0000
LIVESTOCK	-0.036981	0.017365	-2.129624	0.0332
RUBBER	-0.062733	0.012215	-5.135892	0.0000
WATER	-0.040192	0.009859	-4.076547	0.0000
GENERAL	0.003459	0.008497	0.407110	0.6839
ASSET	4.39E-10	3.74E-11	11.73790	0.0000
MEMBER	-1.95E-07	4.20E-07	-0.465441	0.6416
AGE	-0.002983	0.001049	-2.843808	0.0045
AGE2	0.000160	2.80E-05	5.710819	0.0000
DE	-0.001330	0.000532	-2.501780	0.0124
LOAN	0.052974	0.009065	5.843617	0.0000
R-squared	0.327833	Log likelihood		1,581.521

The results indicate a consistent pattern of a positive relationship between cooperative's ratio of loans to assets, and overall, pure technical and scale inefficiencies. That is, cooperatives with more aggressive lending policies are less likely to be efficient as compared to their more conservative counterparts.

The results also show a pattern of a negative relationship between cooperative's ratio of total debts to equity, and overall technical, pure technical and scale inefficiencies. This implies that the cooperatives which have better management's attitudes to financial leverage, also reflecting their ability to raise funds through debts, achieved higher levels of efficiency.

The results also indicate that the cooperatives' asset size has a negative effect on pure technical inefficiency while it has a positive impact on scale inefficiency. This implies that bigger cooperatives achieved higher pure technical efficiency than smaller ones while a bigger cooperative is likely to achieve less scale efficiency compared to a smaller one.

11.5 Conclusions and Policy Implications

An input-oriented VRS DEA model was used for estimating overall technical, scale and pure technical, efficiencies in the agricultural cooperatives of Thailand.

The empirical results indicate that there are significant possibilities to increase efficiency levels in the Thai agricultural cooperatives. The average overall technical inefficiency could be reduced by 28%, on average, by operating at optimal scales and by eliminating pure technical inefficiencies through the application of the best practices of efficient agricultural cooperatives. In addition, the results also indicate that pure technical inefficiency of Thai agricultural cooperatives provides a greater contribution to overall inefficiency.

The results indicate size disadvantages in the bigger Thai agricultural cooperatives. However, extension services and training programs should be used to increase the technical efficiencies of the inefficient cooperatives in Thailand. In addition, the results also indicate that the differences in cooperative locations, the types of agricultural cooperatives, the cooperatives' age, lending policies, management's attitudes to financial leverage and asset size have had different impacts on agricultural cooperatives' operational efficiency. Therefore, development policies focusing on the above areas should be used to increase the technical efficiencies of the inefficient agricultural cooperatives in Thailand.

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Chapter 12

An Empirical Study on the Performance of public Financing for Small Business in Korea

Yongrok Choi

12.1 Introduction

Credit guarantee schemes for small business financing have been one of the most important public support programs to develop the regional economies in many countries. Even if the systems as well as the governance for each program are different in detail, most of theorists and government officials supported the economic necessity and the effective performance.

In Korea, there are three public financial agencies to handle the credit guarantee schemes for small business.¹ The volume of credit guarantees has increased about 20% per annum with total accumulated amount of 55 billion dollars at the end of 2005. Since the micro-financing support for the small companies is so important to survive at their initial stage of the business, the volume may increase even higher in the future, especially as one of the main paradigms to cure the dual-polarizing socio-economic mishaps. A primitive small venture business has a very limited access to the financial market. In order to give the strategic support on some infant business as well as to boost the regional economy, institutional support for these small businesses could result in a highly successful business environment. It is especially much more important when the small businesses are more jeopardized with the unfair competitive market structure, resulting in duo-economy of the more the better, the less the worse.

There are many preceding researches to analyze the efficiency of the performance on the public financing support for the small companies in terms of their contribution on the regional production, regional value-added and the employment, etc. Most of the preceding empirical results showed strong support for the positive performance by the public financing. The paper argues that the reason for the acceptable

Y. Choi

School of International Trade, Inha University, Incheon, South Korea

¹ The three public institutions are, Korea Credit Guarantee Fund (<http://www.shinbo.co.kr/index.jsp>) for general purpose of small business, KIBO Technology Fund (<http://www.kotec.or.kr>) for high-tech venture support, Nationwide Korea Shinbo Credit Federations (<http://www.icredit.or.kr>) for regional business support. The last organization consists of 16 regional credit guarantee agencies in Korea.

performance, however, may come from the methodological bias, instead of the theoretical contents or practical data.

Most empirical models base on the incremental or marginal approaches to analyze the performance or productivity of the public financing using input–output model such as Data Envelopment Analysis (DEA) or cost-benefit approaches. These kinds of approaches may prove the effective performance, but not negatively. Thus, the objective of the research is to investigate whether the public financing support such as credit guarantee is ‘really’ effective. In order to analyze this effectiveness of credit guarantees, the paper shall differentiate why to support with how to support. To compare these questions, the paper shall utilize two sets of approaches toward the public financing system and its governance.

12.2 Literature Review and Theoretical Background

There are many preceding researches to support the role and functions of the public financial support for the small business. As for grass roots of democratic capitalism, the initial stage of the business does definitely demand on the public support, especially on the financial measures. Due to the information asymmetry and market failure on behalf of venture businesses, it is so crucial for the eco-economical environment with the public financial support to these small businesses.²

However, the public financial support should be economically acceptable and sustainable. If the supporting system does not work efficiently, the adverse selection by the financial intermediary as well as the moral hazard by a small business could be harmful for all the other part of the economy (Choi et al. 2001). That is the reason most researchers agree with the urgent need for the structural reform of those public financial institutions (Patrick and O’Hara 1996, p. 25).

Nevertheless, due to the urgent social demand over the economic efficiency, most of empirical researches supported the economic role and functions of the public financial support as positive (U.S. SBA 1995; Levitsky and Bradley 1999). Fukuyama (1995) studied the inter-relationship between technical efficiency and productivity growth of Japanese banks during the 1989–1991 period. He defined the productivity as the relative improvement of outputs compared to the inputs, and then decomposed productivity changes into two components (technical efficiency change or catching up, and technical change or changes in the best practice). He concluded that during the period of study, productivity gains were largely due to technological change rather than technical efficiency change. Even if the Japanese financial sector does not show the technical efficiency, the overall performance defined by the productivity resulted in positive performance.

² Here, we define the public financial support as the volume of the credit guarantees sported by the public institution. Under the Basel II agreement, no government could grant the direct financial support, and thus it utilizes the credit guarantee program for the indirect support to the small business.

Under the basic constraints of the profit maximization or the cost minimization, the productivity or efficiency as a major part of productivity is defined as a relative distance from the most efficient frontier. In that case, the relative deviation between the less effective output and its optimal frontier could not result in the negative relation between the financial support of credit guarantee and its performance.³ Due to this kind of intrinsic limits of frontier approaches of DEA or cost-benefit approaches, as Fukuyama concluded, something could be better than nothing at least by the financial support could. Korea is not the case of exceptions (OECD 1997; Han and Noh 2000).

Based on this line of reasoning, most of empirical studies for the economic performance of the public financial support may result in a bias of the positive role. For example, industrial organization theories such as the input–output model analyze the incremental effect of the public financial support on the small business (Shin et al. 2004). Most cost-benefit analyses are based on the inherent constraint that the incremental cost should not exceed the benefits of the financing (Yang et al. 2001). These approaches, therefore, conclude the public financial support be maintained at least for its sustainable role for the regional economies.

As far as the sustainability is concerned, the public financial supporting system should get more market-oriented and thus self-sufficient governance. Here, the governance is defined as the collaborative strategic link between the business objective and its performance or as the workable platform to promote the value of the business for the fulfillment of the business strategy and objectives (Choi and Lee 2006). The governance is operation-oriented or management-oriented concept, compared with the organization-oriented or structure-oriented ‘system’ (Bechtri et al. 2001). Thus, the public financial supporting system or organizations should be evaluated for the sustainable governance without any prior constraints of the ‘positive’ efficiency. The paper investigates this sustainable governance of the public financial supporting system in Korea.

12.3 Model and Methodology

For the economic performance of the public financial support, the most and generally utilized model is the Data Envelope Analysis (DEA) method. Developed by Charnes et al. (1978), DEA evaluates the efficiency of the organization by the incremental output per input. By the incremental support on the credit guarantees, a company could improve marginal efficiency with more output, directly and indirectly. This kind of integrated incremental approach includes not only direct effect of the financing on the specific field, but also the diverse indirect achievements as well.

³In this paper, the efficiency of the financial performance is defined as the increased (or even decreased) value of outputs such as product sales, employment payment and value added profits, compared with the inputs of credit guarantees.

However, due to the methodological limits based on the incremental sensitivity, the DEA model could not show the adverse or negative effect of the public financial support on the regional economy.⁴ Since we define the efficiency of the performance as the resulting values such as product sales and value-added, coming from the credit guarantees, it could show not only a positive relation between those input and outputs, but a negative performance as well. The general DEA approach could handle the first part of positive relationship. Its main disadvantage is the necessity to compute the relative distance functions. It measures the productivity of the most recent production point relative to the earlier production points by output distance functions, which has a value of greater than unity indicating positive factor productivity growth between two periods (Sufian and Majid 2006. p. 8)

In order to avoid this kind of bias *a priori*, there are few researches with alternative methodologies such as cost-benefit analysis. Here, the analysis bases on the differential or marginal benefits between the economic outputs by the public financial support and related costs for the performance. However, the model could not exactly calculate the overall effect of the financing and it may mislead by too artificial adjustment of the terms such as costs and benefits. Therefore, the model should base on no prior bias such as positive improvement and constrained terminology, and integrate with the direct as well as indirect effect systematically.

In the simple way of empirical studies on the financial institutions without any prior constraints or intrinsic limits, the standard method is to estimate regression equations with pooled ordinary least squares (OLS). It could give us very insightful interpretation of the overall direct and indirect effect as well. Such estimation, however, can create biased and inconsistent estimates due to the interdependent variables (both observed and unobserved) (Hsiao 1986). For that reason, the fixed-effects model or simultaneous equation system with panel data could be an alternative model for unbiased and consistent estimates of the coefficients.⁵ Even if there are some inter-relationships among the variables, however, it should be clear that the independent variable of credit guarantee should have diverse effects on dependent variables, but the opposite cases of inter-relationship could not be true. In order to avoid this inter-dependency issue among the dependent variables as well as no-reversal feedback toward the independent variable, the paper shall handle the stepwise comparison of two approaches of OLS and logit models.

The first part of approaches relates with qualitative bias, and the latter with quantitative one. The reason for the comparative stepwise approaches comes from the diverse characteristics of the dependent variables of economic performance. The approach of output definition used in this study is a variation of the regional economic growth approach, developed by Gale (1991). Since the public financial support for the

⁴See (Banker et al. 1984). Under the DEA model, the more financial support goes, the larger the economic performance shows. It can't show the result of adverse selection with negative performance.

⁵As Sufian and Majid (2006) argued, the fixed-effect model of DEA assumes that differences across data reflect parametric shifts in the regression equation. Since we do not use the whole population, but a sample from it, it may be more appropriate to use the sample selection model. However, due to the limit of data, the approach is based on two separate methodologies together.

small business is aimed to boost the overall regional economic growth, most of researchers define the dependent variables of economic performance in terms of a set of regional production, value-added and the employment increase (Corder 1998; Green 2003).

The problem is raised by these more than one dependent variables with one independent variable, the volume of credit guarantee. In order to merge these variables into one set, we need the panel data approach such as DEA model. However, due to the methodological limit of no-negativity, as mentioned before, the paper handles the set of regression equations as follows,

$$\text{The effect of regional production, } Y_1 = aX + b_1 \quad (12.1)$$

$$\text{The effect of value increase, } Y_2 = aX + b_2 \quad (12.2)$$

$$\text{The effect of employment increase, } Y_3 = aX + b_3 \quad (12.3)$$

Here, $Y_{1,2,3}$ denotes the volume of regional production, value-added and the employment as an output, respectively. X denotes the volume of financial credit guarantees.

However, the model could not show the integrated effect like DEA by a set of dependent variables simultaneously and it could not figure out the qualitative difference between the financially supported companies and no-supported ones. For this complementary purpose, the logit model is used.

$$\text{Log}_e \frac{\Pr(Y = 1/x)}{1 - \Pr(Y = 1/x)} = \alpha + \beta x \quad (12.4)$$

Here, $Y_{0,1}$ denotes the choice variable of financial credit guarantees with zero denoting of no support and one of support. X denotes a set of volume of regional production, value-added and employment.

Note that the logit model shows the inter-relation between the set of independent variables and one dependent variable, not the causal relation between them. The focus of the model is not on the causal role of the credit guarantee but on the relative significance and its direction between the variables as a group.

All these two different approaches show the quantitative and qualitative efficiency of the public financial support on the economic performance complementarily each other. Especially, the model does not have methodological constraints a priori. Moreover, the model shall focus on whether the financial support is qualitatively effective compared with no-supported businesses.

12.4 Empirical Result and its Implications

For the empirical analysis, a total of 2,158 firm data nationwide are used to analyze quantitative as well as qualitative performance of the credit guarantee schemes by two complementary approaches. In order to avoid regional bias, empirical data are

Table 12.1 Regional comparison of the effect of credit guarantees on the economic performance

Regions	Results of regression model			Result of multinomial logit model		
	Production increase	Value added increase	Employment increase	Production increase	Value added increase	Employment increase
Seoul	5.674**	0.808**	NA	-0.001**	-0.010**	NA
Pusan	NA	0.777**	NA	NA	NA	0.193**
Daejeon	1.806*	NA	0.000*	0.001**	-0.127**	-0.486*
Incheon	2.442**	0.220**	NA	NA	NA	NA
Kwangju	12.462**	1.615**	1.630*	NA	NA	NA
Daegu	NA	2.132**	NA	NA	-0.053**	NA
Ulsan	3.807**	0.624**	NA			
Kyunggi	2.473*	0.701**	0.000**	0.003**	NA	NA
Kangwon	NA	1.635**	0.000**	NA	0.030**	NA
Chungbuk	7.837**	0.663**	NA	NA	-0.118**	NA
Chungnam	8.456**	1.125**	0.000**	NA	-0.107**	NA
Kyungbuk	6.714**	1.565**	0.000*	0.005**	-0.075**	NA
Kyungnam	7.574**	0.978**	0.000**	NA	-0.125**	-0.680*
Chunbuk	7.626**	0.243**	0.000**	-0.006**	NA	-0.613**
Chunnam	7.130**	NA	0.000**	NA	0.013*	NA
Jeju	NA	1.204**	NA	NA	-0.118**	0.456*
Nationwide	4.241**	0.773**	0.000**	0.001**	-0.047**	NA

Source: Nationwide Korea Shinbo Credit Federations. *NA* Statistically insignificant (Not Applicable).

*Statistically significant with 90% or over (t-statistics ≥ 1.645). **Statistically significant with 95% or over (t-statistics ≥ 1.960)

randomly collected from all the 16 regional governments of Korea for each with more than 100 financially supported companies' data and 30 of non-supported ones. To control for exogenous factors, such as firm size and type of industry, affecting the firm performance in both equations, all firms data are collected from the same category of annual data reported to the regional credit agencies in a form of application survey.

All performance data are based at the end of 2005, while the financial support of credit guarantee has been done for the year of 2004 and 2005. The empirical result is shown in Table 12.1.

The regression result shows strong support in 13 regions among the 17 regions for the production increase, in 15 regions for the value increase, and only in ten regions for the employment. Especially, including nationwide Korea itself, all credited firms in Korea as a whole shows the significant as well as positive effect on the economic performance of the public financing support overall. There is no negatively significant coefficient in the result of regression. Therefore, it is assured that, in general, the more credit guarantees support the business, the better performance it gets quantitatively.⁶

⁶As shown in the table, some regions show statistically non-significant in some dependent variables. Even so, at least one of three variables shows significantly positive without any negative ones, and thus we can conclude overall performance may be quantitatively positive.

However, the results of the logit model do not support for the positive role of the financial support on the regional economic performance. Over all, only eight among 17 regions are shown to be statistically significant at least by two coefficients. Moreover, many regions show negative relations between financial support and its performance such as production, value-added and employment. The results shows the sharp contradiction between the regression and logit models,

The result of logit model is really a contradict against the previous researches to argue that something is better than nothing at least for financial support on small business (White House Conference on SBC 1995. p. 5). Among a set of performance variables, the effect of value-added is the most significant qualitatively and positive quantitatively, while the employment shows effective only in the less than half regions.

It is intuitive that the financial support helps the financial status of the credited firm directly, and thus increases its performance at least in value-added terms as shown in both analyses. While the indirect effect on the employment could not be easily shown to be significant and/or positive as shown in logit analysis. It means the financial support is not partly successful for the grassroots of democratic capitalism, qualitatively. Rather, it helps for the risky business to improve its financial (or value-added) status in certain period only. Of importance is that the financial support aggravates not only the long-term of financial status of the supported business, but of the regional employment and production by its negative sign. As shown in the nationwide result of logit analysis, the higher a small business increases its employment, the lower its probability is to be selected for financial support, or vice versa. This result shows quite striking implications that the “wrong” selection process may detriment the governance of the public financial system and that a financial remedy for the market failure may require more considerate governance of the system (Drake 2002).

This kind of contradictory empirical results between micro-based regression analysis and macro-oriented logit analysis imply the public financing pitfall by the consultocracy with negative effects on the marginally risky small companies. It requires the innovation not for the system, but for the governance. Here, a consultocracy is defined as an administrative system operated by the supply-oriented principles of intermediary itself, such as subsidiaries of government administration, without considering the market, customer or even the sustainability of the result.⁷ The empirical result suggests that even if the financial support on an individual business could result in economic performance partially shown in the quantitative regression approach, the nationwide Korea overall could not get the significantly positive effect shown by the qualitative logit approach. The logit result suggests that the marginally risky business could exclude and substitute with the more potentially effective company.

Therefore, the problem is not on the public financing system itself, but on the governance of the system. Without the transparent and predictable governance of the

⁷ See (Choi 2005). Here, “Consultocracy” is a kind of combined concept of Consulting intermediary and Bureaucracy.

public financial supporting system, the biased support on the marginally risky business shall deteriorate the sustainability of the public system and lead the social mishap resulting in ever-increasing burden of credit guarantees. The Korean economy already faced this mishap in the year 2005. At the booming period of venture for years of 2000 and 2001, the government issued too much financial support measures such as primary CBO. Within three years as the maturity arrives, the government should pay for 1.5 billion dollars among the total guaranteed 2.2 billion dollars, or 68.5% out of all the primary CBO guarantees.⁸ Sometimes, just blind guarantee without systematic screening measures promoted the risky business to get the blind money. The consultocratic implementation of the financial support aggravated the effectiveness of the economic performance. Now, the issue is how the sustainable governance of the public financing support should be maintained. The following section shall shed some light on the matter, based on the empirical results.

12.5 Suggestions on the Sustainable Financial Support

Most of researches on the financial support handle only the role of the system itself, but not the role of the governance as a workable mechanism in detail. In this paper, however, we differentiate the theoretic framework of financial support between why to support and how to support. Most of the previous empirical researches including DEA approaches try to answer the first questions quantitatively. The first question of why to support is related with the theoretical analysis of supporting system itself, while the second question of how to support should be qualitatively compared with the theoretical frame of governance.

Two different empirical results show the governance of the system is more important for the sustainability in the long term. Quantitatively, as most researchers argued, the regression analysis shows the public support to be effective in general. While the logit analysis points out it is not the case qualitatively. The reverse selection may systematically aggravate the economic performance of the financial support to the financial market as well as the local economy overall. In order to avoid this kind of reverse selection or moral hazard by the consultocratic implementation, the transparent and predictable functions should get involved into financial intermediaries. Since the supporting system itself requires the professional intermediaries, the small business could have the psychological as well as the practical barriers to utilize it fully.

For the effective governance, rather than the productive objectives or consultocratic scheme of financial support, an intermediary should be changed into a more active and effective metamediary in the financial market mechanism. Choi (2004)

⁸ Joongang-Ilbo (Korean Daily Newspaper), Aug. 16, 2005 (http://news.naver.com/news/read.php?mode=LSD&office_id=025&article_id=0000570110&section_id=101&menu_id=101)

suggests the role or functions of metamediary as a facilitator, collaborator and service provider in their governance perspectives.⁹ As a facilitator, three intermediaries in Korea should facilitate the useful feedback between the market demand and the governmental policies, not by appearance but by the contents. As a collaborator, a metamediary should provide with trustful financial initiation for the seed money as a strategic partner rather than just an outside helper. As a service provider, a metamediary should channel the smooth flow of the integrated one-stop services to abolish the psychological as well as the practical barriers of the small business. Overall, a more active multi-tasking intermediary (or simply 'metamediary') should be involved in the financial support not once-for-all lump sum guarantees, but stepwise promotion for the output-oriented sustainability.

12.6 Conclusions and Directions for Future Research

Obviously, the small businesses definitely require the seed money by the public agencies or private banks due to the lack of access to the venture capital market. All the theories assume the public financing is helpful for the regional economy in terms of regional production, value-added and employment increase. The paper showed it might not be the case at least for its governance in Korea. The comparative results by regression and logit models showed the reverse selection by the risky business and moral hazard by consultocratic intermediaries clearly harmful to the regional economy by substituting the potential business with risky marginal ones. Thus, the paper suggests the issues are not for the system itself, but for the governance in the public intermediaries.

The generally accepted hypothesis of public financing support on behalf of effective performance did not support at least in the practice of Korea. The empirical findings suggest that the urgent renovation of intermediaries with the functions of the facilitator, collaborator and service provider.

Even if the stepwise comparisons of the regression and logit models are useful to figure out the difference of the performance between the financial system and its governance, the methodology still needs to be more refined. Especially, the independent variables of the regression model become dependent variables in logit model so that both equations are simultaneously determined. In this case, a simultaneous equation bias should be avoided by an equation system and/or using instrumental variables. Because of no-reversal feedback from output of performance toward the volume of credits, we could not merge two approaches into one equation system, but it is quite possible to think about some instrumental variables such as managerial level. The non-parametric Malmquist Productivity Index (MPI) methodology could be one of the possible approaches to avoid the one-way frontier approach of DEA with more variables altogether.

⁹See Choi (2004). A metamediary means a more aggressive multi-functional intermediary.

Korea is still on the transient economy and thus requires a more advanced managerial or administrative innovation toward the sustainable governance of the economy. The paper suggests the important objectives of the public policies are not on the appearance of the system but on the sustainable contents of it. Instead of outside helper, the role of financial agencies as a metamediary should be changed into a real partner with more active roles.

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Chapter 13

The Impact of Agricultural Loans on the Technical Efficiency of Rice Farmers in the Upper North of Thailand

Y. (Kai) Chaovanapoonphol, G.E. Battese, and H.-S. (Christie) Chang

13.1 Introduction

Rice is the major crop in Thailand and it will remain so as long as it continues to be the major export crop and the staple food of the Thai population. However, the fact is that, although Thailand is the main rice-exporting country in the world, its rice yields are among the lowest in Asia (Office of Agricultural Economics, 2004a, b). This might imply low productivity and high technical inefficiency in major rice production. In an attempt to resolve this problem, the Thai government has promoted the use of inputs in rice production, such as chemical fertiliser, high-yielding varieties and chemicals, to increase the yields. The total amount of chemical fertiliser that was imported increased from about 1.3 million tonnes in 1985 to 3.9 million tonnes in 2004, with an annual growth rate of 4.6%. The value of imported chemical fertiliser also increased with a higher annual growth rate of 8.7%. The increasing use of chemical fertiliser and chemicals whose prices have been rising continuously has resulted in substantial increases in production costs.

The aftermath of the financial crisis in Thailand in 1997 was a higher proportion of non-performing loans in the banking system. The Bank for Agriculture and Agricultural Cooperatives (BAAC) became the major source of funds for the agricultural sector with its loans to farmers increasing from 154,344 million baht in 2000 to 201,839 million baht in 2004. In addition, since 1997, the government has also promoted the non-commercial financial institutions with the aim of alleviating poverty and improving the quality of life in the rural areas. The non-commercial financial institutions have since become another crucial source of loans to farmers who have limited collateral.

Y.(Kai) Chaovanapoonphol

Department of Agricultural Economics, Faculty of Agriculture, Chiang Mai University,
Chiang Mai, Thailand

G.E. Battese

School of Business, Economics and Public Policy, University of New England, NSW, Australia

H.-S. (Christie) Chang

Australian Institute of Sustainable Communities, University of Canberra, ACT, Australia

This paper aims to answer two questions: how has rural credit contributed to the production of rice? and how do agricultural loans from the rural financial institutions affect the technical efficiency of rice farmers? This study is based on data from farmers in Chiang Mai and Chiang Rai provinces which are the main areas for major rice production¹ in the Upper North sub-region. The results from this study will be useful for determining the government policies on rural financial institutions.

This paper is set out as follows: Sect. 2 provides an overview of the rural financial institutions. Section 3 presents survey data on rice farmers and model specifications. Section 4 discusses the results from the translog stochastic frontier production function. The last section provides policy implications and conclusions.

13.2 An Overview of the Rural Financial Institutions

The financial market in Thailand consists of financial institutions that are either government owned or privately owned. These financial institutions can be further divided into two categories, namely, commercial and non-commercial financial institutions.

The commercial financial institutions can be divided into commercial banks, special financial institutions (SFIs) and non-bank financial intermediaries and cooperatives (Table 13.1). Each financial institution plays a role and provides funds to different groups. Commercial banks mobilize funds by accepting term deposits, savings and demand deposits, and issue negotiable deposits, as well as borrowings from other countries. The special financial institutions have specific purposes for operating. For instance, the BAAC focuses on allocating credit to farmers, agricultural cooperatives and farmer groups. The Government Savings Bank (GSB) specialises in mobilizing funds for retail customers. The Industrial Finance Corporation of Thailand (IFCT) focuses on financing fixed assets to various industries by extending medium- and long-term credit. The Small Medium Enterprise Bank (SMEB) specialises in financing small businesses including those in manufacturing, the handicraft industry, and the service industry. The non-bank financial intermediaries and cooperatives are institutions that provide finance for commerce, industry, agriculture, trading, consumption, hire-purchase and housing. These include financial companies, credit companies, life insurance companies, agricultural cooperatives and non-agricultural cooperatives. The finance companies obtain funds mostly through the issuance of promissory notes and through borrowing from commercial banks. Agricultural cooperatives mobilize funds from members by issuing shares and accepting deposits, mainly to finance their members. Life insurance companies raise funds through insurance premiums to finance their members, as

¹ “Major rice” refers to either non-glutinous or glutinous rice that is grown between May and October, irrespective of the time of harvest.

Table 13.1 Branches of Commercial Banks, the Bank for Agriculture and Agricultural Cooperatives (BAAC) and Agricultural Cooperatives in the Upper North of Thailand by province in 2002

Province	Commercial Banks ^a	The BAAC ^a	Agricultural Cooperatives ^b
Chiang Mai	124	17	103
Chiang Rai	51	15	79
Lampang	30	8	38
Lamphun	17	8	37
Mae Hong Son	8	1	21
Nan	8	6	47
Phayao	17	7	30
Phrae	12	6	29
Total	267	68	384

^aBank of Thailand (2003)^bMinistry of Agriculture and Cooperatives (2003)

well as invest in profitable financial instruments. For rural areas, the BAAC and agricultural cooperatives play important roles in terms of the loans that are provided to farmers.

Non-commercial financial institutions or community financial organisations are more significant players for rural areas than the commercial financial institutions (Table 13.2). These can be divided into either formal or non-formal community financial institutions. Formal community financial institutions are registered as cooperatives such as thrift and credit cooperatives and the Grameen Bank. Thrift and credit cooperatives (savings cooperatives), or registered credit unions, are formed mainly on an occupational basis. The main source of funds for savings cooperatives has been their paid-up share capital, whereby each member is required to contribute a minimum monthly subscription that is obtained directly through a payroll-withholding system. Borrowings and other liabilities have been negligible. Savings cooperatives utilize most of their funds as loans to members. These loans can be used for meeting current needs and precautionary demand for money, for financing the purchase of durable goods, and for home repairs and improvements. Some cooperatives also provide long-term credits for the purchase of houses and for financing secondary occupational activities. The legislation governing the establishment and operation of savings cooperatives is the Cooperatives Act B.E. 2511 (1968), which is the same as that for agricultural and other cooperatives.

The Grameen Bank is the financial institution that is similar to a commercial bank but it helps the poorest people or farmers who cannot provide loan guarantees. Initially, the government held 60% of the total shares but this decreased gradually to only 25%.

Non-formal community financial institutions are unregistered and operate informally. There is a small number of private and non-government organisations (NGOs) that have rural finance programs such as savings groups and the credit union groups. Their members do not own these institutions, and, hence, they cannot

Table 13.2 The number of the non-commercial financial institutions in the Upper North of Thailand by province in 1999

Province	Formal community financial institutions		Non-formal community financial institutions		
	Thrift and credit co-ops ^a	Grameen Bank ^b	Savings groups for production ^c	Credit union groups ^d	Other savings groups
Chiang Mai	19 6	254	63 54		
Chiang Rai	8 8	436	38 40		
Lampang	11	31	193	33	2
Lamphun	4	6	182	3	2
Mae Hong Son	4	2	94	5	2
Nan	11	3	292	8	3
Phayao	5	75	119	8	4
Phrae	6	8	129	4	2
Total	68	139	1,689	162	109

^aMinistry of Agriculture and Co-operatives and Ministry of Interior (cited in Srisawart 2000)

^bThailand Village Development Association

^cThe Community Development Office in the upper North

^dThailand Credit Union Association, Northern branch (b, c, and d cited in Cheirmuaengpan and Sriwichailamphun 2001)

be registered as cooperatives. Furthermore, the government established some rural finance programs to provide village funds for the rural sector.

Over the past 10 years, financial intermediaries have significantly increased their roles in mobilizing funds to finance economic activities. The commercial financial institutions, commercial banks, the BAAC and agricultural cooperatives have been the crucial financial institutions in the agricultural sector. However, roles of the non-commercial financial institutions have increased more significantly after the Thai economic crisis. The agricultural cooperatives were the major commercial financial institutions in the Upper North in terms of the number of branches, which amounted to 410 branches (in 2003), followed by commercial banks and the BAAC with 284 and 70 branches at the end of the year 2002, respectively. Chiang Mai is the main province with the most branches of commercial banks, agricultural cooperatives and the BAAC with 124, 17 and 103 branches, respectively (Table 13.1). For non-commercial financial institutions, savings groups for production dominate the Upper North with 1,689 groups (Table 13.2) because people can form a group based on their enterprises.

When considering the loans extended to clients, although commercial banks are large in terms of the ratio of total assets, they provide few loans to the agricultural sector, which amount to only 6.8 billion baht in 1999 (Bank of Thailand 2003). The BAAC provided 66.1 billion baht in 2000.² For non-commercial financial institutions, thrift and credit cooperatives supplied loans to members amounting to 16.3 billion

²This number is for the northern region.

baht, followed by credit union groups which loaned 0.7 billion baht in 1998.³ The Grameen Bank, savings groups for production and other saving groups are the financial institutions that concentrated on savings rather than providing loans. The accumulative deposits in 1998 for the saving groups for production and other saving groups were about 258 and 9 million baht, respectively.

Overall, the most important source of finance in rural areas appears to be the BAAC. In addition, many co-operatives and associations on-lend funds from the BAAC to low-income households in the rural areas. Non-commercial financial institutions, especially the Village Fund, have played a more significant role in providing funds to the rural areas after the Thai economic crisis. The nature of financial services provided in rural Thailand is quite diverse. The market seems to be segmented, with commercial banks serving large farms and agro-industries and the BAAC largely serving small and medium farms, co-operatives and associations, while the poor and landless are served mainly by informal finance, a few government programs, and NGOs.

13.3 Data and Model Specifications

13.3.1 Data on Rice Farmer Samples

In 2004, data were collected from 656 sample farmers based on personal interviews. Of these sample farmers, 331 and 325 were from Chiang Mai and Chiang Rai provinces, respectively. Basic summary statistics of the key variables used in the stochastic frontier models are presented in Table 13.3. These clearly indicate

Table 13.3 Summary statistics of key variables for major rice farmers in Chiang Mai and Chiang Rai provinces

Variable	Sample mean		Sample standard deviation		Minimum		Maximum	
	CM	CR	CM	CR	CM	CR	CM	CR
Output (kg)	5,687	5,613	4,580	3,709	500	224	49,000	23,400
Yield (kg rai ⁻¹)	646	609	177	194	120	37	1,470	990
Land (rai)	9.1	10.2	7.3	6.9	1	2	70	38
Seed (kg)	76	79	65	61	5	10	560	450
Fertiliser (kg)	277	340	287	436	0	0	2,100	6,200
Chemicals (baht)	786	503	770	735	0	0	4,340	8,800
Labour (man-hours)	328	478	491	600	8	16	5,600	6,560
Loan (baht)	9,504	10,136	12,986	10,524	0	0	100,000	67,500
Experience (years)	29	26	15	12	1	2	65	60
Education (years)	4.7	4.5	2.0	2.2	0	0	16	16
Age (years)	54	49	11	10	27	23	97	85

³This number is overestimated since it includes credit union groups and credit union cooperatives.

that the Chiang Mai and Chiang Rai farmers are different in several key aspects. For example, Chiang Mai had higher mean yield than that for Chiang Rai, the means being 646 and 609 kg per rai, respectively. Because of these differences between the two provinces, we consider estimating stochastic frontier production functions separately for Chiang Mai and Chiang Rai provinces.

The average areas on which major rice was grown in these two provinces were similar, but the farm size varied from a small farm of 1 rai to the very large farm, by Thai standards, of 70 rai in Chiang Mai and from 2–38 rai in Chiang Rai. The average seed used in the two provinces were similar (about 76 and 79 kg for Chiang Mai and Chiang Rai provinces, respectively). The summary statistics indicate that some of the sample farmers did not use any fertilisers and/or chemicals (pesticides and herbicides). The average amount of chemical fertilisers applied by Chiang Rai farmers was about 340 kg, which was higher than that for the Chiang Mai farmers (about 277 kg). On the other hand, Chiang Mai farmers used more chemicals than Chiang Rai farmers, the average costs being 786 baht and 503 baht in the respective provinces. Although the chemical fertiliser price was quite high, it is a crucial production input for major rice production in the Upper North sub-region and most sample farmers did use some chemical fertiliser in their production of major rice (91% and 96% for Chiang Mai and Chiang Rai, respectively). For application of chemicals, farmers normally applied these chemicals when infestations of pests and insects occurred. The percentages of farmers who applied pesticides or herbicides were about 88% and 77% of sample farmers in Chiang Mai and Chiang Rai provinces, respectively. The amount of man-hours applied for rice production in Chiang Rai province was about 478 man-hours, which was higher than that for Chiang Mai province (328 man-hours).

The averages of the amount of loans for major rice production in Chiang Mai and Chiang Rai provinces were approximately the same, being about 9,500 and 10,100 baht, respectively. For Chiang Mai province, 202 farmers or 61% of the farmers surveyed were debtors for major rice production. About 77% of the farmers surveyed in Chiang Rai province were debtors for major rice production. For the experience variable, the sample farmers had a wide range of experience on major rice production. However, it was found that the minimum years of experience in major rice cultivation was very small for both provinces. These farmers had another occupation elsewhere and recently returned home to cultivate major rice for their parents because they were getting very old. The average educational levels of the farmers were similar in both provinces, being about 4.6 years. In addition, about 73% of the total farmers had only four years of formal education while about 3% of the total farmers did not study in school. The ranges of age of sample farmers in Chiang Mai and Chiang Rai provinces were similar. The highest ages of the sample farmers in both provinces were very high with 97 and 85 years in Chiang Mai and Chiang Rai provinces, respectively. Although these farmers were very old, they were still heads of households who were involved in rice production. Our results indicate that the rice farmers in Chiang Mai and Chiang Rai provinces tended to be quite old with considerable experience in major rice production, but had relatively little formal education.

13.3.2 Model Specifications

This paper applied a translog functional form for the stochastic frontier production model for the empirical analysis of the data on major rice farmers in each province. Several tests of hypotheses were conducted to obtain the preferred models for inference about the effect of financial loans on the output and the technical efficiencies of the major rice farmers in the two provinces, Chiang Mai and Chiang Rai, of the Upper North of Thailand. The translog stochastic frontier production function model involved is defined by:

$$\ln Y_i = \beta_0 + \sum_{j=1}^3 \beta_{0j} D_{ji} + \sum_{j=1}^5 \beta_j \ln X_{ji} + 0.5 \sum_{j \leq k=1}^5 \sum_{k=1}^5 \beta_{jk} \ln X_{ji} \quad (13.1)$$

$$\ln X_{ki} + V_i - U_i, i=1, 2, \dots, N;$$

where the subscript, i , indicates the i -th farmer in the sample:

- Y represents the quantity of rice harvested for the sample farmer (in kilograms)
- D_1 is the debtor dummy variable for farmers who borrowed money for major rice production, which has value 1 if the sample farmer had a loan, and 0, otherwise
- D_2 is the fertiliser dummy variable, which has value 1 if the sample farmer applied chemical fertiliser, and 0, otherwise
- D_3 is the chemicals dummy variable, which has value 1 if the sample farmer applied pesticides or herbicides, and 0, otherwise
- X_1 is the total area planted to major rice (in rai)
- X_2 is the total amount of seed sown (in kilograms)
- X_3 is the amount of chemical fertiliser applied (in kilograms)⁴
- X_4 is the total cost of chemicals (pesticides and/or herbicides) applied (in baht)⁵
- X_5 is the total labour used in cultivation of major rice (in man-hours)
- The V_i^S are random errors, assumed to be independent and identically distributed as $N(0, \sigma_v^2)$
- The U_i^S are non-negative technical inefficiency effects, assumed to be independently distributed among themselves and between the V_i^S , such that U_i is defined by the truncation of the $N(\mu_i, \sigma^2)$ distribution, where μ_i is defined by:

$$\mu_i = \delta_0 + \delta_0^* D_{1i} + \sum_{j=1}^5 \delta_j Z_{ji} \quad (13.2)$$

⁴More technically, the chemical fertiliser variable, X_3 , is defined by the maximum value between the quantity of chemical fertiliser used and one minus the fertiliser dummy variable. This approach really substitutes any zero chemical fertiliser values with ones, which permits the logarithm of the chemical fertiliser variable to be defined. This uses the approach of Battese (1997) for handling zero-input values.

⁵As for the fertiliser variable, X_3 , is the maximum of the total cost of chemicals spent and the variable, $1-D_3$.

Where:

- D_1 is the debtor dummy variable, as defined above
- Z_1 represents the total area planted to major rice, which is the same as X_1
- Z_2 represents the total amount of loans used in major rice production (in baht)
- Z_3 represents the experience of the head of household in rice cultivation (in years)
- Z_4 represents the formal education level of the head of household (in years)
- Z_5 represents the age of the household head (in years)
- N denotes the number of sample farmers involved

The variables included in the frontier production function comprise land, seed, chemical fertiliser, chemicals and labour. These variables are important physical inputs into major rice production. The model for the technical inefficiency effects contains the total amount of loans used in major rice production and variables associated with human capital, such as experience in major rice cultivation, amount of schooling and the age of the head of the household. The variables other than the amount of loans have been used in the models for the technical inefficiency effects in several previous studies, such as Kalirajan and Flinn (1983), Kalirajan (1984), Ekanayake (1987), Bravo-Ureta and Evenson (1994), Battese et al. (1996) and Sriboonchitta and Wiboonpongse (2004a, b).

The reason for including the loan variable in the technical inefficiency component, but not in the production component of the model, is as follows. Since the loan is used mainly for purchasing inputs to include it in the production component along with the inputs, would result in double-counting. However, production theory would suggest that financial variables such as the amount of loans obtained for major rice production should not affect the productivity or efficiency of farmers, except that the interest paid on any loans obtained to purchase production inputs could be reasonably included as production costs. However, we include the amount of loans in the empirical model to test if there is any significant statistical effect on the efficiency of the major rice producers.

13.4 Empirical Results

13.4.1 Hypotheses Testing

We consider various tests of hypotheses that are cases of nested hypotheses, for which the null hypothesis is a subset of that of the alternative hypothesis. Thus, under the null hypothesis, the model involved is a restriction of the more general model that applies under the alternative hypothesis. The generalised likelihood-ratio test is applied to test various hypotheses.⁶

⁶The formal approaches to testing hypotheses for nested models include the Wald test (or F-test), the likelihood-ratio (LR) test, and the Lagrange multiplier (LM) test. In all these approaches, two models are compared, a restricted model and an unrestricted model. The Wald test starts with the unrestricted model and asks whether the restricted model is adequate. The likelihood-ratio test is a direct comparison of the two hypotheses. The Lagrange multiplier approach starts with the restricted model and asks whether the unrestricted model is preferred, see Ramanathan (1995, p. 303).

This likelihood-ratio statistic is defined by $\lambda = -2 \ln[L(H_0)/L(H_1)]$, where $L(H_1)$ is the value of the likelihood function for the more general and unrestricted frontier model; and $L(H_0)$ is the value of the likelihood function for the frontier model in which the parameter restrictions that are stated by the appropriate null hypothesis, H_0 , are imposed. If the null hypothesis is true, then the generalised likelihood-ratio statistic has approximately a chi-square (or a mixed chi-square) distribution with degrees of freedom equal to the difference between the number of parameters estimated under H_1 and H_0 , respectively.

In preliminary analyses, null hypotheses were tested that the frontier models for both provinces were the same and also that the frontier models were the same except that the intercept parameters may be different. These hypotheses were strongly rejected.

Formal tests of the various null hypotheses were conducted to determine the preferred model for inference about the productivity and efficiency of the major rice farmers in the two provinces. The null hypotheses involved are listed below. The results of the tests of these hypotheses are presented in Table 13.4.

The first null hypothesis, $H_0: \beta_{jk} = 0$, for all $j \leq k = 1, 2, \dots, 5$, states that the second-order coefficients in the translog production function have zero values and so, if this hypothesis is true, then the Cobb-Douglas production function applies. For both provinces, this null hypothesis is rejected, even if the size of the test is as small as $\alpha = 0.005$.

The second null hypothesis, $H_0: \gamma = \delta_0 = \delta_0^* = \delta_1 = \dots = \delta_5 = 0$, specifies that the technical inefficiency effects are not present in the frontier model. If this hypothesis is true, this implies that the traditional average response function is an adequate representation of the data, given the specifications of the translog stochastic frontier

Table 13.4 Generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function models for Chiang Mai and Chiang Rai provinces

Null hypothesis	Test statistic, λ	p-value ^a
Chiang Mai province		
$H_0: \beta_{jk} = 0$, for all $j \leq k = 1, 2, \dots, 5$	33.916	0.003
$H_0: \gamma = \delta_0 = \delta_0^* = \delta_1 = \dots = \delta_5 = 0$	65.652	0.000 ^b
$H_0: \delta_0^* = \delta_1 = \dots = \delta_5 = 0$	27.590	0.000
$H_0: \beta_{01} = \delta_0^* = \delta_2 = 0$	19.134	0.000
$H_0: \delta_0^* = \delta_2 = 0$	19.438	0.000
$H_0: \delta_1 = 0$	1.490	0.222
Chiang Rai province		
$H_0: \beta_{jk} = 0$, for all $j \leq k = 1, 2, \dots, 5$	38.062	0.001
$H_0: \gamma = \delta_0 = \delta_0^* = \delta_1 = \dots = \delta_5 = 0$	151.714	0.000 ^a
$H_0: \delta_0^* = \delta_1 = \dots = \delta_5 = 0$	31.264	0.000
$H_0: \beta_{01} = \delta_0^* = \delta_2 = 0$	5.538	0.136
$H_0: \delta_0^* = \delta_2 = 0$	4.120	0.127
$H_0: \delta_1 = 0$	20.584	0.000

^aThe p-values are given correct to the third digit behind the decimal point

^bBecause $\gamma = 0$ is included in H_0 then, if H_0 is true, λ has a mixed chi-square distribution. Kodde and Palm (1986) present the percentile values for these distributions. For this case, H_0 is rejected because the value of λ exceeds the critical value of 14.853 for the size of the test, $\alpha = 0.05$

production function model. This null hypothesis is also rejected for both provinces even if the size of the test is as small as $\alpha = 0.005$.

The third null hypothesis that is considered is, $H_0: \delta^*_{\cdot 0} = \delta_1 = \dots = \delta_5 = 0$, which indicates that all the coefficients of the explanatory variables in the inefficiency model are equal to zero. If this hypothesis is true, then the explanatory variables in the inefficiency model do not influence the technical inefficiencies of major rice production. This third null hypothesis is also rejected for both provinces.

The fourth null hypothesis, $H_0: \beta_{01} = \delta^*_{\cdot 0} = \delta_2 = 0$, states that there are no effects of financial services on the productivity and efficiency of the major rice farmers. If this hypothesis is true, then the financial services of rural financial institutions do not influence the performance of the major rice farmers in the province involved. This fourth null hypothesis is rejected for Chiang Mai province even if the size of the test is as small as $\alpha = 0.005$. However, for Chiang Rai province, this null hypothesis would only be rejected for a much larger size of the test, such as $\alpha = 0.15$. Because we are conducting a preliminary test of significance for our frontier model, we use the size of the test of $\alpha = 0.20$.⁷ Thus, we reject the null hypothesis that the rural financial services have no effects on the major rice farmers in Chiang Rai as well as in Chiang Mai. The fifth null hypothesis, $H_0: \delta^*_{\cdot 0} = \delta_2 = 0$, specifies the coefficients of the inefficiency model that are associated with the financial services are all zero. If this is the case, then there is no impact of financial services on the technical inefficiencies of the major rice farmers. This fifth null hypothesis is rejected for the size of the test of $\alpha = 0.20$ for both provinces, but, for Chiang Mai it would be rejected at a much smaller size of the test than for Chiang Rai.

In the specified stochastic frontier model, the land variable is included in both the production function and the inefficiency model. If the coefficient of land in the inefficiency model is non-zero, then the stochastic frontier model is called a non-neutral stochastic frontier model (Huang and Liu 1994; Battese and Broca 1997). Thus, we are interested to test the null hypothesis, $H_0: \delta_1 = 0$, to decide if the stochastic frontier model is a neutral one. This last null hypothesis is not rejected for Chiang Mai but rejected for Chiang Rai, given the size of the test of $\alpha = 0.20$ for our preliminary test.⁸

For the Chiang Mai rice farmers, we conclude that the preferred frontier production function model is a neutral stochastic frontier because the inefficiency effects are not a function of the size of the major rice farming operation. For the Chiang Rai rice farmers, we conclude that the frontier production function is a non-neutral stochastic frontier because the inefficiency effects are a function of the area of land under major rice.⁹ In addition, for farmers in both provinces, we conclude that the amounts of loans have significant effects on the productivity and efficiency of major rice farmers.

⁷Literature on preliminary testing is quite extensive, but basic references are Bancroft (1968, pp. 8, 73) and Judge, et al. (1988, p. 833).

⁸The t-test for testing $H_0: \delta_1 = 0$ versus $H_1: \delta_1 \neq 0$ gives a p-value of 0.443 for Chiang Mai. Given this result, we would not reject $H_0: \delta_1 = 0$, which is consistent with our decision for Chiang Mai based on the generalised likelihood-ratio test procedure.

⁹From the estimates presented in the next section, the coefficient of land area in the inefficiency model is estimated to be positive. This indicates that farmers with larger farms in Chiang Rai tended to be more inefficient in major rice production.

13.4.2 Production Frontier Estimates

The empirical results from production function, which are presented in Table 13.5, indicate that land and labour are crucial factors for major rice production and the impacts of these two variables on the mean major rice outputs are similar in both provinces. In addition, it is found in this study that, when the dummy variable for debtors is included in the production function, the estimated mean rice outputs in the two provinces are significantly different. However, we cannot identify the reasons for the different estimates for the coefficient of the debtor dummy variable in the two provinces.

For Chiang Mai province, all of the explanatory variables for the inefficiency effects, except experience of the head of household in major rice cultivation, have negative estimated coefficients. The empirical results suggest that the dummy variable for debtors, the amount of loans for major rice production, the formal education

Table 13.5 Maximum-likelihood estimates for parameters of the preferred stochastic frontier production models for major rice farmers in Chiang Mai and Chiang Rai provinces

Variable ^a	Chiang Mai (331 observations)				Chiang Rai (325 observations)		
	Coeff	Est.	Stand. error	p-value	Est.	Stand. error	p-value
Production function							
Constant	β_0	9.05	0.68	0.000	8.81	0.61	0.000
Debtor Dummy	β_{01}	-0.206	0.054	0.000	0.062	0.033	0.065
Fertiliser Dummy	β_{02}	-0.32	0.42	0.441	-0.09	0.50	0.862
Chemicals Dummy	β_{03}	0.16	0.66	0.812	-0.02	0.35	0.964
Land	β_1	0.910	0.049	0.000	0.849	0.046	0.000
Seed	β_2	-0.005	0.037	0.889	0.013	0.034	0.701
Fertiliser	β_3	0.025	0.024	0.286	0.027	0.029	0.355
Chemicals	β_4	-0.059	0.043	0.174	0.026	0.023	0.258
Labour	β_5	0.049	0.021	0.024	0.047	0.017	0.005
0.5 (Land) ²	β_{11}	-0.10	0.14	0.479	-0.24	0.12	0.051
0.5 (Seed) ²	β_{22}	0.038	0.097	0.696	-0.139	0.092	0.135
0.5(Fertiliser) ²	β_{33}	0.010	0.033	0.774	-0.005	0.034	0.889
0.5(Chemicals) ²	β_{44}	-0.011	0.033	0.727	0.003	0.019	0.899
0.5 (Labour) ²	β_{55}	0.035	0.023	0.129	-0.007	0.025	0.776
Land $\times$ Seed	β_{12}	0.009	0.092	0.924	0.189	0.093	0.042
Land $\times$ Fertiliser	β_{13}	0.060	0.039	0.131	0.032	0.037	0.382
Land $\times$ Chemicals	β_{14}	0.038	0.023	0.104	0.066	0.014	0.000
Land $\times$ Labour	β_{15}	-0.012	0.047	0.799	0.013	0.040	0.751
Seed $\times$ Fertiliser	β_{23}	-0.060	0.034	0.077	-0.030	0.029	0.298
Seed $\times$ Chemicals	β_{24}	-0.002	0.019	0.901	-0.007	0.012	0.552
Seed $\times$ Labour	β_{25}	0.025	0.033	0.450	0.032	0.044	0.471
Fertiliser $\times$ Chemicals	β_{34}	-0.0188	0.0047	0.000	-0.0096	0.0038	0.012
Fertiliser $\times$ Labour	β_{35}	-0.035	0.016	0.028	-0.019	0.016	0.212
Chemicals $\times$ Labour	β_{45}	0.008	0.012	0.534	-0.0145	0.0056	0.010

^aIn this column, the input variables are expressed in logarithmic form. For example, the variable 0.5 (Land)² denotes $0.5 \times [\ln(\text{land})]^2$, as defined in (13.1)

and the age of the head of household have highly significant effects on the technical inefficiency levels of farmers in Chiang Mai. The negative sign for the debtor dummy variable shows that debtor farmers tended to have smaller technical inefficiencies in major rice production than those for non-debtor farmers, other things being equal. The negative coefficient for the amount of loans used for major rice production indicates that farmers who obtained loans were more likely to have smaller technical inefficiencies. The negative coefficients of formal education and age of the head of household indicate that household heads with higher levels of schooling and those who were older tended to have smaller technical inefficiencies in major rice production.

For Chiang Rai province, the estimates for the inefficiency parameters suggest negative relationships between the technical inefficiencies of major rice production and the amount of loans used for major rice, experience, formal education and age of the head of household, but a positive relationship between the technical inefficiencies and the area planted to major rice. However, only the coefficients associated with the area planted to major rice and amount of loans used for major rice production are statistically significant at the 10% level. The positive sign for the debtor dummy variable shows that debtor farmers tended to have higher technical inefficiencies in major rice production than those for non-debtor farmers for given levels of the variables involved. The positive sign of land means that the larger the area farmed the larger the technical inefficiencies in major rice production. The estimated coefficient for the amount of loans used for major rice for Chiang Rai province is negative, as is that for Chiang Mai province. Thus, farmers who obtained larger loans for major rice were more likely to have smaller technical inefficiencies. Finally, the results show that the individual coefficients of experience, formal education and age of the head of household are not statistically significant.

The area planted major rice had a significant and positive impact on the technical inefficiencies of farmers only in Chiang Rai province. The empirical results indicate that farmers who had larger farms in Chiang Rai province were less likely to manage their production efficiently. This may be due to the fact that the rice production technique in Chiang Rai province still relies on labour-intensive techniques. The lack of proper equipment or machinery might lead to the farmers with larger farms having less efficiency than those with smaller farms.

The empirical results from this study are consistent with those of some previous studies although few previous studies on rice included farm size in the technical efficiency model but used the two-step method of estimation. Tadesse and Krishnamoorthy (1997) included a dummy variable for farm size (small and medium size) in the technical efficiency model and found that its coefficient was positive and statistically significant, which implies that the small- or medium-sized paddy farms operated at a higher level of technical efficiency than large-sized farms. In this regard, Lahiri (1993) stated that it is likely that accessibility to financial institutions depends on collateral, particularly land, and so small farms are forced to allocate their resources more effectively. In addition, Bagi (1981) studied the technical efficiency of mixed croppers and showed that using

more of their own resources such as human labour, bullock power, and chemical fertiliser per hectare of land, small farms tended to get more output and higher technical efficiency than larger farms. However, Squires and Tabor (1991), who also took farm size into account in studying the technical efficiency of Java rice production, found this variable to have no significance impact.

Furthermore, the coefficients of the amount of loans for major rice production, formal education and the age of the head of household in the technical inefficiency model had negative signs. The significant negative impact of the amount of loans for major rice production on the technical inefficiencies is due to the fact that farmers could buy production inputs at the most appropriate times and change their production practices when funds were available. Ekayanake (1987) used a dummy variable for bank loans and found that the farmers who received bank loans were more technically efficient because the availability of bank loans facilitated the timely application of inputs. However, this study includes the amount of loans from both rural financial institutions and individuals. In addition, the loans variable is included in the technical inefficiency model, as well as the dummy variable for debtors. It is found that the results of this study are consistent with the previous study in that receiving loans results in higher technical efficiencies. A loans variable was also included in analysis of the technical efficiency of production in previous studies, using the two-step method. For example, Taylor and Shonkwiler (1986) showed that credit had no significant impact on the technical efficiency, but Bravo-Ureta and Evenson (1994) showed there was a positive effect.

Almost all previous studies on rice production using cross-sectional data have included socio-economic variables in the technical inefficiency model, such as formal education of farmers, age of farmers, household size, experience in rice cultivation of farmers, extension hours, farm region, tenure, etc. (for example, Sriboonchitta and Wiboonpongse 2004a, b). For this study, the empirical results indicate that experience in major rice production had no significant effect on the technical inefficiencies in both provinces, while formal education and age of the head of household had significant impacts on the technical inefficiencies only for Chiang Mai province. However, most previous studies showed that experience in production had a positive impact on the technical efficiencies of farmers, for example, Kalirajan and Flinn (1983), Kalirajan (1984) and Ekanayake (1987). Moreover, formal schooling was found to have no significant impact on the technical efficiencies of rice production in previous studies, such as Kalirajan and Shand (1986), Ali and Flinn (1987) and Battese et al. (1996). There appears to be no apparent reason for these differing results.

13.4.3 Elasticity Relationships and Returns to Scale

The coefficients of the first-order terms of the production inputs of the production function for the translog model can be interpreted as elasticities at mean values of the inputs because the values of the variables used in the analysis are mean-corrected. For the translog model, the elasticities of mean rice output with respect to the

different inputs depend on several parameters and values of the inputs. The elasticity of mean rice output with respect to the j -th input variable is defined by the following expression (Battese and Broca 1997, p. 12):

$$\frac{\partial \ln E(Y_i)}{\partial \ln X_{ji}} = \left\{ \beta_j + \sum_{k=1}^5 \beta_{jk} \ln X_{ki} \right\} - C_i \left(\frac{\partial \mu_i}{\partial \ln X_{ji}} \right) \quad (13.3)$$

where μ_i is defined in (13.2);

C_i is defined by

$$C_i = 1 - \frac{1}{\sigma} \left\{ \frac{\phi\left(\frac{\mu_i}{\sigma} - \sigma\right)}{\Phi\left(\frac{\mu_i}{\sigma} - \sigma\right)} - \frac{\phi\left(\frac{\mu_i}{\sigma}\right)}{\Phi\left(\frac{\mu_i}{\sigma}\right)} \right\}$$

and ϕ and Φ represent the density and distribution functions of the standard normal random variable, respectively.

Table 13.6 indicates elasticities of mean rice output with respect to the different inputs, evaluated at the mean input levels. The empirical results show that, from the estimates of the translog production function models for Chiang Mai province, the estimated elasticities of mean rice output with respect to land, seed, chemical fertiliser, chemicals and labour, at mean input values, are 0.910, -0.005 , 0.025, -0.059 , and 0.049, respectively, at the mean input values. This indicates that, if land under major rice, chemical fertiliser application and labour uses were to be individually increased by 1%, then the mean production of major rice is estimated to increase by 0.910, 0.025, and 0.049%. Further, the elasticities with respect to seed and the cost of chemicals are estimated to be negative values, but not statistically significant. However, only the estimated land and labour output elasticities are found to be positive and statistically significant for Chiang Mai farmers.

For Chiang Rai province, the elasticities of mean rice output with respect to all input variables are estimated to be positive, but only the land and labour elasticities are statistically significant.

Table 13.6 Elasticities of mean major rice output with respect to different inputs, estimated at the mean input values

Input	Chiang Mai	Chiang Rai
Land	0.910 (0.049)	0.849 (0.046) ^a
Seed	-0.005 (0.037)	0.013 (0.034)
Fertiliser	0.025 (0.024)	0.027 (0.029)
Chemicals	-0.059 (0.043)	0.026 (0.023)
Labour	0.049 (0.021)	0.047 (0.017)
Returns to scale	0.920 (0.088)	0.962 (0.088)

Figures in the parentheses are standard errors, given to two significant digits

^aThis land elasticity for Chiang Rai farmers involves only the frontier elasticity of mean output with respect to land

Table 13.7 Percentages of technical efficiencies of major rice farmers in Chiang Mai and Chiang Rai provinces within decile ranges

Interval	Chiang Mai	Chiang Rai
<0.50	3.0	14.5
0.50–0.60	6.7	10.5
0.60–0.70	6.3	12.5
0.70–0.80	13.0	16.9
0.80–0.90	36.9	22.8
0.90–1.00	34.1	22.8
Mean technical efficiency	0.819	0.732

The returns to scale estimates, evaluated at the mean input values, are 0.920 and 0.962 for Chiang Mai and Chiang Rai, respectively, as presented in the bottom of Table 13.6. These values are not significantly different from one, which indicate constant returns to scale in rice production in Chiang Mai and Chiang Rai provinces.

13.4.4 Technical Efficiency Indexes

Table 13.7 shows the distribution of the predicted technical efficiencies of the sample rice farmers in Chiang Mai and Chiang Rai provinces. For Chiang Mai province, the mean technical efficiency was estimated to be 0.819, with the maximum of 0.966 and the minimum of 0.210. This implies that, on the average, the major rice farmers in Chiang Mai province were producing major rice about 82% of the potential (stochastic) frontier production levels, given the technology currently being used. For Chiang Rai province, the technical efficiency of farmers varied between 0.045 and 0.971, with the mean technical efficiency estimated to be 0.732. This indicates that the major rice farmers in Chiang Rai province produced major rice about 73% of the potential frontier production levels. Thus, in the short run, there is scope for increasing major rice production by 18% and 27% by adopting the techniques used by the best practice major rice farms in the two respective provinces. It is found that the mean technical efficiency indexes of this study are somewhat higher than those obtained by Sriboonchitta and Wiboonpongse (2004b), which were 0.679 for Jasmine rice and 0.716 for non-Jasmine rice.

13.5 Policy Implications and Conclusions

In the past, the Thai government has tried to increase rice production by increasing input use. However, low productivity remains a serious issue in major rice production in Thailand. The government attempted to encourage farmers to adopt new

agricultural technology such as high-yielding varieties and modern agricultural machinery, but the average yield of major rice has only increased slowly. There is some evidence showing that some farmers are not able to get access to agricultural inputs because they have insufficient funds for their production activities. This study concentrates on investigating the impact of agricultural loans from the rural financial institutions on the technical efficiency of major rice farmers.

The findings from the stochastic frontier production analysis indicate that land and labour are still the crucial inputs for rice production. The agricultural loans from the rural financial institutions have no direct impact on the rice production level but have a negative and significant influence on the technical inefficiency of rice farmers in the two provinces. One explanation is that loans from the rural financial institutions might have affected the production practices or the timing of the application of the inputs that influence the technical efficiency of major rice farmers. Therefore, the government policies should continue to encourage the provision of rural financial services to rural people, particularly the loans for agricultural activities. Moreover, since the application of inputs also affects the rice production level, the provision of loans in a timely manner should be encouraged.

In addition, the empirical results indicate that formal education level also has a significant negative effect on the technical inefficiency of rice production in the province of Chiang Mai. This suggests that the higher the education level, the smaller the technical inefficiency in rice production for farmers. This implies that the government should aim to improve the formal education levels of farmers, which is expected to result in higher technical efficiency in rice production, especially in Chiang Mai province.

The results of this study suggest that the rice farmers could increase output through better use of available resources given the technology involved. The technical efficiencies of rice farmers are different in the two provinces. Farmers in Chiang Mai province tend to have higher technical efficiencies relative to their production technology than those in Chiang Rai province. This implies that a training program for improving the technical efficiency of major rice farmers in the province of Chiang Rai might be beneficial.

The findings indicate that most farmers applied chemical fertiliser in small amounts despite the Thai government's efforts to promote chemical fertiliser application. However, for this policy to be effective in achieving its intended purpose, more and timely rural finance needs to be made more accessible to rice farmers.

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Part IV

Efficiency of ICT Firms

Chapter 14

Efficiency Analysis of the Digital Content Industry in Korea: An Application of Order-m Frontier Model

D.O. Choi and J.E. Oh

14.1 Introduction

It is a very strategic and efficient policy for Korea, a small country with few natural resources, to develop information and communication technology (ICT) as an alternative source of development. The surprisingly rapid development of the ICT industry is a result of long term and optimal R&D investment and also due to the national uniqueness of this industry field. Specially, the fast diffusion of super-highway internet has enabled the advanced foundation for this industry. With the development of ICT, a new type of industry has emerged. The digital content industry has enjoyed the benefits of the ICT industry development and has the distinct characteristics compared to traditional industries. Economic scholars are forecasting the various future possibilities and the next generation of ICT. They emphasize the necessity of moving the axis from communication network-based services to content-based services.

The digital content industry includes industries related to the production, storage, and distribution of digital content (Pattinson consulting 2003; Korea IT Promotion Agency (KIPA) 2004). As a narrow definition, digital content means digitalized information which includes digital movies, digital music, video games, software, and so on. The digital content industry is distinct from manufacturing industries as the products are intangible goods like these. As a broader definition, digital content includes products from cultural industries and all the services provided by ICT industries.

In many countries, including Korea, the digital content industry is considered as one of the most promising industries due to its huge added value. In 2005, the total market size of the global digital content industry was about 243 trillion dollars, and the compound annual growth rate (CAGR) from 2005 to 2010 is expected to be about 15% (KIPA 2006b). The market size in Korea has grown to 800 billion dollars with CAGR of 29.3% from 2001 to 2005 (KIPA 2006a). In addition, the market

D.O. Choi, J.E. Oh

Technology Management, Economics, and Policy Program, Seoul National University, Seoul, South Korea

size in 2005 was 133 trillion dollars of the US and 64 trillion dollars in Europe (KIPA 2006b). In Europe, the digital content industry was selected as one of the next large scale strategic industries for creating an innovative Europe (EC 2006).

This study tries to analyze the relative production efficiency of the digital content industry which is thought to be very promising in the near future. The present study differs from other existing efficiency studies of similar industries such as the Internet or e-commerce companies in its analysis of a large sample size of more than two thousand in the case of the software industry. Such a large sample enables the whole industry to be analyzed. Furthermore, we apply statistical methods capable of determining and excluding outliers that would otherwise distort the relative efficiency distribution by adopting the concept of super-efficiency. We hope to derive meaningful implications from this analysis for stake-holders such as entrepreneurs, policy makers, and also academic researchers.

Our research questions are:

- In terms of production efficiency, what are the characteristics of the digital content industry?
- How did the efficiency of the digital content industry evolve between 2000 and 2004?
- How do the sub-sectors of the digital content industry differ in terms of efficiency?
- What policy implications can assist in improving the competitiveness of the digital content industry?

This paper is organized as follows. In Sect. 14.2, we explain the basic concepts of the methods used in this analysis. In Sect. 14.3, we describe the data specification and overview the target industry. The study data are presented in Sect. 14.4, the empirical results and discussion in Sect. 14.5 and the conclusions in Sect. 14.6.

14.2 A Brief Review of the Literature

Digital content has been the subject of debate at the OECD level for a number of years. The debate has been held mainly through its Working Party on the Information Economy (WPIE) and Indicators for the Information Society (WPIIS) and their parent committee, the Committee for Information, Computer and Communications Policy (ICCP). When WPIIS was established in 1996, it developed a work program aimed at initially defining and setting standards for the measurement of the ICT sector, to be followed by the definition and measurement of the content that was communicated by that sector.

The digital content industry is composed of various sub-sectors, each of which has distinctive characteristics. We divided the digital content industry into three sub-sectors according to groupings defined by KIPA: (1) production/publishing, (2) online distribution, and (3) software provision, as shown in Table 14.1. Since the role of each sub-sector is different, identifying their individual characteristics and

Table 14.1 Classification of the digital content industry (KIPA 2004)

Digital content industry		
Production & publishing	Online distribution	Software provision
Game, digital movie, digital music, e-learning, character, publishing	Internet portal service	Software manufacanimation, turing (tools, security, billing)

production efficiency is important to promote the overall industry and improve its competitiveness.

The production and publishing sector includes activities like producing and publishing games, digital movies, music, animation, e-learning, and digital books. The online distribution sector includes internet portal services who deliver digital content and services. The software provision sector includes making software such as tools, security, and billing.

Despite the growing importance of the industry, academic research on the competitiveness of the industry is insufficient to meet the demands, while many studies have investigated the production efficiency of traditional manufacturing industries (Leachman et al. 2005; Diaz and Sanchez 2005). The digital content industry has many characteristics which differ from those of manufacturing industries. Some studies which investigated the efficiency of internet or e-commerce companies presented good implications for determining these characteristics (Alpar et al. 2001; Wen et al. 2003; Barua et al. 2004; Serrano-Cinca et al. 2005). When analyzing the digital content industry in the sense of production efficiency, we can refer to the efficiency analyses of non-manufacturing industries or the service industry (Keh and Chu 2003; Keh et al. 2006).

14.3 Methods

The analysis is performed in two stages. Firstly, the efficiency distribution is estimated with non-parametric frontier models and secondly, the explanatory variables which are correlated to the efficiency scores are determined by applying censored regression analysis. We introduce non-parametric frontier models because these methods do not require the production techniques to be specified in advance when estimating efficiency. In addition, we investigate a newly rising industry with a presently unknown production function (Serrano-Cinca et al. 2005). In the process of non-parametric frontier analysis, we first apply the typical data envelopment analysis (DEA) method (Charnes et al. 1978) which assumes variable returns to scale (VRS) production technology, and thereafter apply the order-m frontier model (Cazals et al. 2002; Simar 2003) based on the free disposal hull (FDH) method (Deprins et al. 1984). The one important characteristic of the digital content industry is that output does not increase in proportion to increasing input. For example, even if the development cost doubled for a software manufacturer, the sales revenue would not simply double to match. Therefore, it would be a mistake to assume that

the production technology in the digital content industry should show constant returns to scale (CRS), so we assumed the industry to exhibit VRS technology when applying the DEA method. However, due to the presence of some outliers showing super-efficiency when the typical DEA method is applied, most firms seem to be placed in a relatively inefficient region. As described in more detail below, the order- m frontier model using stochastic approach is introduced to treat this kind of problem. After applying this method, the distribution of the relative production efficiency of the industry is significantly changed from the distribution determined by applying the typical DEA method. In addition, this frontier model is based on the FDH method which excludes the convexity assumption from the typical DEA method. The convexity assumption means that if there are two producible points, a linear combination of the two points can also be producible. We decided that it would be more plausible to assume only disposability, which is the most basic assumption of production technology, when we do not know the precise functional relationship of the digital content industry. Detailed information on the analysis methods we applied follows.

The order- m frontier model is used to estimate efficiencies with detecting and removing outliers. We used a statistical approach proposed by Cazals et al. (2002). When analyzing data statistically with the order- m frontier model, m number of decision making units (DMUs) are repeatedly selected and potential outliers which are excluded more frequently with a certain probability are identified. In this approach, m can be viewed as a “trimming” parameter of the frontier, and the order- m frontier and DEA/FDH frontiers coincide at large values of m (Simar 2003). By iterative sampling m number of DMUs from a population, some DMUs are easily included in a producible set while some other DMUs are excluded more frequently. Therefore, if we can decide the proper value of m and the significance level α , it is easy to determine the outliers which have a low probability of inclusion in the producible set. In other words, the procedure of choosing m and α is the important step, and it can be done in a reasonable way by using sensitivity analysis.

To determine the proper value of m and α , sensitivity analysis is performed. While applying various values of m and α , we carefully keep track of the changes in the number of outliers which are excluded. If the number of outliers tends to a constant after a certain point with increasing value of m , then this number can be considered to be the proper value as the criterion in deciding outliers. However, this method is not rigorous and depends on arbitrary judgments of the researcher.

Using the values of m and α , we can obtain the efficiency scores of each firm and identify the outliers which should be omitted in the subsequent analysis. Since the efficiency scores are relative values to the frontiers, the previously relatively inefficient DMUs can display a higher efficiency level when super-efficient outliers are excluded. If we assume that our data set has no noises or errors, the outlier can be defined as a datum which has a low probability of being drawn from the data gathering process (Simar 2003). Therefore, we can estimate the efficiency better with careful detection of the outliers.

When estimating efficiency scores, the FDH approach is applied. The method requires only an assumption of disposability, without needing the convexity

assumption required in the typical DEA approach. The production possibility set of the FDH approach is as follows:

$$\begin{aligned}
 P = \left\{ (x, y) \mid y \leq \sum_{j=1}^J z^j y^j, \right. \\
 x \geq \sum_{j=1}^J z^j x^j, \\
 \left. \sum_{j=1}^J z^j = 1, z^j \in \{0, 1\} \right\}
 \end{aligned} \tag{14.1}$$

As shown in (14.1), when one DMU is found to be producible, we can assume that the points which show more input and less output are also producible (disposability assumption) in FDH. This assumption is the minimal condition of the estimating efficiency in a non-parametric way. As we have little information about the production model of the digital content industry, this FDH approach was decided to be proper for this analysis.

The next step in frontier analysis is to find explanatory variables which are correlated with the efficiency scores. We use the censored regression (Tobit) model to analyze the efficiency data in the second stage. The Tobit model is explicitly designed for using limited dependent variables in econometric analysis (Greene 2003; Wooldridge 2006).

14.4 Data

We gather data from the Korea Investors Service (KIS) that collects financial data from most Korean companies. During this process, we have to reconcile industry groupings of KIPA with groupings of KIS. The production and publishing sector is matched to the game industry in the KIS data since the game publishing industry is the biggest one in the production and publishing sector and as there are few available data except game companies. The information provision sector represents the online distribution sector. Lastly, software manufacturing and consultancy companies are used to examine the software provision sector.¹

Game publishing includes all game-related activities from making program codes to delivering them to end users. Developing games requires creative manpower, large scale investment, and high-level hardware or software computing technology. The market size of the game industry in Korea was approximately 2 billion U.S. dollars in 2004 (KIPA 2006a), and since the game industry is the biggest in the production/publishing sector, it can be representative of the sector. In

¹Game publishing, information provision, and software manufacturing and consultancy sectors are indexed as M72100, M72200, and M72400, respectively, in KIS data.

case of information provision, internet portal service is the representative sector. Internet portal service providers create new types of business model while they run large scale databases, collect diverse information, and deliver it to consumers effectively. Their market size was about 1.5 billion US dollars (KIPA 2004) in Korea, and the industry is now growing faster together with the game industry. The software manufacturing and consultancy industry (henceforth, software) consisted of package software manufacturing (4.5 billion) and ICT service consultancy (13 billion) in 2004 (KAIT 2004), a total of about 17.5 billion U.S. dollars. The software industry has a longer history and larger number of firms than the other two sectors. In observing the software industry, we go further by dividing software firms into two sub-sectors in order to compare the different business models and production technology. Being different from package software manufacturers, software consultancy firms just design systems and purchase software products from others to compose the system. Interestingly, they have distinct characteristics in efficiency analysis which are introduced in the following chapter. In this way, we analyze the sub-sectors of the digital content industry from the perspective of productivity and efficiency.

KIS data were obtained for the years 2000 and 2004, and the samples size is shown in Table 14.2. From the early 2000s, the digital content industry grew explosively, but in 2004, the growth rate was lowered and the market became stabilized (KIPA 2006a), as shown in Fig. 14.1. Considering this change, we decided to compare the data from the 2 years.

The data collected are mainly composed of firm size, capital stock, R&D expenditure, labor expenditure, and other information such as group code, date of foundation, and number of employees. Based on these data, efficiency scores are estimated as follows. Labor expenditure and capital stock are used as input variables and sales revenue is used as an output variable (Fig. 14.2). Although the input variables commonly used in production efficiency analysis are labor and capital, the variables used here have a quite different meaning. We applied labor expenditure instead of the number of employees and capital stock in place of capital, because the structure of the labor force in the digital content industry is quite different from that in other industries, and because the workers who are doing main jobs such as developing are paid much more than others. Therefore, it is better to consider expenditure on employees than to simply use the number of employees. This seems to be an important characteristic in which the digital content industry can be differentiated from other industries. We apply the number of employees into the second stage analysis as the size of a firm. In many studies, the method of defining capital is a crucial problem. The capital stock used in this study is different from the capital in a given year. We applied stock value for two reasons. First, our analysis is a cross-sectional study, so stock value can be comparable among firms. Second, fixed cost is important in developing digital content, and capital stock can reflect the size of fixed cost because capital stock indicates how much money is invested in a production activity in the early stage. As an output, although value-added is usually used in analyzing manufacturing industries, sales revenue is chosen here instead because material cost used in the industries is not included in the given data. The

Table 14.2 Number of observations in each sector

	Number of observations	
	2000	2004
Game publishing	75	134
Information provision	208	270
Software manufacturing and consultancy	1,536	2,157

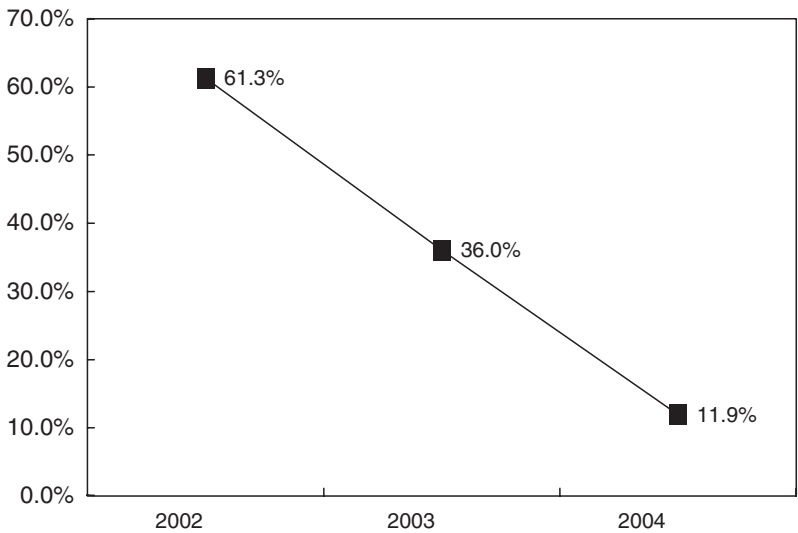


Fig. 14.1 Growth rate of firm numbers in the digital content industry

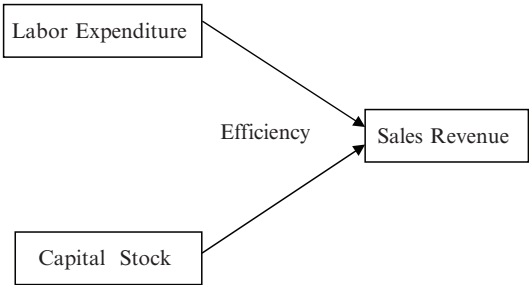


Fig. 14.2 Input and output structure of the first-stage analysis

final point regarding the data is that deflation of the monetary values is not necessary since the first-stage is based on the procedure of comparing two cross-sectional analysis results of each year. That is, the inflation rate does not affect the efficiency score of a certain year.

Table 14.3 Definition of explanatory variables in the second stage regression

Name	Definition
Age	Accumulation of business knowledge (Know-How) in years
Firm size (Number of employee)	Size of a firm in numbers
Labor intensity (Labor/capital)	Importance of labor compared to capital
R&D expenditure	Degree of R&D activity in Korean won
Debt ratio	Firms' ability(potentiality) to attract investment

In the second stage analysis, other explanatory variables such as age, number of employees, labor intensity, R&D expenditure, and debt ratio are used in the analysis. The meaning of the variables is explained in Table 14.3.

14.5 Empirical Results and Discussion

In this section, we compare the results of two methods, DEA/VRS (non-statistical) and order-m/FDH (statistical), and then justify why the latter is appropriate in analyzing this industry.

We first present the results of the DEA efficiency scores, as shown in Fig. 14.3. The distribution of efficiencies in a sub-sector of digital content firms (information provision) is distorted which suggests the existence of outliers. This industry is likely to have an outlier problem when the non-statistical approach is applied since too many firms in this industry are included in an extremely inefficient area.

The result of the order-m statistical method is shown in Fig. 14.3b. A comparison of Fig. 14.3a, b indicates that most firms are underestimated as being inefficient when the DEA method is applied. The results are more congregated in the efficient region because of the exclusion of outliers.

14.5.1 First Stage: Efficiency Distribution

When performing efficiency estimation of these industries as the first-stage analysis, we observe and compare the distribution of efficiency scores of each sub-sector in the digital content industry. We thereby obtain the overall picture of the industry and its problems from a policy maker's perspective. Simply, we can interpret the efficiency scores, given output, obtained by firms in frontiers with the least input, while others use more input than frontiers, even though we do not know the true production technology. Firstly, the common characteristics of the three sub-sectors are described and then their characteristics are compared.

A common feature that is evident in the distribution is the congregation of most digital content industry firms in the inefficient area, despite the application of the order-m frontier method. Furthermore, the inefficiency is sustained from 2000 to

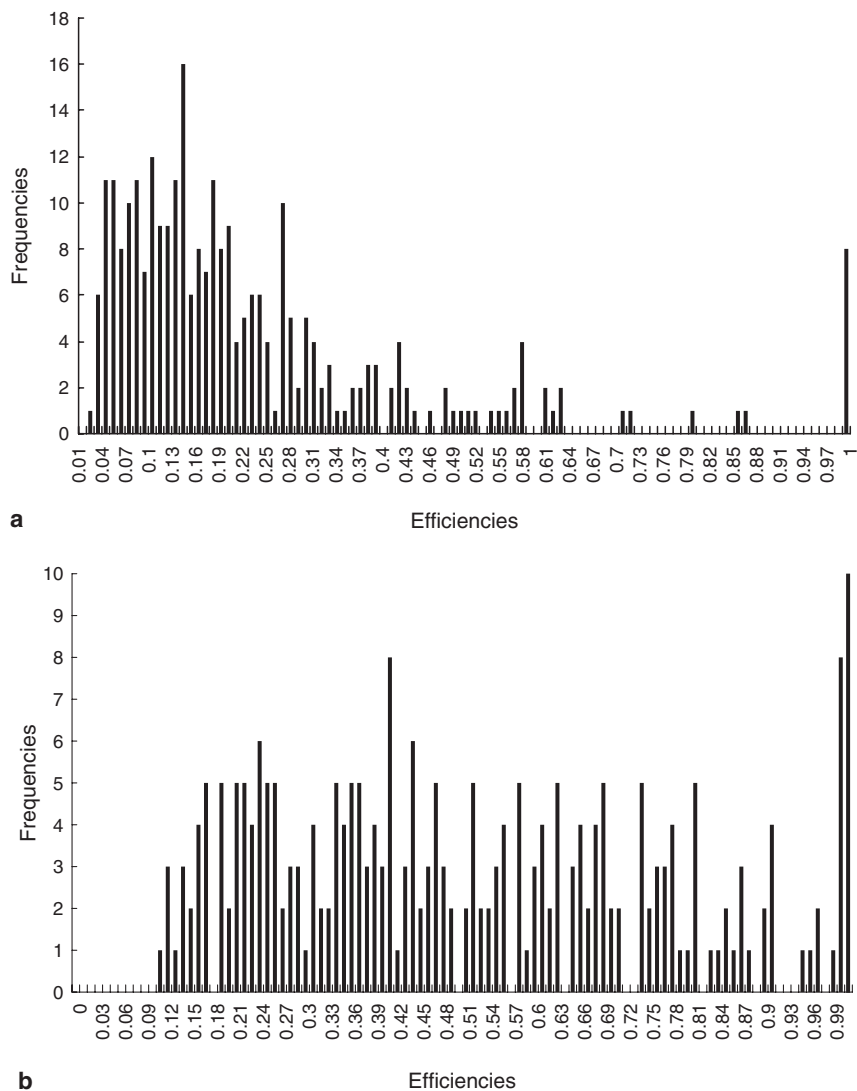


Fig. 14.3 Comparison between DEA efficiency and order-m frontier efficiency when applied to the information provision sector in 2004

2004. This continued inefficiency indicates low dynamics in this industry because high dynamics in an industry indicate low entry and exit barriers from the industry. In the sense that firms showing low efficiency should be able to exit easily from the field, this result indicates that the industry has a problem which must be rectified. In addition, appropriate policy measures will also be required. The continued presence of inefficient firms in the market can be explained by the following two reasons:

mismatched governmental promotion policy and firms' expectation of future profit. In the sense that the Korean economic situation did not improve from 2000 to 2004, the policy problem is strongly asserted. Because market pressure and the environment affect efficiency analysis, we can inversely estimate the market situation based on the efficiency characteristics.

When examining the efficiency distribution of each industry, the overall shape of the relative efficiency distribution changed between 2000 and 2004 in all three industries. The distribution was slightly moved from left to right in all three sub-sectors. However, the degree of change differed according to each sector. The software sector exhibited the smallest change among the three sub-sectors, whereas the information provision firms showed the most distinctive efficiency distribution changes.

The efficiency distribution in the game publishing sector is shown in Fig. 14.4. This sector is similar to others in having the presence of many inefficient firms. However, the average efficiency score in 2004 was decreased compared to 2000. The Korean government has tried to support this industry through an affiliated organization named the Korea Game Promotion Agency (KGPA), but to no significant avail. Game developing companies are increasing in numbers, but most firms are small-sized and unprofitable, such as mobile game developers. To develop a game for mobile phones, merely two developers and a 1-month period is sufficient on average. Since this easy developing environment lowers the entry barrier, the competition in the mobile game industry has increased while the profitability has decreased.

The information provision sector is one of the most rapidly growing sectors, as shown in Fig. 14.5. NHN and Daum are famous companies in this sector. The online advertisement market is growing especially fast because of the introduction of new business models such as keyword advertising. The change of the efficiency distribution supports this growth. The average efficiency scores are increased and the variance decreased. This change also indicates the growth of competition.

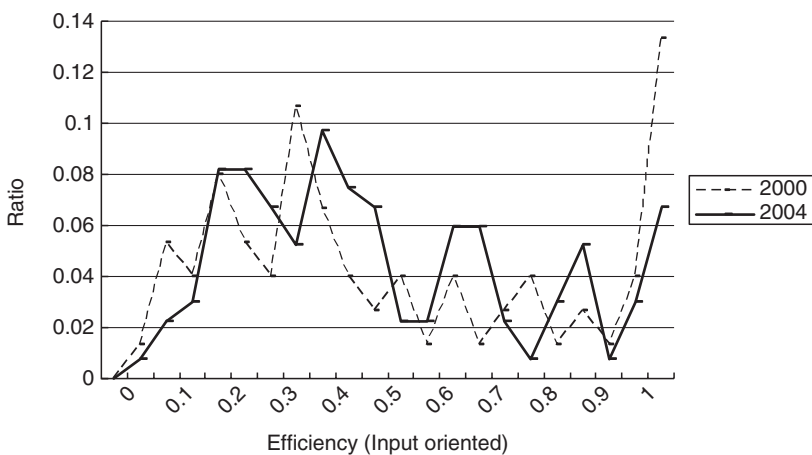


Fig. 14.4 Efficiency distribution of game publishing

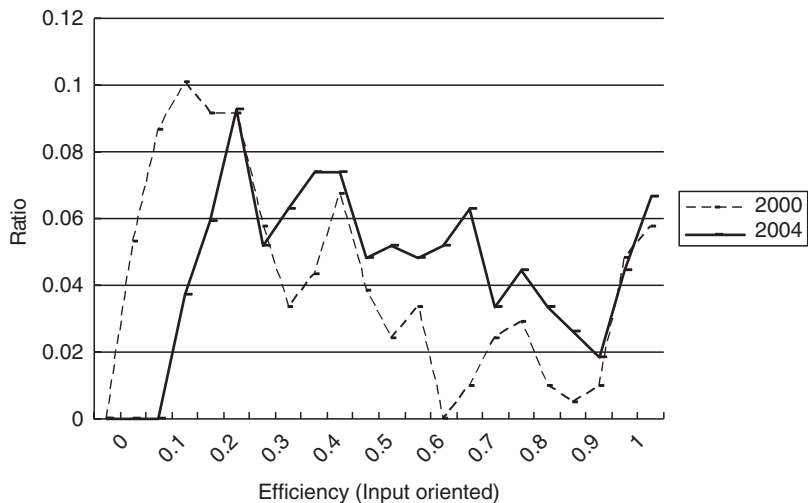


Fig. 14.5 Efficiency distribution of information provision

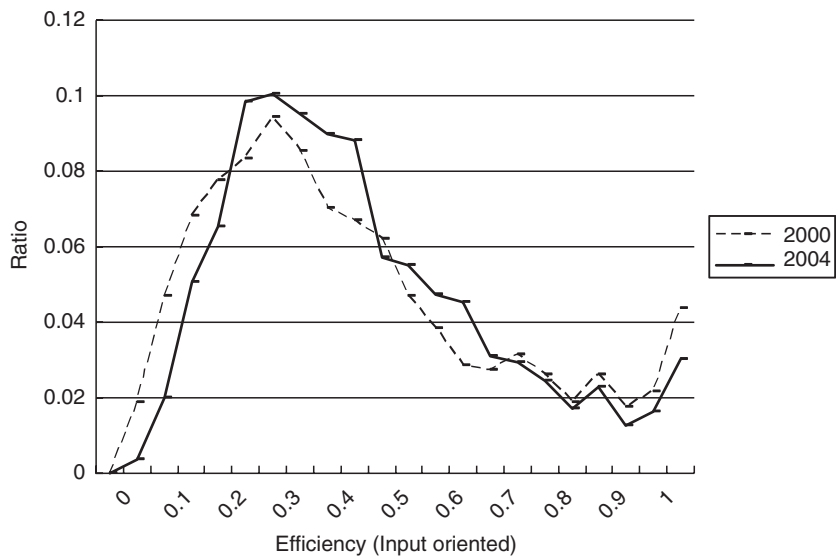


Fig. 14.6 Efficiency distribution of software manufacturing and consultancy

The change of efficiency distribution in the software sector is very slight compared to that of the others, as shown in Fig. 14.6, but the average efficiency score is slightly increased. In contrast to the game publishing and information provision markets, the software market seems to be stable according to the distribution change.

We can infer the degree of competition according to the change of distribution. In all three sub-sectors, variance is decreased, due to the increased sample size, but this also indicates a reduced efficiency gap between the higher and the lower players in the market and an increased degree of competition. In practice, the overall number of firms is increased in the digital content industry which increases the degree of competition. We also observe the second and third moments of distribution in each sector, as shown in Table 14.4. In the game publishing and information provision sectors, both kurtosis and skewness are decreased, indicating that the shapes of the distribution become flat and the right tail is shrunken, whereas the software sector changes in the opposite direction. With the changes in moment of higher degree, it is evident that the efficiency distribution is changed to a more efficient shape. Therefore, when we compare the efficiency distribution between 2000 and 2004, although most firms are located in the inefficient region, the distribution shape is nevertheless slightly improved and also the degree of competition is increased.

14.5.2 Second Stage: Variables Influencing Efficiency Scores

In the second stage analysis, we examine the factors which affect the efficiency scores and the extent of their influence. The results of the second stage analysis in the three sub-sectors are presented Table 14.5. The explanatory variables are the firm's age, size (number of employees), R&D investment, and labor intensity. The firm's age is the measure of how the efficiency scores are changed with age

Table 14.4 Efficiency score description of the three sectors

	Game		Information		Software	
	2000	2004	2000	2004	2000	2004
Average	0.67	0.5	0.47	0.53	0.43	0.44
Variance	0.6	0.09	0.52	0.08	0.07	0.06
Kurtosis	20.73	-0.43	70.21	-0.75	-0.26	0.1
Skewness	3.98	0.66	7.34	0.46	0.76	0.84
Observations	73	129	196	264	1,536	2,157

Table 14.5 Parameter estimates on the three sectors

	Parameter estimates on efficiency scores		
	Game	Information	Software
Age	-0.104*** (0.039)	-0.017 (0.013)	-0.014** (0.006)
Size	0.005*** (0.002)	-0.0002 (0.00014)	0.002*** (0.0004)
R&D	0.104*** (0.039)	-	0.018 (0.014)
Labor intensity	-0.072 (0.084)	0.069** (0.03)	0.156*** (0.019)
Debt ratio	0.07 (0.062)	-	0.067*** (0.019)

Significant at 5% level, *Significant at 1% level

among the examined firms. In general, since managers and workers in a firm can learn how to improve their performance as time passes, researchers expect a positive correlation between age and efficiency. The firm's size can show whether or not the number of employee is important in increasing efficiency. The number of employees can have both positive and negative effects on the efficiency according to the marginal cost of labor. Since we use cross-sectional data in this analysis, we can only identify if a large firm shows a more efficient performance than others do. Labor intensity is computed according to the labor expenditure per capital and indicates how the share of labor expenditure is important in efficiency.

In the case of the game sector, age, size, and R&D investment are significant with efficiency scores. Size and R&D investment have a positive correlation with efficiency. However, age has a negative correlation, indicating that younger firms, with more original ideas, are more efficient than older ones. Nevertheless, this also indicates that most game companies which succeeded with their first developed games cannot sustain profitability in the subsequent games in Korea. This result verifies the Korean situation. The important influence factors differ according to the sectors in the digital contents industry. In the information provision sector, only labor intensity shows a significant relationship, while age, size, labor intensity, and debt ratio are significant in the software sector. The result of the age and efficiency scores is also similar to the game sector. For the firms in the digital content industry, a larger investment is required to sustain competitiveness, which increases the inefficiency in the production process. Surprisingly, the debt ratio shows a positive correlation with efficiency in the software sector, because large size and large investment are needed for a firm to be competitive and this indicates that firms with good credit drawing investments will be more competitive. R&D investment is a more important factor than labor intensity for the game sector, which needs the highest production creativity among the three sectors. In contrast, the information provision and software sectors that perform information processing and diffusion are more affected by labor intensity for the production efficiency.

14.6 Conclusion

It was a very strategic and efficient policy for Korea, a small country with few natural resources, to develop ICT as an alternative source of development. In the next generation, creative and diverse digital contents will be the main factors to ensure the sustainable development of the ICT industry. Therefore, the present period is a very critical time for Korea to inspect its ICT policy. In this paper, we have tried to determine the performance of Korean digital content firms and present the policy implications for the future industry. For these purposes, the measurement of efficiency in an industry is a critical tool in policy making. This study has analyzed the production efficiency of a newly emerging industry with different characteristics than those of the current manufacturing firms. We have applied the non-parametric approach to show that the digital content industry suffers from outlier problems

when estimating efficiency scores. As the presence of outliers causes most DMUs to be underestimated in the efficiency measure, we introduce a statistical method called the order-m frontier model and form the input and output factors by proper decision-making according to the industry characteristics.

The crucial problem of this industry is the continued presence of many firms in the inefficient region despite the removal of outliers. A policy to solve this problem should be devised. We compared the changes in efficiency distribution from 2000, when the industry was growing rapidly, to 2004, when the growth had become relatively stable according to each sub-sector. The distribution shapes were slightly improved in 2004, but the changes differed in each sub-sector. The second stage analysis examined how the explanatory variables affected the efficiency score.

Our analysis has several policy implications. The important influence factors differed according to the sectors in the digital contents industry. Most game companies which succeeded with their first developed games could not sustain profitability in their subsequent games in Korea. R&D investment was a more important factor than labor intensity for the game sector. However, the information provision and software sectors that perform information processing and diffusion were more affected by labor intensity for the production efficiency.

In sum, newly emerging industries like the digital content industry require a new method to analyze efficiency, while various promotion policies are also needed by the sub-sectors to sustain this explosive growth.

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Chapter 15

Analysis on the Technical Efficiency and Productivity Growth of the Korean Cable SOs: A Stochastic Frontier Approach

K. Kim and A. Heshmati

15.1 Introduction

Cable TV in Korea started in 1995 to provide service of multi-channel broadcasting and this marked the beginning of the new media era as well as the initial launching of video subscription services in Korea. Thereafter, new multimedia broadcasting such as digital satellite broadcasting (DSB) in 2001 and digital multimedia broadcasting (DMB) in 2005 were subsequently introduced. At the early stage of development of the Korean Cable TV industry, operators were separately permitted as program provider (PP), system operator (SO) and network operator (NO). In order to minimize the negative structural effects from belonging to specific companies such as the Press, large conglomerates and so on, they were not allowed to have cross-ownership. As first and second SO licensees, 53 metropolitan-centered SOs and 24 provincial-centered SOs were licensed in 1994 and 1997 respectively. Thereafter, Relay Operator (RO) were two times switched to SO for the revitalization of Cable TV through the unification of the laws and regulations in this industry.

After the introduction of Cable TV in 1995, the market performance in early 5 years is evaluated to be weak in comparison with the expectations. This partly resulted from the early stage of launching the new service, macroeconomic shock from the Asian Financial crisis in late 1990s and so on, but mostly due to the competition structure such as SO and RO and over-regulation in Cable TV industry. In the year 2000, the New Broadcasting Act of year 2000 was enacted and it helped to set the stage for early-stage Cable TV consolidation through the deregulation of cross-ownership restrictions to allow ownership of both PPs and SOs to solve these difficult conditions in this industry.

The condition of Cable broadcasting on its tenth anniversary, March 1 2005, was very good. The service that began with 48 SOs and 24 PPs has grown threefold in

K. Kim

Technology Management, Economics, and Policy Program, Seoul National University,
Seoul, South Korea

A. Heshmati

University of Kurdistan Hawler, Federal Region of Kurdistan, Kurdistan, Iraq

10 years to 119 SOs and 179 PPs. Subscribers of Cable TV also grew from 229,469 households in 1995 to over 13 million as of now. It has grown more than 60 times, despite the fierce competitive multi-channel broadcasting environment. The size of Cable SOs in the year 2005 can also be estimated through its revenue (1.6 trillion won) and the total assets (4.0 trillion won). Currently, this industry is attempting a second takeoff through a mandate of digital transformation. However, the Korean Cable TV industry is facing a lot of challenges with prevailing low-priced competition environment, the shortage of diverse appealing contents, and continuing introduction of new media such as Digital Satellite Broadcasting (DSB), Digital Multimedia Broadcasting (DMB), and Internet Protocol Television (IP-TV) with technology progress.

In recent years, the process of convergence between telecommunications and broadcasting industries is accelerating than ever. In Korea, the Cable SOs, which had been providing Cable TV service to their local areas, recently has began to provide bundled high-speed Internet access services through Cable TV network infrastructure and the number of subscribers has reached 2.78 million households as of January 2006. The number of customers is about 20% of total market share of broadband service in Korea. According to the research from the Korean Cable TV Association (KCTA) and Media Partners Asia (MPA), analog cable TV penetration is peaking in Korea. More than 77% of household or a total of 13 million subscribers, subscribed to analog cable in 2005, while only less than 1% subscribed to digital Cable TV. In 2005, the Cable SO industry's turnover grew by 14% to 1.6 trillion Won, of which 47% was derived from Cable TV subscription, 26% from broadband and 19% from home shopping and advertising. The net profit reached at 105 billion Won.

As mentioned above, Korean Cable TV industry has been experiencing policy changes such as deregulation as well as convergence between telecommunications and broadcasting sectors. Therefore it is meaningful to investigate the impacts of policy and deregulation on the firms' performance by the analyses of several factors such as licensing sequence, competition environment, the availability of broadband internet, mergers and acquisitions and service regions of SOs. The aim of this paper is to analyze Cable SOs' technical efficiency and productivity growth by using the stochastic frontier approach in order to investigate the impact of various policy changes. This paper provides a detailed analysis of technical efficiency and productivity growth for a sample of specialized Korean Cable SOs from the year 2000 to 2005. The data is unbalanced and it covers Korean Cable SOs. A total of 551 observations are analyzed for 119 SOs firms observed. The efficiency effects or determinants of level of efficiency are the number of employee, capital, material cost and other characteristic variables.

The remainder of this study is organized into several sections. In the following section, we review and summarize the related literature for methodology. We then describe our research model, data and specification and present our results. Finally, we present our discussion and policy implications. The findings provide helpful insights to the Korean Cable TV industry as well as to the researchers pursuing inquiry in this dynamic research area.

15.2 Review of the Literature

The concept of the technical efficiency of firms has been central for the development and application of econometric models of frontier functions. Since Farrell (1957) introduced the definition of a frontier production function, i.e. the fundamental concept of measuring the technical efficiency of individual firms. Since then, the literature has developed and many researchers have contributed to the study of productive efficiency. The measurement of efficiency has been the main motivation for the study of frontier functions. The frontier is used to measure the efficiency of production units by comparing observed and potential outputs. Potential output is obtained by using the best practice technology from a given vector of inputs, produced by the most productive firm(s) in the sample data.

The literature on the estimation of frontier functions to measure the economic efficiency of firms has been developed in different directions. The different approaches to production, cost and profit frontiers are used to estimate the components of economic efficiency, i.e. technical and allocative efficiency components. The former is a measure of possible reduction in inputs to produce a given level of output, or alternatively, potential increase in output for a given level of input usage and technology, while the latter is a measure of the possible reduction in the cost of using the correct input proportions to produce a given level of output. Frontier functions can be classified according to the way the frontier is specified and estimated. The classification might be based on the parametric/non-parametric, deterministic/stochastic and cross-section/panel data specifications of the frontier functions.

The frontier is called deterministic if all the observations must lie on or below the frontier and stochastic if observations can be above the frontier due to random events. Prior to the introduction of stochastic model, Aigner and Chu (1968), Timmer (1971), Afriat (1972), Richmond (1974), and Schmidt (1976) considered the estimation of deterministic frontier models whose values were defined to be greater than or equal to the observed values of production for different levels of inputs in the production process. The stochastic frontier production, which was independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), has been a significant contribution to the econometric modeling of production and the estimation of technical efficiency of firms. Schmidt (1986), Greene (1997), Kalirajan and Shand (1999), Kumbhakar and Lovell (2000) and Heshmati (2003) present an overview of the concept, modeling, estimation of models and methods involved in making efficiency comparisons.

The stochastic frontier involves two random components, one associated with the presence of technical inefficiency and the other being a traditional random error. The stochastic frontier models can be estimated by corrected ordinary least square, methods of moments, generalized least square or maximum likelihood methods. The random component is assumed to be independently and identically normally distributed, while the inefficiency component is assumed to be distributed as either exponential, half-normal, truncated normal or gamma.

Applications of frontier functions have involved both cross-sectional and panel data. Panel data models in the stochastic frontier literature can be divided into two main groups. The first group assumes technical efficiency to be time-invariant (Pitt and Lee (1981); Schmidt and Sickles (1984); Battese and Coelli (1988)). The second group allows technical efficiency to be time-varying (Cornwell et al. (1990); Kumbhakar (1990); Battese and Coelli (1992); Lee and Schmidt (1993)). Each of these two groups can be further sub-classified depending on whether or not any distributional assumptions or functional forms are imposed on the error component. These studies have made a number of distributional assumptions for the random variables involved and have considered various estimators for the parameters of these models.

The distance function applications were at first almost entirely based on non-parametric data envelopment analysis (DEA) models which have the advantage of being easily applicable to cases with multiple outputs, without price information. Löthgren (1997) suggested ray frontier production function, closely related to the distance function of Shephard (1970) to develop a multiple-output generalization of the single-output stochastic frontier production model. The advantage of the non-parametric techniques is the minimum requirements needed about the technology for the calculation of distance functions, but on the other hand, only an econometric approach may allow for stochastic circumstances affecting production and productivity. On the other hand, econometric techniques require assumptions to be made about the functional form, which despite limited testing possibilities may not be correctly chosen.

In principle, the productivity change can be decomposed into four components: technical change, technical efficiency change, scale effect and price (allocative) effect. The term of technical change refers to shift in the production function as a result of change in the production technology that can come from an improved method of using the existing inputs (disembodied technical change), through changes in input quality (embodied technical change), or through the introduction of new processes and new inputs. In the case of several inputs and outputs, it is possible to apply the Malmquist productivity index to measure total factor productivity. The Malmquist index serves in identifying various sources of productivity change since several decompositions for this index have been proposed (Färe et al. 1994; Orea 2002; Lovell 2003). This index has the advantage that it does not require price information or behavioral assumptions, however, a representation of the production technology is needed in the form of distance functions which is applicable to case with multiple production function analysis. Recently, several authors have developed parametric approaches for those distance functions (Fuentes et al. (2001); Brummer et al. (2002); Orea (2002); Sipiläinen and Heshmati (2004); Goto and Tsutusi (2006)).

In earlier studies on Korean Cable TV industry, most of these researches have been applied to the competition and market performance of Korean Cable TV industry using cross-sectional data. Lee et al. (1999) investigated the development process of the Korean Cable TV and subsequently analyzed the dual-franchise structure, especially for the relationship between SO and RO. They indicated the

existence of substitutability and the necessity of policy for mutual competition between SO and RO. Yun et al. (2001) suggested that multi-RO (MRO) should be encouraged because of RO's low price, high quality, market penetration and so on. Kwon and Kim (2004) studied the actual condition of this industry and indicated that the competition was beneficial to subscribers, but harmful to the operators and it did not affect the improvement of service quality, instead affected a drop in prices. Recently Jeon (2005) found that consumer's social benefit was high when there was competition among MSOs under competitive market structure rather than monopolistic market structure, and the efficiency was highest when SOs were moderately integrated.

15.3 The Methodology

15.3.1 Distance Functions

In this paper, we apply econometric methods for the measurement and analysis of technical efficiency and total factor productivity of the sample firms. A production technology transforming inputs into outputs can be represented by the technology set, which is a list of the technological feasible combinations of inputs and outputs. If the vector of M outputs is denoted by $y = (y_1, y_2, \dots, y_M)$ and the vector of N inputs is denoted by $x = (x_1, x_2, \dots, x_N)$, the technology set can be defined by:

$$T = \{(x, y) : x \in R_+^N, y \in R_+^M, x \text{ can produce } y\} \quad (15.1)$$

For each input vector, x , let $P(x)$ be the set of feasible output vectors, y , that are obtainable from the input vector x then:

$$P(x) = \{y : (x, y) \in T\} \quad (15.2)$$

The output distance function can be defined in terms of the output set as

$$D_o(x, y) = \min \left\{ \theta > 0 : \frac{y}{\theta} \in P(x) \right\} \quad (15.3)$$

$D_o(x, y)$ is non-decreasing, positively linearly homogenous and convex in y , and it is decreasing in x (Färe and Primont 1995). It is defined as the maximum feasible expansion of the output vector with the input vector held fixed. That is, given an input vector, x , the value of the output distance function, $D_o(x, y)$, places $y/D_o(x, y)$ on the outer boundary of $P(x)$ and on the ray through y . The value of the distance function is less than or equal to one for all feasible output vectors. On the outer boundary of the production possibilities set, the value of $D_o(x, y)$ is one. Thus, the output distance function indicates the potential radial expansion of the production to the frontier. Stochastic frontier production function analysis can be extended to stochastic output distance function analysis if there are multiple outputs.

Assume now that firm's output-oriented distance function follows a translog functional form (TL is an abbreviation):

$$\begin{aligned}
 \ln D_o^t(x_i^t, y_i^t) = & \alpha_0 + \sum_{k=1}^n \alpha_k \ln x_{ki}^t + \beta_0 D_i^t + \sum_{j=1}^m \beta_j \ln y_{ji}^t \\
 & + \frac{1}{2} \sum_{k=1}^n \sum_{h=1}^n \alpha_{kh} \ln x_{ki}^t \ln x_{hi}^t + \frac{1}{2} \sum_{j=1}^m \sum_{h=1}^m \beta_{jh} \ln y_{ji}^t \ln y_{hi}^t \\
 & + \sum_{k=1}^n \sum_{j=1}^m \gamma_{kj} \ln x_{ki}^t \ln y_{ji}^t + \phi_0 t + \phi_{00} t^2 + \\
 & \sum_{k=1}^n \xi_{kt} t \ln x_{ki}^t + \sum_{j=1}^m \tau_{jt} t \ln y_{ji}^t
 \end{aligned} \tag{15.4}$$

where D_o is the output distance function, x :s are inputs, y :s outputs, t is time trend, D_i is dummy and $\alpha, \beta, \gamma, \phi, \xi, \tau$: s are coefficients to be estimated.

It is not possible to estimate the function in (15.4) in its current form unless the property of linear homogeneity in outputs is applied. The output distance function is by definition linearly homogenous in outputs. Dividing the outputs by one of the outputs imposes the linearly homogeneity in outputs.

Homogeneity in output implies that $D_o(x, \mu y) = \mu D_o(x, y)$, $\mu > 0$, and by arbitrarily choosing one of the outputs (ex. m -th), such as y_{mi} , we can set $\mu = 1/y_{mi}^t$:

$$D_o^t(x_{ki}^t, y_{ji}^t / y_{mi}^t) = D_o^t(x_{ki}^t, y_{ji}^t) / y_{mi}^t \tag{15.5}$$

Transforming the variables in logarithms and rearranging the equation gives the translog functional form, yielding a regression of the general form as:

$$-\ln y_{mi}^t = TL(x_{ki}^t, y_{ji}^t / y_{mi}^t, t; \alpha, \beta, \gamma, \phi, \xi, \tau) - \ln D_o^t(x_{ki}^t, y_{ji}^t) \tag{15.6}$$

Setting $D_o^t(x_i^t, y_i^t) = \exp(-u_{it})$ and adding a stochastic error term (v_{it}), our presentation is similar to that of a parametric stochastic frontier with a decomposed error term:

$$-\ln y_{mi}^t = TL(x_{ki}^t, y_{ji}^t / y_{mi}^t, t; \alpha, \beta, \gamma, \phi, \xi, \tau) + u_{it} + v_{it} \tag{15.7}$$

where $u_{it} \geq 0$ are time-varying inefficiency effects and represent factors that can be controlled by the firm. V_{it} is statistical noise assumed to be independently and identically distributed.

15.3.2 The Efficiency Effect Model

The technical inefficiency effect, u_{it} , is assumed to be a function of a set of explanatory variables, Z_{it} s, being treated as determinants of technical inefficiency and an unknown vector of coefficients, δ s:

$$u_{it} = \sum_s \delta_s z_{sit} + \omega_{it} \quad (15.8)$$

The explanatory variables in the inefficiency model may include some input variables in the stochastic frontier, provided the inefficiency effects are stochastic. Following Battese and Coelle (1995), we assume $\omega_{it} \sim \text{i.i.d. } N(0, \sigma_u^2)$ truncated at $-\sum_s \delta_s z_{sit}$ from below, or equivalently, $u_{it} \sim N\left(\sum_s \delta_s z_{sit}, \sigma_u^2\right)$ truncated at zero from below.

15.3.3 Malmquist Productivity Index

At early stages of development of the methodology of productivity analysis, productivity change was considered identical with technological change. Technological change describes how the sets of feasible input–output combinations expand or contract. Later on, technical efficiency change was invented as an important factor in productivity growth. When technological change is related to shifts of the frontier, efficiency change shows if the firm is getting closer to or further away from the frontier. The use of the Malmquist index enables us to combine these changes. However, according to Balk (2001, p.160), there remain two problems: first, whether to use actual or artificial technology and second, how to take scale effect (scale efficiency) into account. The scale of production may affect the productivity (in the sense of output–input relation), and thus also the productivity changes, even if the firm operates on the frontier but in a different scale (or size). Therefore, we define scale effect as a part of productivity change. In addition to changes in levels of inputs and outputs, in a multiple input multiple output case, input and output mixes may change over time. These changes may also affect productivity change. With regard to this, e.g. Kumbhakar and Lovell (2000) emphasize that also price or market effects should be taken into account when TFP changes are evaluated.

In order to measure productivity change, time has to be incorporated. Let's denote t and $t + 1$ as two adjacent time periods. Thus, $D^t(x^t, y^t)$ refers to the evaluation of the firm's distance in the period t from the frontier of the same period. When evaluated against the technology of the period t , the Malmquist productivity index is:

$$M^t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \quad (15.9)$$

but, when evaluated against the technology of the period $t + 1$, it is written as:

$$M^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \quad (15.10)$$

However, the choice of the time period is arbitrary. Caves et al. (1982) presented that under the assumption of technical and allocative efficiency (s.t. translog

functional form) productivity change is equal to a geometric mean of these two indices:

$$M = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \quad (15.11)$$

15.3.4 Generalized Malmquist Productivity Index

Recently Orea (2002) suggested a generalized Malmquist productivity index. Starting from Diewert's (1976) quadratic identity lemma, he derived a natural logarithmic productivity index that can be defined as the difference of the weighted average rates of growth of outputs and inputs. Using this identity, changes in the distance function (15.4) from one period to the next can be written as:

$$\begin{aligned} \ln D_o(t+1) - \ln D_o(t) &= \frac{1}{2} \sum_{j=1}^m \left[\frac{\partial \ln D_o(t+1)}{\partial \ln y_j} + \frac{\partial \ln D_o(t)}{\partial \ln y_j} \right] \cdot (\ln y_j^{t+1} - \ln y_j^t) \\ &+ \frac{1}{2} \sum_{k=1}^n \left[\frac{\partial \ln D_o(t+1)}{\partial \ln x_k} + \frac{\partial \ln D_o(t)}{\partial \ln x_k} \right] \cdot (\ln x_k^{t+1} - \ln x_k^t) \\ &+ \frac{1}{2} \left[\frac{\partial \ln D_o(t+1)}{\partial t} + \frac{\partial \ln D_o(t)}{\partial t} \right] \end{aligned} \quad (15.12)$$

where $D_o(t)$ is short for $D_o(x^t, y^t, t)$. Let M_o be an index of productivity that can be defined in natural logs as:

$$\begin{aligned} \ln M_o &= \frac{1}{2} \sum_{j=1}^m \left[\frac{\partial \ln D_o(t+1)}{\partial \ln y_j} + \frac{\partial \ln D_o(t)}{\partial \ln y_j} \right] \ln \left(\frac{y_j^{t+1}}{y_j^t} \right) \\ &- \frac{1}{2} \sum_{k=1}^n \left[\frac{\partial \ln D_o(t+1)}{\partial \ln x_k} + \frac{\partial \ln D_o(t)}{\partial \ln x_k} \right] \ln \left(\frac{x_k^{t+1}}{x_k^t} \right) \end{aligned} \quad (15.13)$$

This productivity index can be broadly defined as the difference between the weighted average rates of growth of outputs and inputs, where the weights are output distance elasticities and (negative) input distance elasticities respectively. Rearranging (15.13), $\ln M_o$ can be decomposed as:

$$\begin{aligned} \ln M_o &= [\ln D_o(x^{t+1}, y^{t+1}, t+1) - \ln D_o(x^t, y^t, t)] - \\ &\frac{1}{2} \left[\frac{\partial D_o(x^{t+1}, y^{t+1}, t+1)}{\partial t} + \frac{\partial D_o(x^t, y^t, t)}{\partial t} \right] \end{aligned} \quad (15.14)$$

Equation (15.14) provides a meaningful decomposition of $\ln M_o$ into changes in technical efficiency and technical change. The negative sign of the second term transforms technical progress (regress) into a positive (negative) value.

This decomposition has the same structure as the traditional output-oriented Malmquist productivity index introduced by Caves et al. (1982), which can be defined as (15.11). As is customary, the right-hand side of this index can be rewritten as the product of the technical efficiency change (EC) and technical change (TC) components. That is written as:

$$M_c = \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^{t+1}, y^{t+1})} \frac{D_c^t(x^t, y^t)}{D_c^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \quad (15.15)$$

Equation (15.15) decomposes M_c in the same way that (15.14) decomposes $\ln M_o$, except for two minor differences. First, the decomposition in (15.14) is expressed in terms of proportional rates of growth, while it is expressed as a product of indexes in (15.15). Second, the technical change component in (15.14) is based on the estimates of the parameters, whereas it is calculated by evaluating several distance functions in (15.15). Thus $\ln M_o$ is a parametric counterpart to M_c when the output-oriented distance function is translog, but here the subscript c indicates that the frontier is defined under the assumption of constant returns to scale. The decomposition can be extended to allow also non-constant returns to scale. This is possible if scale effect will be taken into account.

Starting from the ideas of Denny et al. (1981) who developed measures of productivity growth from an estimated multi-output cost function, Orea (2002) proposed a generalized output-oriented Malmquist productivity index where he aggregated growth in inputs by distance elasticity shares instead of distance elasticities:

$$\ln G_o = \frac{1}{2} \sum_{j=1}^m [\varepsilon_j(t+1) + \varepsilon_j(t)] \cdot \ln \left(\frac{y_j^{t+1}}{y_j^t} \right) - \frac{1}{2} \sum_{k=1}^n [e_k(t+1) + e_k(t)] \cdot \ln \left(\frac{x_k^{t+1}}{x_k^t} \right)$$

where

$$\varepsilon_j(t) = \frac{\partial \ln D_o(x^t, y^t, t)}{\partial \ln y_j}, \quad e_k(t) = \frac{\partial \ln D_o(x^t, y^t, t) / \partial \ln x_k}{\sum_{k=1}^n \partial \ln D_o(x^t, y^t, t) / \partial \ln x_k} \quad (15.16)$$

Equation (15.16) measures the growth in outputs not accounted for by the growth in inputs. $\ln G_o$ is now a total factor productivity because it satisfies the proportionality property (as its input weights sum to one), as well as the identity, separability, and monotonicity properties.

Using (15.12), the productivity index of (15.16) can be decomposed into $\ln M_o$ and returns to scale term. That is:

$$\ln G_o = \ln M_o + \frac{1}{2} \sum_{k=1}^n \left[\left(- \sum_{k=1}^n \frac{\partial D_o(x^{t+1}, y^{t+1}, t+1)}{\partial \ln x_k} - 1 \right) \cdot e_k(t+1) + \left(- \sum_{k=1}^n \frac{\partial D_o(x^t, y^t, t)}{\partial \ln x_k} - 1 \right) \cdot e_k(t) \right] \cdot \ln \left(\frac{x_k^{t+1}}{x_k^t} \right) \quad (15.17)$$

The productivity index $\ln M_0$ can also be decomposed into technical efficiency change and technical change using (15.14). The scale term relies on scale elasticity values and on changes in input quantities, and therefore it vanishes under the assumption of constant returns to scale or constant input quantities. When these do not exist, the scale term evaluates the contribution of non-constant returns to scale on productivity growth when firms move along the distance function changing their inputs levels over time.

15.4 The Data

Our unbalanced panel data covering the period 2000–2005 are obtained from the population of 119 Cable SOs. The panel data contains a total of 551 observations over 6 years. The number of observations of a given SO varies from 1 to 6, due to the lack of required information or late entry into this industry.

In our analysis, we apply three revenue based output measures of: subscription fee, internet fee and other fee for Cable TV service. The input used in the analysis includes: the number of employees, capital, and material cost. Subscription fee, internet fee and other fee, capital and material cost are measured in monetary values and deflated to fixed year 2000-prices. The variable employee is measured in number of employees. Table 15.1 presents the descriptive statistics of the data.

Table 15.1 shows that the mean of the variable sales revenues of subscription fee, internet fee and other fee were 4.1, 1.7 and 2.7 billion Won, respectively. The mean number of employee was 50, capital of 20.1 billion Won and material cost of 5.1 billion Won. The corresponding minimum values are: 4.2 million Won, zero Won, 40.0 million Won, 3 employee, 390.0 million Won, and 40.0 million Won, respectively. The corresponding maximum values are: 18.4 billion, 31.3 billion, 12.6 billion Won, 257 employee, 414.0 billion Won, and 38.0 billion Won, respectively.

Table 15.1 Descriptive statistics of the sample data set

All year from 2000 to 2005, obs = 551					
Variables	Unit	Mean	Std dev	Minimum	Maximum
Outputs					
Subscription fee (Y_s)	1,000 Won	4,138,631	3,264,300	4,253	18,401,448
Internet fee (Y_i)	1,000 Won	1,695,875	3,109,907	0	31,338,302
Other fee (Y_o)	1,000 Won	2,713,649	2,234,341	40,000	12,592,346
Inputs					
Employee (L)	Number	50	32	3	257
Capital (K)	1,000 Won	20,181,211	33,839,413	390,004	414,030,236
Material cost (M)	1,000 Won	5,087,334	5,048,089	40,043	37,978,358

15.5 Specification and Estimation of the Model

We adopt the following translog functional form to represent Cable SOs' production technology. The generic output distance function in (15.4) can, therefore, be written as:

$$\begin{aligned}
 -\ln y_{0i}^t = & \left[\alpha_0 + \sum_{k=1}^3 \alpha_k \ln x_{ki}^t + \beta_0 D_{li}^t + \sum_{j=1}^2 \beta_j \ln y_{ji}^{*t} + \frac{1}{2} \sum_{k=1}^3 \sum_{h=1}^3 \alpha_{kh} \ln x_{ki}^t \ln x_{hi}^t \right. \\
 & + \frac{1}{2} \sum_{j=1}^2 \sum_{l=1}^2 \beta_{jl} \ln y_{ji}^{*t} \ln y_{li}^{*t} + \sum_{k=1}^3 \sum_{j=1}^2 \gamma_{kj} \ln x_{ki}^t \ln y_{ji}^{*t} + \varphi_0 t + \varphi_{00} t^2 \left. \right] \\
 & + \sum_{k=1}^3 \xi_{kt} t \ln x_{ki}^t + \sum_{j=1}^2 \tau_{jt} t \ln y_{ji}^{*t} \left. \right] + v_{it} + u_{it}
 \end{aligned} \quad (15.18)$$

where i represents the SOs firm ($i = 1, \dots, 119$) and t the year of observation ($t = 1, \dots, 6$). The output variables applied in the analysis are: subscription fee (y_{0i}), internet fee (y_{1i}^*) and other fees (y_{2i}^*) measured by each type of fees variable divided by the subscription fees. D_{li} is a dummy variable to capture the effect of zero internet fee, which has value one if internet fee was zero, i.e. no service, and zero, otherwise. This dummy variable permits the intercept to be different for SOs with positive and zero internet service fee. The input variables denoted as x_1 to x_3 are: the number of employee, capital, material cost.

The error term is decomposed into two components. The first component, v_{it} , is a standard random variable capturing effects of unexpected stochastic changes in production conditions, measurement errors in output or the effects of left-out explanatory variables. It is assumed to be independent and identically distributed with $N(0, \sigma_v^2)$. The second component, are independently distributed with a truncation at zero of $N(\mu_{it}, \sigma_u^2)$, where μ_{it} is modeled in terms of determinants of inefficiency as:

$$\begin{aligned}
 \mu_{it} = & \delta_0 + \delta_{lch} CHN + \delta_{int} D_{int} + \delta_t TIME + \delta_{comp} D_{comp} + \delta_{mso} D_{mso} + \\
 & \sum_{i=1}^3 \delta_{sopi} D_{sopi} + \sum_{j=1}^2 \delta_{regj} D_{regj} + \delta_{intt} D_{int} * D_{year2000}
 \end{aligned} \quad (15.19)$$

where the D_j^s are dummy variables having value one and zero. CHN refers to the logarithmic variable of the number of channels, D_{int} refers to the availability of internet service dummy variable (1 = available, 0 = unable), is a time trend variable, D_{comp} to competition environment dummy (1 = monopoly, 0 = competition), D_{mso} is MSO dummy (1 = MSO, 0 = single SO), D_{sopi} s are dummy variables for the licensing sequence, D_{regj} s refer to service regional dummy variables, $D_{year2000}$ refers to year 2000 (1 if year is 2000, zero otherwise). Licensing sequence of Cable services is classified as first, second, third, and fourth. Service regions are classified as

Seoul, metropolitan cities exclusive of Seoul and other provincial areas. Competition environment is classified as monopoly, competition (duopoly) and two SOs under the same MSO in a franchise area are treated as monopoly in this model. The δ :s are unknown efficiency effects regression coefficients. Therefore, the inefficiency effects part of the equation make it possible to test whether technical efficiencies differ by characteristics such as the number of channels, the availability of internet service, time trend, competition environment, MSO, the licensing sequence, and service region.

The variance parameters are defined as $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma_s^2$ where γ takes the value between 0 and 1. This parameterization allows us to search across this range to obtain a good starting value for γ , for use in an iterative maximization process involving the Davidon–Fletcher–Power algorithm (Coelli 1996). Under these assumptions, maximum likelihood estimation method will give asymptotically efficient estimates for all the parameters in (15.18). Given translog stochastic frontier specification of output distance function, technical efficiency of production can be obtained from the conditional expectation of $TE_{it} = \exp(-u_{it}) = \exp(-z_{it}\delta - \omega_{it})$, given the random variable ε_{it} ($\varepsilon_{it} = v_{it} - u_{it}$; Battese and Coelli 1988). The level of estimated technical efficiency is by definition between 0 and 1, and it varies across firms and over time.

We applied the following approach proposed by Horrace and Schmidt (1996) and also applied in Hjalmarsson et al. (1996) for the estimation of confidence intervals for individual points estimates of technical efficiency. Given the distributional specification for u_i , it can be shown that a $(1-\alpha)100\%$ confidence predictor for u_i is defined by $[u_i(\text{upper}), u_i(\text{lower})]$, where $u_i(\text{upper})$ and $u_i(\text{lower})$ are defined by

$$\begin{aligned} u_i(\text{lower}) &= \mu_i + \sigma\Phi^{-1}[1 - (1-\alpha/2)\Phi(\mu_i/s)] \text{ and} \\ u_i(\text{upper}) &= \mu_i + \sigma\Phi^{-1}[1 - (\alpha/2)\Phi(\mu_i/s)] \end{aligned} \quad (15.20)$$

Where $\Phi(\bullet)$ denotes the standard normal distribution function. Thus a $(1-\alpha)100\%$ confidence predictor for $[\exp(u_i) - 1]$ can be defined by:

$$\{ \exp[u_i(\text{lower})] - 1, \exp[u_i(\text{upper})] - 1 \} \quad (15.21)$$

Horrace and Schmidt (1996) have suggested that the confidence prediction should be based on conditional distribution of u_i , given $v_i - u_i$ in the context of a production function. However, the conditional distribution of $u_i(\varepsilon_i = v_i + u_i)$ is the truncation at zero of the normal distribution with mean and variance:

$$\mu_i^* = \frac{-\varepsilon_i\sigma^2 + \mu_i\sigma_v^2}{\sigma^2 + \sigma_v^2}, \sigma_v^2 = \frac{\sigma^2\sigma_v^2}{\sigma^2 + \sigma_v^2} \quad (15.22)$$

The parameters of the model are estimated by the method of maximum likelihood. All estimations were conducted using the Frontier (Version 4.1) econometric software package developed by Coelli (1996).

15.6 Empirical Results

15.6.1 *The Parameter Estimates*

Analyses of the results presented below are based on the specification and estimation of a stochastic frontier translog distance model incorporating the technical efficiency effects to explain the effects of determinants of inefficiency.

Estimated parameters of the translog stochastic frontier model with non-neutral rate of technical change term described above are presented in Table 15.2. Several nested model specifications were estimated and tested before the selection of the final model as shown in Table 15.3. The specifications of Cobb–Douglass models and translog model with neutral rate of technical change term were all rejected against translog specification with non-neutral rate of technical change.

The signs of the coefficients of the stochastic frontier are generally in conformity with the sign expectations, with the exception of the positive estimate of material cost, but the coefficient of material cost is statistically insignificant.

The estimated coefficients in the inefficiency model are of particular interest to this study. The coefficients of all variables are statistically significant, except for those of broadband internet service. The sign of internet service is positive unlike our expectation of scope economics. Only the sign of internet service for year 2000, the early period of service, is negative as expected, but the estimate is insignificant. The positive estimate for the number of Cable channels implies that the inefficiencies increase with the number of Cable channels. The negative coefficient for time trend suggests that the inefficiencies tended to decline throughout the period. The negative estimate for competition environment dummy implies that SOs at monopoly franchise areas tend to be less inefficient, i.e. more efficient than competitive (duopoly) SOs. The coefficients of licensing sequence dummies are positive, which indicates that the early entry SO firms are more efficient than the later entry SOs. The coefficients of regional dummies for franchise are positive and increase to the non-metropolitan areas, which indicate that SOs in Seoul and metropolitan are more efficient than SOs from non-metropolitan, i.e. provincial areas. Overall, the estimation results suggest that the technical efficiency improved over the years and is higher in MSOs, more dense regions, and in the absence of internet serviced and monopoly SOs.

The estimate for the variance parameter, γ , is close to one, which indicates that the inefficiency effects are likely highly significant in the analysis.

The first null hypothesis in the inefficiency part, which specifies that the inefficiency effects are absent from the model, and Korean Cable SOs are fully technically efficient, is rejected at 5% level of significance. The second null hypothesis in the inefficiency part, considered in Table 15.3, specifies that the inefficiency effects are not a linear function of the characteristic variables, i.e. simultaneously equal to zero. This null hypothesis is also rejected at the 5% level of significance. This indicates that the joint effects of these characteristic explanatory variables on the inefficiencies of production is significant although the individual effects of one or

Table 15.2 Estimated parameters of translog distance function

Variable	Param	Coeff.	Std err	t-ratio	Variable	Param	Coeff.	Std err	t-ratio
Constant	α_0	-12.3881	1.5569	-7.9568	t	ϕ_0	0.0632	0.1155	0.5475
D_{y_i}	β_0	0.1332	0.1119	1.1896	t^2	ϕ_{00}	0.0241	0.0091	2.6457
$\ln(Y_i)$	β_1	0.0761	0.0345	2.1999	$t \ln(L)$	ζ_1	-0.0005	0.0135	-0.0441
$\ln(Y_i)^2$	β_2	0.3942	0.2534	1.5553	$t \ln(K)$	ζ_2	-0.0139	0.0079	-1.7434
$\ln(L)$	α_1	-1.5483	0.3776	-4.0998	$t \ln(M)$	ζ_3	0.0059	0.0079	0.7490
$\ln(K)$	α_2	-0.2419	0.2045	-1.1831	$t \ln(Y_i)$	τ_1	0.0012	0.0011	1.0259
$\ln(M)$	α_3	1.0386	0.2089	4.9708	$t \ln(Y_o)$	τ_2	0.0357	0.0094	3.7645
$\ln(L)^2$	α_{11}	-0.1421	0.0376	-3.7798	Constant	δ_0	-3.2367	0.9300	3.4801
$\ln(K)^2$	α_{22}	0.0728	0.0240	3.0221	$\ln \text{ CHN}$	δ_{0h}	0.5063	0.1903	2.6598
$\ln(M)^2$	α_{33}	-0.1035	0.0229	-4.5136	Internet	δ_{int}	0.1676	0.1079	1.5525
$\ln(L)\ln(K)$	α_{12}	-0.0641	0.0254	-2.5235	T	δ_t	-0.5183	0.0368	-14.0847
$\ln(L)\ln(M)$	α_{13}	0.1814	0.0273	6.6433	COMP	δ_{comp}	-0.6410	0.0856	-7.4859
$\ln(K)\ln(M)$	α_{23}	-0.0466	0.0219	-2.1260	MSO	δ_{mso}	-0.1669	0.0665	-2.5077
$\ln(Y_i)^2$	β_{11}	0.0144	0.0019	7.6126	SOP2	δ_{sep2}	1.0103	0.179	5.6153
$\ln(Y_o)^2$	β_{22}	0.1669	0.0105	15.7753	SOP3	δ_{sep3}	0.9384	0.1850	5.0719
$\ln(Y_i)\ln(Y_o)$	β_{12}	-0.0071	0.0025	-2.7857	SOP4	δ_{sep4}	1.7364	0.2244	7.7351
$\ln(L)\ln(Y_i)$	γ_{11}	-0.0019	0.0036	-0.5295	REG2	δ_{reg2}	1.3847	0.1656	8.3598
$\ln(L)\ln(Y_o)$	γ_{12}	-0.0124	0.0292	-0.4268	REG3	δ_{reg3}	1.4633	0.1610	9.0834
$\ln(K)\ln(Y_i)$	γ_{21}	0.0017	0.0023	0.7568	Internet*t	δ_{int}	-0.1864	0.1426	-1.3072
$\ln(K)\ln(Y_o)$	γ_{22}	0.0192	0.0174	1.1052		σ^2	0.3522	0.0551	6.3908
$\ln(M)\ln(Y_i)$	γ_{31}	0.0022	0.0027	0.8014		γ	0.9485	0.0111	84.9122
$\ln(M)\ln(Y_o)$	γ_{32}	-0.0253	0.0158	1.6029					

NT = 551 observations. The log likelihood ratio test value is 91.5

Table 15.3 Tests of hypotheses for parameters of the stochastic frontier model with production and inefficiency parts

Null hypothesis	Test statistics(λ) ^c	$\chi_{0.95}$ -value	Decision
H_0 : Cobb Douglass – no TC vs. H_1 : neutral TC (df 2)	14.20	5.99	Reject H_0
H_0 : Cobb Douglass – neutral TC vs. H_1 : translog-neutral TC (df 15)	307.80	25.00	Reject H_0
H_0 : translog-neutral TC vs. H_1 : translog-non-neutral TC (df 5)	20.20	11.07	Reject H_0
H_0 : No technical inefficiency ^a	287.20	21.74	Reject H_0
H_0 : No technical efficiency effect ^b	220.40	21.03	Reject H_0
H_0 : Not stochastic ($\gamma = 0$)	215.20	3.84	Reject H_0

^aNo technical inefficiency:

$$H_0: \gamma = \delta_0 = \delta_{lch} = \delta_{int} = \delta_t = \delta_{comp} = \delta_{mso} = \delta_{sop2} = \delta_{sop3} = \delta_{sop4} = \delta_{reg2} = \delta_{reg3} = \delta_{int t} = 0$$

The critical value is obtained from Table 15.1 in Kodde and Palm (1986, p.1246) which shows the statistics for a mixed Chi-square distribution with degrees of freedom equal to 12

^bNo technical efficiency effect:

$$H_0: \delta_0 = \delta_{lch} = \delta_{int} = \delta_t = \delta_{comp} = \delta_{mso} = \delta_{sop2} = \delta_{sop3} = \delta_{sop4} = \delta_{reg2} = \delta_{reg3} = \delta_{int t} = 0$$

^cLog likelihood test: $\lambda = -2\{\log L(H_0) - \log L(H_1)\}$

more of the variables may not be statistically significant. The third null hypothesis in inefficiency part, which specifies that the inefficiency effects are not stochastic, is also rejected. The inefficiency effects in the stochastic frontier are clearly stochastic and are not unrelated to the explanatory variables applied in (15.19).

15.6.2 The Distance Elasticities

The first order coefficients as expected show that, at the sample mean, the output distance function is decreasing in inputs and increasing in outputs. In the model, the distance elasticities (Table 15.4) are highest for material and lowest for capital. All the input elasticities are negative. Returns to scale is significant and calculated to 1.0252. This average scale elasticity is slightly higher than 1.0, but we can not reject the hypothesis of constant returns scale for any sample size. This indicates that this industry does not experience increasing returns to scale until now.

When standard errors of some regression coefficients are large, the standard errors of calculated elasticities also become large. The elasticities of other fee, labor, capital are insignificant.

Table 15.5 shows how the elasticities evolve over the time period under investigation. Output distance elasticities are highest for subscription fee, followed by other fee and internet fee. The output distance elasticities did not show any particular pattern over time. Input distance elasticities are on average highest for material,

Table 15.4 Statistics of distance elasticities

Elasticities	Mean	Std error	t-value
Subscription fee (y0)	0.4585	—	—
Internet fee (y1)	0.2084	0.0331	6.2979
Other fee (y2)	0.2401	0.2353	1.0202
Labor (x1)	−0.3980	0.3569	−1.1151
Capital (x2)	−0.0537	0.1978	−0.2715
Material (x3)	−0.5735	0.1949	−2.9419
Return to scale (scale of elasticity)	−1.0252	0.3141	−3.2641

Table 15.5 Mean distance elasticities over time

Year	Subscription fee	Internet fee	Other fee	Labor	Capital	Material	RTS
2000	0.5782	0.1969	0.2249	−0.4178	−0.0285	−0.5445	−0.9908
2001	0.5217	0.2034	0.2748	−0.4200	−0.0350	−0.5525	−1.0076
2002	0.5315	0.2009	0.2676	−0.4284	−0.0412	−0.5491	−1.0187
2003	0.5402	0.2013	0.2585	−0.4053	−0.0447	−0.5778	−1.0278
2004	0.5621	0.2186	0.2194	−0.3857	−0.0687	−0.5824	−1.0368
2005	0.5741	0.2204	0.2055	−0.3560	−0.0826	−0.6080	−1.0466

with labor followed by capital. Elasticities of capital and material increase, but that of labor has been decreasing. Over time, the sample average RTS has increased slightly as shown in Table 15.5.

15.6.3 Technical Efficiency

In the model, technical efficiency (TE) on the sample Cable SOs was on average 0.839 and the standard deviation being 0.144. The maximum technical efficiency is estimated to 0.970 and minimum technical efficiency to 0.129. This would mean that the firms should on average be able to increase their outputs by 16.1% without increasing their input use.

Table 15.6 presents technical efficiencies and confidence intervals (upper and lower bounds) by several characteristics of firm such as: year of observation, competition environment, the availability of internet service, SO type, service region, and the licensing sequence of Cable SOs.

The results suggest that there is efficiency increase over time and that there exists a negative association between efficiency and regions from Seoul to provincial areas and licensing sequence of Cable SOs. Technical efficiency is higher at the monopoly area compared to the competitive area, and at the MSO compared to the single SO and in the no internet service.

Table 15.6 Average technical efficiencies and 95% confidence intervals by year, competition level, internet availability, SO type, service region, licensing sequence of SOs

Year	Lower	Mean	Upper	Range
2000	0.614	0.762	0.884	0.269
2001	0.615	0.765	0.893	0.278
2002	0.663	0.810	0.923	0.260
2003	0.699	0.849	0.962	0.262
2004	0.734	0.882	0.984	0.250
2005	0.751	0.895	0.989	0.238
Competition level				
Competitive (duopoly)	0.666	0.816	0.934	0.268
Mono	0.723	0.867	0.966	0.243
Internet availability				
No service	0.703	0.849	0.953	0.250
Service	0.689	0.837	0.948	0.259
SO type				
Single-SO	0.646	0.797	0.920	0.274
MSO	0.723	0.868	0.968	0.245
Service region				
Seoul	0.773	0.913	0.994	0.222
Metro	0.700	0.850	0.963	0.263
Provincial	0.625	0.775	0.903	0.277
Licensing sequence				
First	0.741	0.886	0.981	0.240
Second	0.611	0.758	0.883	0.272
Third	0.687	0.840	0.957	0.270
Fourth	0.539	0.695	0.859	0.320

15.6.4 Evaluating Dominance Ranking of Inefficiency by Cable So's Characteristics

In this section, we employ the extended Kolmogorov–Smirnov test of first and second order stochastic dominance as implemented by Massoumi and Heshmati (2000) to examine the evolution and distribution of inefficiency of Cable SOs. We follow an alternative bootstrap procedure for estimating the probability of rejection of the stochastic dominance (SD) hypothesis with a suitably extended Kolmogorov–Smirnov test for first and second order stochastic dominance. All results are based on 10,000 bootstrap samples, with 5% inefficiency partitions. In comparing two distributions, the first group is denoted the X-distribution, and the second by Y-distribution. Thus, FSDxoy denotes first order stochastic dominance of X over Y, and SSDxoy is similarly defined for second order dominance of X over Y. The FOMax and SOMax denote the join tests of X vs. Y and Y vs. X, referred to as first order and second order maximality by McFadden (1989). The probability (denoted as “prob” in the table) rejects the null of no dominance when the statistics are negative.

We compare 6 years of survey data on Cable SOs for the years 2000–2005. The efficiency in production function is obtained from the estimation of a stochastic production function. It should be noted that for the bootstrapping test, we use percent inefficiency (100-efficiency) rather than percent efficiency. This implies that the cumulative distribution function (CDF) to the right (more inefficient) are dominated by those to the left (more efficient). The characteristics for Cable SOs that we control for are: internet availability, SO type and competition environment.

Summary statistics by characteristics and dominance test results including the means, standard errors and probabilities are given in Table 15.7. Graphs of the CDF by various sub-groups are shown in Figs. 15.1–15.3.

Table 15.7 Comparison of mean inefficiency by internet service, SO type and competition environment

Dummy	N	Internet service (1 = Service, 0 = No Service)			SO type (1 = MSO, 0 = Single SO)			Competition environment (1 = Monopoly, 0 = duopoly)		
		Mean	Std dev	N	Mean	Std dev	N	Mean	Std dev	
1	440	16.2627	14.6228	254	13.2631	12.5438	330	13.1547	12.1256	
0	111	15.1437	13.8553	297	18.4099	15.5595	221	20.3416	16.4989	
		Mean	Std err	Prob.	Mean	Std err	Prob.	Mean	Std err	Prob.
FSDxoy	0.0371	0.0244	0.0500	0.1977	0.0357	0.0000	0.2464	0.0365	0.0000	
FSDyox	0.0863	0.0423	0.0000	0.0007	0.0055	0.4600	0.0097	0.0048	0.0200	
FOMax	0.0302	0.0192	0.0500	0.0007	0.0055	0.4600	0.0097	0.0048	0.0200	
SSDxoy	0.0685	0.1444	0.3700	1.3021	0.2561	0.0000	1.6574	0.2687	0.0000	
SSDyox	0.3237	0.2311	0.0400	-0.0389	0.0161	1.0000	-0.0317	0.0125	1.0000	
SOMax	0.0159	0.0452	0.4100	-0.0389	0.0161	1.0000	-0.0317	0.0125	1.0000	

Note: First (second) order stochastic dominance of x over y FSDxoy (SSDxoy). First (second) order maximum FOMax (SOMax)

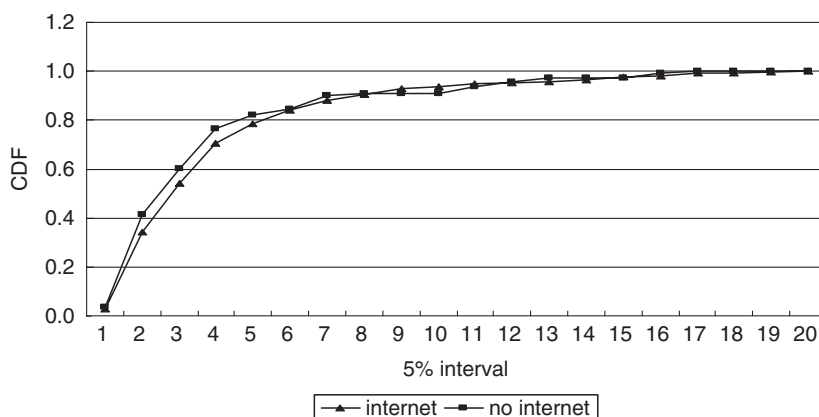


Fig. 15.1 CDF of inefficiency distribution by internet availability

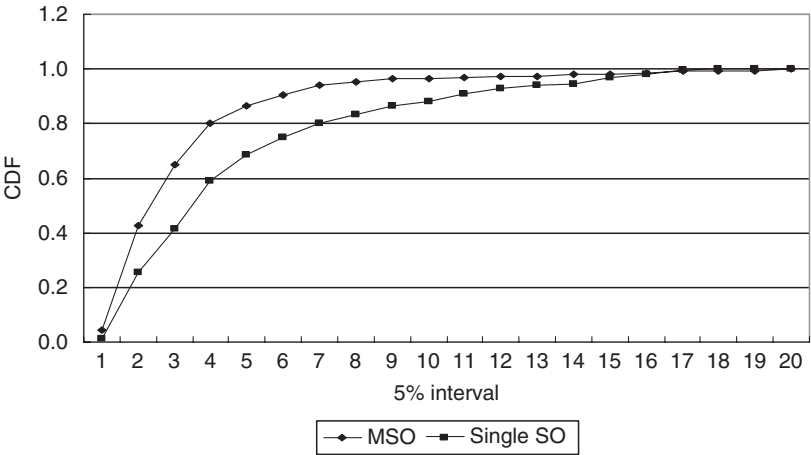


Fig. 15.2 CDF of inefficiency distribution by SO type

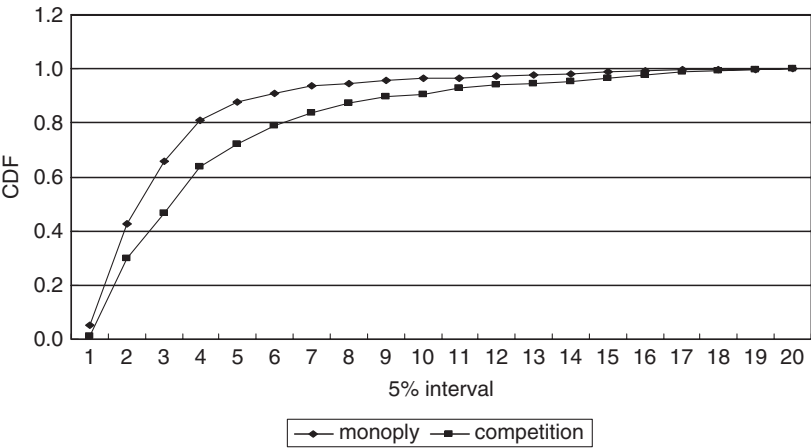


Fig. 15.3 CDF of inefficiency distribution by competition environment

Table 15.7 summarizes our data to test stochastic dominance by internet availability, SO type and competition environment. The mean inefficiency of SOs with internet service is slightly higher than that of no internet service, but test does not indicate the presence of any first or second dominance. The distributions of inefficiency whether internet is serviced or not is not first and second order maximal (unrankable). As for SO type and competition environment, the mean inefficiency is clearly different. The distributions of inefficiency by measured at SO type and competition environment are second order maximal.

Table 15.8 Average productivity change and its component

Period	Productivity % change	Technical efficiency % change	Technical % change	Scale % effect
2000/2001	5.91	0.39	5.53	-0.01
2001/2002	8.51	5.72	2.85	-0.05
2002/2003	5.63	4.70	0.80	0.13
2003/2004	3.29	3.81	-1.19	0.67
2004/2005	-0.87	1.46	-3.19	0.86
Annual average	4.49	3.22	0.96	0.32

In summary, we have been able to show second order stochastic dominance of Cable SOs' inefficiency according to SO type (MSO, single SO) and competition environment (monopoly, competition). This means that they are rankable or different in performance by SO type and competition environment.

15.6.5 The Component of TFP Growth

The productivity growth of the Korean Cable SOs is calculated by applying the approach of Orea (2002). The productivity growth is decomposed to technical change, technical efficiency change and scale effect. The TFP growth results are presented in Table 15.8.

According to the analysis, the average annual productivity growth was 4.49% over the sample period. The highest productivity is observed in the year 2001/2002 and productivity growth varied from positive to negative in 2004/2005. As for the contribution to the productivity growth, technical efficiency is highest, followed by the technical change and scale effect. The productivity and technical change show steady decreasing tendency under the study period.

15.7 Discussion of the Results and Policy Implications

In this paper, we have analyzed the technical efficiency and productivity of the Korean Cable SOs by using stochastic frontier function approach. This involves estimation, identification of determinants of inefficiency and stochastic dominance in distribution of inefficiency.

From the first order coefficients of input variables, we find that capital is insignificant to multi-outputs of subscription fee, internet fee and other fee. The most plausible explanation on this issue is that the Cable SOs have been over-investing to construct their own infrastructures. Returns to scale in this industry is estimated

to be 1.0252, which is interpreted as a CRS unlike our expectation. It seems that the effect of increased market share of MSOs with active M&A after deregulation in the year 2000 is not so significant in the aspect of scale economics. Additionally, this may be caused from the fact that Cable SOs' service areas are confined to a limited franchise area and they can not fully enjoy the scale economy even with the help of mergers and acquisitions in this industry. The calculated productivity changes are 4.49 and the contribution of technical efficiency is highest, followed by technical change and scale effect. The productivity and technical change show steady decreasing tendency during the study period.

The main results and analysis derived from the technical efficiency with characteristic variables are summarized as follows.

First, technical efficiencies have varied over time and from the viewpoint of the change of technical efficiency, efficiency relatively highly increased especially in the year 2003. The overall revenues such as subscription fees (35.5% increase), internet service (66.1% increase), advertising (44.3% increase), etc. increased by about 36.3% compared with the previous year and there were active M&A among SOs.

Second, this study shows that the technical efficiency is higher at monopolistic SOs and this indicates that inputs are inefficiently utilized in competitive regions with higher pressure of competition due to the undifferentiated services. Likewise, Jeon (2005) found that the introduction of competition to the Cable television market in Korea resulted in providing subscribers cheaper service fee, more channels, and even channel diversity. However, this competition reduced the firm's performance considering the aspect of business.

Third, technical efficiency is higher at Cable SOs that have not provided broadband internet services and this is contrary to the general expectations that Cable SOs have increased the usage of their Cable (HFC) from broadcasting to broadcasting plus broadband, i.e. convergent services. This might be caused by the over-investment to their infrastructure to have their own line.

Fourth, technical efficiency has decreased with the licensing sequence of Cable SOs. This may imply that the first entry in a franchise area, mainly focused on highly dense population has a lot of competitive advantages in obtaining market share and brand power compared with later entry and results in high technical efficiency, i.e. high profitability and the later entry depends on the low-priced strategy in order to penetrate undifferentiated competitive Cable TV market.

Fifth, the results show that MSOs are more efficient than single SOs considering that Cable SO needs large scale of infrastructure for its service, but the effect of returns to scale is not so significant. The share of MSOs will be higher in the future with deregulation of ownership and permission of the investment from foreigners and accordingly their individual efficiency is expected to improve.

Overall, the recent policy changes such as deregulation in ownership, M&A in the Korean Cable TV industry seem to be partly effective and it seems that their fruits are realizing slowly. However, the effect of cross entry of Cable SOs to telecommunication sector is not yet analyzed and identified.

Appendix

Bootstrap Procedure for Dominance Rankings

Let X_1 and X_2 be two variables (such as efficiency in production) at either two different points in time or for different attributes like regional location. Let $X_{ki}, i = 1, \dots, N; k = 1, 2$ denote the not necessarily i.i.d. observations. Let U_1 denote the class of all von Neumann–Morgenstern type utility functions, u , such that $u' \geq 0$, (increasing). Also, U_2 denote the class of all utility functions in U_1 for which $u'' \leq 0$ (strict concavity). Let $X_{(1p)}$ and $X_{(2p)}$ denote the p -th quantiles, and $F_1(x)$ and $F_2(x)$ denote the cumulative distribution functions, respectively. Following the notation in Massoumi and Heshmati (2005), the first and second order SD are defined as follows.

X_1 First Order Stochastic Dominates X_2 , denoted by X_1 FSD X_2 , if any of the following equivalent conditions holds:

- $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_1$, with strict inequality for some u ; or
- $F_1(x) \leq F_2(x)$ for all x with strict inequality for some x ; or
- $X_{(1p)} \geq X_{(2p)}$ for all $0 \leq p \leq 1$, with strict inequality for some p .
- X_1 Second Order Stochastic Dominates X_2 , denoted by X_1 SSD X_2 , if any of the following equivalent conditions holds:
 - $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_2$, with strict inequality for some u ; or
 - $\int_{-\infty}^x F_1(t)dt \leq \int_{-\infty}^x F_2(t)dt$ for all x with strict inequality for some x ; or
 - $\Phi_1(p) = \int_{-\infty}^p X_{(1t)}dt \geq \Phi_2(p) = \int_{-\infty}^p X_{(2t)}dt$ for all $0 \leq p \leq 1$, with strict inequality for some value(s) p .

Weak orders of SD are obtained by eliminating the requirement of strict inequality at some point. When these conditions are not met, as when Generalized Lorenz Curves of two distributions cross, unambiguous First and Second order SD is not possible. Any strong ordering by specific indices that correspond to the utility functions U_1 and U_2 classes, will not enjoy general consensus.

This approach fixes the critical value (zero) at the boundary of our null, and estimates the associated significance level by bootstrapping the sample or its blocks. This renders the test asymptotically similar and unbiased on the boundary. This is similar in spirit to inference based on p -values. This method could also be used to compare the two distributions up to any desired quantile, for instance, for performance rankings. The test statistics are as follows.

Suppose that there are 2 prospects X_1, X_2 and let $A = \{X_k: k = 1, 2\}$. Let $\{X_{ki}: i = 1, 2, \dots, N\}$ be realizations of X_k for $k = 1, 2$. Let $F(x_1, x_2)$ be the joint c.d.f. of $(X_1, X_2)'$. Now define the following functionals of the joint distribution.

- $d = \min_{k \neq 1} \sup_{X \in \mathcal{X}} [F_k(X), F_1(X)]$
- $s = \min_{k \neq 1} \sup_{X \in \mathcal{X}} \int_{-\infty}^x [F_k(t), F_1(t)]dt$

Where χ denotes a given set contained in the union of the supports of X_{ki} for $k = 1, 2$, that are assumed to be bounded. The hypotheses of interest are:

- $H_0^d: d \leq 0$ vs. $H_1^d: d > 0$
- $H_0^s: d \leq 0$ vs. $H_1^s: d > 0$

The null hypothesis H_0^d implies that the prospects in A are not first-degree stochastically maximals, i.e., there exists at least one prospect in A in which the first-degree dominates the other. This too applies for the second order case.

In our applications, we report probabilities $\{d_N \leq 0\}$ and $\{s_N \leq 0\}$ are able to identify which distribution dominates, if any. These are the maximum test sizes associated with our critical value of zero which is clearly the boundary of our null. Thus, we are reporting the critical level associated with this non-rejection region.

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