Vera Magin

Competition in Marketing

Two Essays on the Impact of Information on Managerial Decisions and on Spatial Product Differentiation

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With a foreword by Univ.-Prof. Dr. Oliver P. Heil

Deutscher Universitäts-Verlag

Bibliografische Information Der Deutschen Bibliothek
Die Deutsche Bibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über <http://dnb.ddb.de> abrufbar.

Dissertation Universität Mainz, 2006

1. Auflage Juli 2006

Lektorat: Brigitte Siegel / Nicole Schweitzer

Der Deutsche Universitäts-Verlag ist ein Unternehmen von Springer Science+Business Media.
www.duv.de

Umschlaggestaltung: Regine Zimmer, Dipl.-Designerin, Frankfurt/Main
Druck und Buchbinder: Rosch-Buch, Scheßlitz
Gedruckt auf säurefreiem und chlorfrei gebleichtem Papier
Printed in Germany

ISBN-10 3-8350-0432-8
ISBN-13 978-3-8350-0432-0

Foreword

The first portion of Dr. Magin's dissertation research focuses on the impact of demand related information on marketing activity. More precisely, Dr. Magin addresses important questions such as the degree to which firms equipped with demand-related information (DRI) introduce more products, satisfy consumers better, and, most fundamentally, make more money than firms without such DRI. This portion of Dr. Magin's dissertation work involves condensing the broad extant knowledge pertaining to marketing information and creating new hypotheses, empirically testing these hypotheses, and linking results to managerial practice as well as linking the findings to research opportunities.
In addition to this, Dr. Magin's dissertation research entails a more theoretical and quantitative portion that addresses the problem of product differentiation. Here, she immerses herself into the areas of distance functions, distance measures, and spatial product differentiation. This portion of her dissertation is more quantitative and theoretical.

In the first portion of her dissertation, Dr. Magin augments extant knowledge from economics, game theory, decision research, and social psychology into a sizeable set of hypotheses. To empirically test these hypotheses, she makes a large effort to collect primary data. More precisely, she uses a complex market simulation to conduct experiments through the course of three full years. Next, she tests her hypotheses using a variety of conservative tests. Her results are very interesting as she finds much support for the linkages she hypothesized.
Most interesting, however, is her overall and general insight: Managers provided with DRI do seemingly over-act. More precisely, this means that managerial activity appears to frequently go over-board as mangers appear to do too much of a good thing.
Such managerial conduct entails not only the introduction of seemingly too many products. Even more important might be the finding that such over-acting may be especially difficult to deal with as a number of the "over-acting-based" products do not seemingly harm a firm as these products tend to be profitable.
Obviously, one over-arching research opportunity emerges in form of a large challenge to identify an optimal product mix without managerial over-acting. Furthermore, one might investigate the economics of having too many products not as profitable entities but as

competitive preemptors instead. More generally, Dr. Magin's work should have a significant impact on the assessment of marketing productivity.

The second portion of Dr. Magin's dissertation research deals with spatial product differentiation. She develops a creative and even somewhat normative set of requirements that measurement instruments in this area of knowledge should satisfy. Next, she evaluates several existing distance functions and arrives at an interesting and surprising insight: Several commonly accepted distance measurement approaches fail to satisfy generally accepted criteria in the area of product differentiation. Additional results of her initial steps in this area of knowledge entail several suggestions to develop a measure of (spatial) product differentiation. The results have been, at least in part, obtained by her willingness to extend her reach into disciplines seemingly unrelated to product differentiation such as botany, geostatistics or forestry.

Overall, Dr. Magin's dissertation shows her ability to produce creative hypotheses, using a rather complicated experimental set-up such as one involving a complex simulation to collect primary data, test hypotheses using state-of-the-art statistical methodology to arrive at interesting insights. Also, the dissertation shows that Dr. Magin can attack research opportunities that qualify as being rather quantitative and theoretical. Dr. Magin arrived at the aforementioned achievements speedily and reliably.

Univ.-Prof. Dr. Oliver P. Heil (Ph.D.)
Chaired Professor of Marketing

Preface

The work described in this dissertation was carried out between March 2002 and December 2005 at the Johannes Gutenberg-Universität at Mainz, Germany. As described in the summary, the work addresses two topics related to competition in marketing. The first part is an empirical investigation of the impacts of demand-related information on managerial over-acting, marketing productivity, and competition. The second part addresses the measurement of product differentiation, generally considered as an indicator of competitive intensity.

I am indepted to many people for the successful completion of this document. I am grateful for the generous support of my doctoral advisor, Professor Dr. Oliver P. Heil, who has been my mentor throughout four years at the Johannes Gutenberg-Universität. Professor Heil has encouraged my research in many respects. He has offered me enormous opportunities to present my work in front of an international audience and thereby extend my knowledge in the discussion with competent researchers. I am also indepted to Professor Dr. Dr. h.c. mult. Reinhard Selten, who patronized the experiments of my empirical investigation. I am thankful for Professor Selten's comments throughout the development of this work, which helped improve it significantly. Also, I would like to thank Professor Dr. Otwin Becker for his helpful assistence with the SINTO simulation. Let me point out that it was thanks to an exchange with Professor Heil, Professor Selten and Professor Becker that the foundation of the experimental part of my work was laid.

Further, I have derived enormous personal and scientific benefit from my time spent as a research scholar at the University of Florida, Gainesville (U.S.A.) from December 2003 to June 2004. At this point I would like to thank Professor Bart Weitz who invited me to the Marketing Department at the Warrington College of Business Administration at the University of Florida. I am indepted to Professor Alan Cooke for his insightful comments that helped refine and improve my empirical data analysis. Further, I thank all the other faculty members and Ph.D. students for their great hospitality that made the time at the University of Florida so special to me. And last but not least, I am grateful to Professor Heil for making this research scholarship possible.

Further, my friends and colleagues at the Johannes Gutenberg-Universität deserve a special mention: I am indepted to all of them, especially to Dipl.-Kfm. Andreas Waldeck, Frau Dorothea Rector and Dr. Ronny Fürst for their support and the „family-like" working atmosphere they helped to create at the Chair of Marketing.

Also, I owe a lot to my family: I am grateful for their love, help and understanding in any respect. Especially, I would like to thank my significant other, Dipl.-Kfm. Alexander Winkelmann, for his helpful and critical comments throughout the process of this dissertation. Without his continuing love and support this dissertation would have been a lot more difficult.

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List of Abbreviations

aggr.	aggregate
b/w	between
CEO	Chief Executive Officer
CI	Competitive intensity
csr	complete spatial randomness
DRI	Demand-related information
DSS	Decision support system
ex	example
feq	financial equity
MD	Minkowski distance
MDS	Multidimensional scaling
MDSS	Marketing decision support system
NNI	Nearest neighbor index
NP	New product
NPI	New product introduction
n.s.	not significant
R&D	Research and Development
RM ANOVA	Repeated measures analysis of variance
ROI	Return on investment
P&G	Procter&Gamble
SCD	Sum of City Block distances
SED	Sum of Euclidean distances
SKU	Stockkeeping unit
U.S.	United States of America
USP	Unique selling proposition
VBA	Visual Basic

ESSAY I: Managerial Over-Acting

Abstract

The overall impact of marketing activities on firm performance constitutes one of the most fundamental questions in our discipline. Naturally, marketing's provision of demand-related information (DRI) constitutes a major pillar in this context. Almost "by default" exists the presumption that provision and usage of DRI leads to more satisfied consumers, more products, and, subsequently, higher profits. Remarkably, very little research has investigated the overall effects of DRI. Further, few pieces of research have empirically investigated the impact of DRI on competition.

To explore the effects of DRI, I collect primary, experimental data. The results indicate that DRI indeed leads to more products, a higher primary demand and a higher satisfaction of customer preferences. Also, firms provided with DRI set prices which correspond less to a product's quality. Surprisingly and more importantly, however, I do not find significant impacts of DRI on firms' profitability.

These findings suggest that managers tend to over-act. By over-acting I mean that managers pursue too many new product activities that only seemingly amount to new product opportunities. Importantly, such over-acting diminishes firm profits and marketing productivity. This occurs even though those new products do have a positive profit. Furthermore, the often applauded ideal of "segment size one" may turn out to be a myth as managers may over-segment and, thus, cause marketing's productivity to decline. The relationship between DRI and competition requires a clear definition and measure of competition. Comparing several alternative measures of competitive intensity, I find ambiguous results regarding the relationship between DRI and competition. Managerial and interesting research opportunities conclude this paper.

1. Introduction

1.1 Motivation

Usually managers feel much uncertainty about the precise development of their markets, consumer preferences, or how many new products they should introduce. Marketing research provides information to reduce such uncertainty. Firms spend high amounts of money on market research information (more than $ 6 billion per year in the U.S.[1]). If the information is helpful, it increases the decision maker's probability to identify the true underlying state of the world (e.g., Pasa and Shugan 1996) and for example, allows a manager to identify consumer preferences and introduce new products that are profitable. In a sense, a decision maker should, thus, not be worse off when possessing additional information.[2] Yet, some researchers have shown that more information does not necessarily increase decision quality or performance (Dennis 1996; Hart and Diamantopoulos 1993). In fact, information can even have a negative impact (Glazer et al. 1992).

Apparently, more information is not per se advantageous. It also involves risks consisting in an increased complexity of the decision task (Van Bruggen et al. 2001), reduced salience of important information (Dennis 1996) or there might be a distracting effect of the additional information (Glazer et al. 1992). Subsequent decision making may result in over-acting. For example, over-acting may occur in the form of too much new product development. It seems worth noting that such over-acting may occur even if (most of) the new products show a positive profit.

The purpose of this essay is to empirically investigate the impact of demand-related information (DRI). More precisely, I ask how the provision of DRI influences the behavior of oligopolists and their profits. As has been assessed by Moorman et al. 2005, firm responses (as opposed to consumer responses) to information represent an underresearched domain. Existing research addresses firm responses to firm-level information *revealed primarily to customers*, e.g., product or service quality information, information provided by consumer reports, etc. (Foreman and Shea 1999; Moorman 1998; Moorman et al. 2005; Moorman and

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[1] See Honomichl 2005.

[2] Even though strictly competitive situations may result in a negative value of information (Ponssard 1976), the decision maker is free not to use the information in such a case. I.e., from the information economics perspective information is always a "good thing". That is, the information is defined as an observable signal that is correlated to an unobservable state of nature. If the information is "fine" enough, it helps the decision maker to infer the underlying the state of nature, i.e., the probability to identify the underlying state of nature increases. If the information is not "fine" enough, the decision maker simply ignores it. Thus, a decision maker cannot be worse off when possessing additional information according to the information economics perspective.

Slotegraaf 1999). There is very little empirical research on firm and/or market responses to information *revealed to firms* (for exceptions, see Abramson et al. 2005; Glazer et al. 1992; Huck et al. 1999; Huck et al. 2000). In this context, there is even less research on impacts of *demand-related* or *customer-related* information. Further, the laboratory experiments conducted in some of the existing research imply only a limited number of decision variables - often only one decision variable - and thus suffer from a lack of realism. In contrast to the various papers on the impacts of market orientation that often treat information as an implicit component but fail to measure it separately, there is little research that investigates explicitly the effect of information per se. One exception is provided by Glazer et al. 1992 who empirically investigate the impact of different types of information on managerial decisions.

Interestingly, there is very little research on the aforementioned over-action. However, several papers address a form of over-acting, i.e., over-reacting (these will be reviewed in the next section). Anecdotal evidence illustrating that managers may have over-acted, e.g., by trying to be "too good" to their consumers, exists. For example, Procter&Gamble (P&G) offered 52(!) versions of Crest toothpaste. The number of distinct stockkeeping units (SKUs) for Crest toothpaste in supermarkets increased from 15 SKUs in 1970 to 45 SKUs in 1999 (Cristol and Sealey 2000). Upon closer inspection, P&G executives found that such a variety may have diluted Crest's overall contribution potential to the company. As a result, the number of varieties was cut which prompted Crest's level of profitability to increase significantly. In short: Managerial over-acting in the form of to many products reduced marketing productivity.

This essay tries to fill the gap in the literature and empirically investigates the effect of DRI on marketing decisions, firm and industry performance and competition. Contrary to previous research I do not only investigate main impacts of DRI, but I extend my empirical analysis to testing the time-by-DRI interactions, i.e., the time-related effects of DRI. Additionally, this essay hopes to ignite a sensitivity on the issue of over-acting. Marketing researchers and managers seem to think that "a good thing cannot be bad." However, too much of a good thing can, at least, become sub-optimal - which is exactly what over-acting is about. That is, over-acting looks good at the marketing surface such as rate of new product introductions, exhaustion of consumer preferences, even stimulation of primary demand but appears to fall short at the end of the business day, i.e., when the profitability is assessed.

I try to answer several important questions that arise in the context of investigating the impact of DRI and over-acting. First, I analyze whether and how much DRI has the potential to increase the exhaustion of customer preferences, enhance (new) product activity and primary demand. Next, I inquire whether and in which direction the price-quality correlation of products is affected when firms are better informed about demand. Finally, I investigate the degree to which DRI may increase firm and industry performance. In my experiment I investigate a scenario in which all firms have access to DRI and contrast it against a control / base scenario. If no increase in performance, i.e., profitability, can be found, managers may indeed over-act causing marketing productivity to decline.

I collect primary data over fifteen business periods using the dynamic market simulation "SINTO Market". The game simulates an oligopolistic market with differentiated products. I simulate one scenario where no firm gets any market research information. In a second scenario, all firms have access to a market research tool enabling them to estimate future demand.

1.2 Course of analysis

The remainder of the paper is organized as follows: Section two summarizes the literature on information value, market orientation and information processing, impacts of information and decision aids, and managerial over-acting. Next, I provide a definition of demand-related information (DRI), detail the conceptual framework and develop several hypotheses. The fourth section entails a discussion and motivation of the applied methodology, including a description of the experimental design and the simulation used, a discussion of measurements, data analysis and empirical results. The measurement part comprises an extensive discussion of competition and product differentiation measurement. Section five includes the discussion of my results, implications for managers and researchers and limitations of the work at hand.

2. Related literature on information and over-action

2.1 Overview

In the following I review the literature on information value, market orientation, and information processing and discuss the literature that links marketing information to other marketing variables. Further, I review the little literature related to over-acting.

A large part of the literature related to the work at hand entails work on the nature and effects of (marketing) information. Researchers investigate the nature and effects of such information in a variety of contexts. More precisely, studies examine the value of information and its determinants employing economic and game theory, analyze the impacts of different types of information, and investigate information implicitly as a part of the marketing orientation construct. These papers focus on firm performance, new product success, examine the impact of information on organizational structure, or explore the issue of competitive or consumer access to information. It seems worth pointing out that the studies are rarely empirical.

2.2 The value of information – insights from information economics and decision theory

Economists define information as a phenomenon to reduce uncertainty. Following decision theory, the value of information constitutes the maximum amount a decision maker should spend on information before making a decision (Lawrence 1987). Since the value of information usually depends on the information's content[3], which is only revealed in the future (Repo 1989), the computation of its value often amounts to the computation of its expected value. "The theory of information economics constitutes the most comprehensive normative structure for information evaluation" (Hilton 1981). In the information economics discipline information is considered a commodity whose price or value depends on factors such as the information's accuracy, consequences resulting from alternative decisions, or the question which decision makers have access to the information.

Hilton's 1981 article offers a crisp overview of the value of information concept. The author examines how factors such as the decision maker's risk aversion, the set of decision

[3] More precisely, the value of a piece of information depends on its content and on the question what a person would have done without the information. E.g., for someone who goes for a walk without taking an umbrella, an information telling him there will be no rain that day will not be of any value. However, if the information tells him that it is going to rain, that person would value the information highly because it would have prevented him from getting wet.

alternatives, the function mapping actions and states of nature into consequences, initial uncertainty about the states of nature, and the accuracy of the information itself (e.g., the "fineness" of information meaning the ability of a signal to identify an underlying state of nature) influence the value of information.

Hilton investigates the existence of monotonic relationships between certain decision and information-related factors and the value of information. Using three definitions of information value from the information economics literature, the author identifies determinants of the value of information and examines the existence of monotonic relationships between these determinants and the value of information. The three definitions of the value of information entail (1) the utility surplus provided by the information, (2) the buying price someone without the information would be willing to pay, and (3) the selling price someone who currently possesses the information system would charge to give up the information[4]. The determinants include characteristics of the decision setting (i.e., decision flexibility in terms of possible action alternatives, the decision outcomes[5] and the uncertainty about the states of nature), the decision maker (i.e., the decision maker's risk aversion), and the information itself.

The model shows a decision situation consisting of a decision maker with any utility function, a set of possible states of nature (continuous or discrete) with a priori probabilities[6] (or an a priori density function in the continuous case), a set of actions (i.e., decision alternatives) the decision maker can take, an outcome function assigning outcomes to tuples of states and actions, and an information tool providing information signals that hint to one or several underlying states of nature.

The underlying assumptions of Hilton's model rest on the definitions of information value:

Utility surplus *U(h)*:

$$U(h) = \int_{y_h \in Y_h} \max_{x \in X} \int_{s \in S} u(w(x,s)) p(s \mid y_h) p(y_h) - \max_{x \in X} \int_{s \in S} u(w(x,s)) p(s)$$

with

S : *Set of possible states of nature* $s \in S$

X : *Set of actions (alternative decisions)* $x \in X$

$p(s)$: *Probability of state s (discrete probability or continuous density function)*

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[4] Note that, given a risk neutral decision maker, the three definitions come up with the same resulting value of information.

[5] A decision outcome is determined by an outcome function applied to the combination of a state of nature and an action taken.

[6] The existence of a priori probabilities corresponds to the Bayesian theorem. It represents a statistical approach of combining probabilities of uncertain events: $P(B \mid A) = \frac{P(A \cap B)}{P(A)} = \frac{P(A \mid B) \cdot P(B)}{P(A)}$ (Zellner 1996).

$w(x,s)$: Outcome/payoff resulting from action x and state s

$u(.)$: Utility function of decision maker

Y_h : Set of signals $y_h \in Y_h$ (information).

Here, the value of information is defined as the expected utility surplus gained from information Y compared to the expected utility without information.

(2) Buying price $F(h)$:

$$\int_{y_h \in Y_h} \max_{x \in X} \int_{s \in S} u[w(x,s) - F(h)]p(s \mid y_h)p(y_h) = \max_{x \in X} \int_{s \in S} u(w(x,s))p(s).$$

The buying price of information is defined as the price $F(h)$ at which a person is indifferent between not having the information and buying the information.

(3) Selling price $G(h)$:

$$\int_{y_h \in Y_h} \max_{x \in X} \int_{s \in S} u(w(x,s))p(s \mid y_h)p(y_h) = \max_{x \in X} \int_{s \in S} u[w(x,s) + G(h)]p(s).$$

The selling price is the price $G(h)$ at which a person is indifferent between keeping the information by herself (i.e., not selling it) and giving up the information.

A formal analysis of the three definitions leads to the following results:
For the decision setting characteristics, the author finds no general monotonic relationships between

- flexibility and the value of information,
- possible outcomes and the value of information, and
- initial uncertainty about the states of nature and the value of information.

For the decision maker's risk aversion, the author finds no monotonic relationship between the degree of absolute and relative risk aversion and the value of information.
A "better" information (in terms of its ability to hint as precisely as possible at the underlying state of nature[7]) is monotonically related to a higher value of information.

[7] The idea of "better" information can also be explained in terms of information fineness. A piece of information is finer than another piece of information if it partitions the states of nature in finer (more detailed) subsets or segments.

Hilton's paper illustrates the fact that information may be valued differently, depending on whether someone is in a buyer's or a seller's position.[8] That is, it can make a difference whether someone without the information wants to buy it or if someone in possession of the information considers selling it.

Raju and Roy 2000 offer a paper investigating the determinants of information value. More precisely, the authors investigate the impact of firm and market characteristics on the value of market information. Much of the paper's motivation is based on the growing importance of information in increasingly competitive markets while, at the same time, technological advances enhance accessibility and accuracy of the information offered. Raju and Roy 2000 develop a game-theoretic model for a duopolistic market that contains asymmetric firms offering differentiated products. The authors make assumptions about the firms' demand functions, the distribution of market size, each firm being able to forecast market size with a certain predictive accuracy, and each firm setting its price by maximizing its expected profit (given its forecast of market size). Subsequently, a Nash equilibrium solution is derived to serve as a basis for further analyses. Starting from expected profits in the Nash equilibrium, the authors show how important changes moderate the impact of a (more) accurate forecast on equilibrium profits. These important changes include a change in uncertainty about market size (measured as a change in variance of market size), a change in product substitutability (measured as a change in cross-price elasticity), a change in industry size, a change of relative firm size, and a change in the mode of conduct (Bertrand vs. Stackelberg competition). In the latter case, the value-based difference between an information improvement in a Bertrand vs. Stackelberg competition is derived by computing Stackelberg equilibrium profits and comparing them to the Nash profits.

In the Bertrand-Nash equilibrium, Raju and Roy 2000 show that the expected profit of a firm given its forecast depends on the uncertainty about market size (denoted by V), the accuracy of the two firms' forecasts (s_i and s_j), the firms' relative market shares (α), the cross-price elasticity (c) and the price elasticities (b_1 and b_2).

The increase in profits achieved by an improvement in predictive accuracy of a firm's forecast is computed by differentiating $E\,[\Pi_i{}^N]$ with respect to s_i. Next, the authors derive their

[8] A somewhat similar phenomenon can be found in prospect theory which postulates that utility functions are contingent on reference points (this means that gains and losses are evaluated instead of absolute earnings) and that gains from the references point are valued differently than losses from the reference point (Kahneman and Tversky 1979).

findings by differentiation of $\partial E(\Pi_i^N)/\partial s_i$ with respect to the variables of interest (e.g., V, c, $\bar{a}$, α). This analysis leads to the following findings:

- An improvement of forecast accuracy has a greater impact on expected profits when uncertainty about market size is higher.
- An improvement of forecast accuracy has a greater impact on expected profits when product substitutability is higher.
- An improvement of forecast accuracy has a greater impact on expected profits for a firm that is relatively large compared to its competitor.
- An industry's size has no impact on the assessed value of an improvement of forecast accuracy.
- An improvement in forecast accuracy has a greater impact on expected profits in a Stackelberg competition than in a Bertrand-Nash competition, unless the level of forecast precision is very high.

Iyer and Soberman 2000 derive the value of information (i.e., the value of product modification information) in a competitive context. In their paper on the value of product modification information, the authors analyze optimal selling strategies from the information provider's point of view and investigate how information use affects competition in a duopoly. The authors develop a game-theoretic model to examine contracting strategies for a monopolistic information provider selling product modification information to two firms competing in a downstream product market. Depending on the scope of information the seller possesses (one-sided vs. two-sided), two scenarios are designed and an equilibrium contracting strategy for each scenario is derived. In the one-sided scenario, the information provider possesses only information about one of the two firms. Given the provider sells this (one-sided) information to the focal firm, the firm can use the information to modify its product in a way to keep hold of its loyal customers. Information used in such a way is called "retention information". On the other hand, given the vendor sells one-sided information to the other firm, this firm can use the information to modify its product to lure away customers from its competitor. In this case, information is called "conquesting information". The authors show that in a one-sided information equilibrium, the information provider will sell the information exclusively to the firm to whom the information serves as an instrument for customer retention. In the two-sided scenario, the vendor possesses information on both firms. Hence, each firm can use the information and modify their products to retain customers or to lure away customers from its competitor. The authors show that in the two-sided equilibrium, the vendor will sell the same complete package of information to both firms. Thus, each firm is in possession of both retention and conquesting information. However, knowing that the competitor disposes of the same information, the firms will only implement product modifications for customer retention and will not use the conquesting information. The authors explain this phenomenon by the "passive power" of information. They claim that information has not only a value due to the benefits derived from its use, but also from the negative consequences a firm would face were it not in possession of the information.

The model starts with specifying consumer preferences in the duopolistic product market. Consumers are assumed to be heterogeneous with respect to their preferences for the two products. The consumer surplus (CS) that a consumer with preference x achieves by a product modification of firm i is expressed as:

$$CS_1 = R + v_1(x) - p_1 - xt$$

$$CS_2 = R + v_2(x) - p_2 - (1-x)t$$

$x: \textit{position of consumer}$

$R: \textit{reservation value for unmodified product}$

$p_i: \textit{price of firm i's product } (i = 1,2)$

$t: \textit{travel cost}$

$v_i(x): \textit{added value from firm i's product modification for consumer located at x.}$

A retention modification of firm i is assumed to have the following functional form:

$$v_1(x) = \beta(1-x)$$

$$v_2(x) = \beta x$$

$\textit{with } \beta > 0: \textit{ impact of modification.}$

Likewise, a conquesting modification of firm i can be expressed as:

$$v_1(x) = \beta x$$

$$v_2(x) = \beta(1-x).$$

The two downstream firms are aware of their customers' preference structure. Given the information provider's offer, the firms decide whether to accept or refuse the offer by maximizing their profits. The two firms are assumed to behave according to a Bertrand-Nash competition.

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9 The underlying illustration of the differentiation between the competing products is the following: The two products are located at point 0 and point 1 in a one-dimensional market space represented by a straight line of unit length. A consumer's ideal point is represented by his location in the market space denoted by x. The closer a consumer's ideal point is to 0 (1), the stronger becomes his preference for product 1 (2).

The information provider knows the two firms' decision problem and incorporates it in his own decision. In the one-sided and the two-sided scenario, the information provider maximizes his profits by choosing an optimal contracting strategy.

Sarvary and Parker 1997 define the value of information as a customer's taste for information accuracy. Unlike many other articles (e.g., Hilton 1981; Iyer and Soberman 2000; Raju and Roy 2000), Sarvary and Parker allow for competition between the information providers. More specifically, the authors model a market with a population of customers and two competing information vendors. The customers can choose whether they want to buy provider 1's forecast, provider 2's forecast, both forecasts or no forecast at all.

The paper's goal is to find out whether competitive structures in information markets (markets with firms selling information) differ from markets with traditional goods or services. The analysis focuses on competition between two information providers each of them selling a forecast to a population of customers. The information offered is characterized by two dimensions: Predictive accuracy (in terms of a low variance) and correlation with the competitor's forecast. The customers are assumed heterogeneous in their willingness to pay for the accuracy of information. They can either buy provider 1's forecast, provider 2's forecast, both forecasts or no information at all.

Using a game-theoretic analysis, the authors find that the nature of competition changes with changing quality of the information offered: When information products are accurate and correlated, they compete as substitutes, i.e., consumers tend to buy only one firm's forecast instead of buying two forecasts. In this case, competitive intensity is likely to be strong and each information provider would make higher profits if it were a monopolist. In contrast, when information products are inaccurate and uncorrelated, they tend to act as complements thus making competition less intense. In the latter case, each provider is better off in the duopoly than if it were a monopolist.

The information of provider i is modeled as a random draw from a normal distribution with unknown mean m and known variance σ_i^2. The mean m denotes the true value (e.g., true business opportunities, market size, optimal marketing strategy etc.) and σ_i^2 represents the accuracy of provider i's information. The forecasts of both vendors are correlated with correlation coefficient ρ. Given a consumer has provider i's forecast x_i, his expectations of the true value m will be x_i. In contrast to Raju and Roy 2000's work, customers have no general expectation of the true value without using any information, so their expectation comprises only the forecast instead of being a convex combination of general expectation and forecast. If a consumer has the forecasts of both providers, he combines the information by weighting the more accurate forecast more than the less accurate one while accounting for the correlation between the forecasts.

The degree to which a consumer values the information depends on his utility function:

$$U = \begin{cases} \theta(1-\Sigma^2) - p_1 - p_2 & \textit{if both forecasts are bought} \\ \theta(1-\sigma_i^2) - p_i & \textit{if only provider i's forecast is bought} \\ 0 & \textit{otherwise.} \end{cases}$$

with

$0 < \theta < 1$: *consumer's taste parameter*

Σ^2 : *joint variance of both forecasts*

σ_i^2 : *variance of forecast i*

p_i : *price of forecast i.*

For later analyzes, the taste parameter θ is assumed uniformly distributed within the range (0;1).

Contingent on his utility, a consumer is either going to buy both forecasts, or only one firm's forecast, or decides for no forecast. For given forecast variances and correlation, the demand for the forecasts is computed by integrating across those consumers who have an incentive to buy (determined by their taste parameter θ). In equilibrium, the providers choose prices by optimizing individual profits. If it exists, an equilibrium for given levels of forecast accuracy and correlation between forecasts is characterized by forecast prices, resulting demand for the different forecasts bundles, and the information provider's profits.

The papers by Hilton 1981, Raju and Roy 2000, Iyer and Soberman 2000, and Sarvary and Parker 1997 entail different concepts of the value of information. Below I summarize and contrast these concepts (see also Table I-1).

Similarly to Raju and Roy 2000 and Iyer and Soberman 2000 who measure the value of information in terms of a profit increase or a profit surplus, Hilton 1981 and Sarvary and Parker 1997 measure the value of information in terms of utility. While Raju and Roy and Sarvary and Parker address the value of information from the information user's point of view (buyer's price), Hilton uses three definitions of the value of information: the utility surplus gained from information, the seller's price (i.e., the compensation price someone who has the information would charge in order to be willing to give up the information), and the buyer's price (i.e., the buyer's willingness to pay for the information). As has been mentioned before, the three definitions are equal if the decision maker is risk-neutral.

In Iyer and Soberman 2000's paper, the value of information can be assessed from three different perspectives: the information seller's perspective, the two information buyers' perspective, and the information buyers' customers' perspective. The perspective of the two information buyers (the two competing downstream firms) is the most interesting.[10] For the two potential information buyers, the value of information is determined by the information's content as well as the question if the competing firm has the information or not. The so-called "passive power of information" relates to the latter question: The mere possession (and not use!) of information can be valuable for a buyer. Although this definition of the value of information might appear different from the previous definitions at first glance, a closer look reveals that there is actually nothing new about this definition. That is, Hilton's definition illustrates that the value of information is always assessed by incorporating the consequences resulting from having or not having the information. Hence, it is possible to derive Iyer and Soberman 2000's result by using Hilton's definition. All that would have to be done is differentiate two cases (one case in which the competing firm has the information and one in which it does not have the information).

Sarvary and Parker 1997 define the value of information as a customer's taste for information accuracy. A customer's utility increases with increasing information accuracy, where accuracy is defined as (1-*information variance*)[11]. Interestingly and contrary to Hilton 1981, Raju and Roy 2000 and Iyer and Soberman 2000, a customer's value of information (i.e., information utility) does not depend on consequences resulting from not having the information.

Table I-1: Synopsis: Value of information

	Hilton (1981)	***Raju & Roy (2000)***	*Iyer & Soberman (2000)*	***Sarvary & Parker (1997)***
Model background	Information economics	Game theory	Game theory	Game theory

[10] For the information seller, the value of information is given by the price it is able to charge. As information is treated like any other product, there is nothing information-specific about this definition. For the consumers (i.e., the information buyers' customers), the value of information results from the products offered by the two information buyers. This value is directly determined by the product characteristics, and is only indirectly related to the information.

[11] The variance of a forecast is restricted to $\sigma^2 < 1$.

	Hilton (1981)	*Raju & Roy (2000)*	*Iyer & Soberman (2000)*	*Sarvary & Parker (1997)*
Information provider(s)	Monopolistic	Monopolistic / integrated market research	Monopolistic	Duopolistic competition
Information user(s)	One decision maker	2 firms (price competition)	2 firms (price competition)	Population of customers
Content of information	Not specified	Market size / demand	Product modification, product retention	Not specified (e.g., business opportunities)
Randomness of information	Random (Partition of states)	Random	Deterministic	Random
Information modeled	Exogenous	Exogenous	Exogenous	Exogenous
Buying costs of information	+	0	+	+
Information production costs	0	0	0+ (sunk costs)	0+ (sensitivity analysis)
Value of information	Utility surplus (*U(h)*), buyer's price (*F(h)*), seller's price (*G(h)*)	Firm using the info: $\partial E[\Pi(.)] / \partial s_i$, impact of a more accurate forecast on expected firm profits	Firm buying the information: profit surplus with info, given a specific contract offered	Information buyer: θ, consumer's taste for accuracy of information
Role of competition	n/a	Competitive intensity → value of information	Information → competitive intensity	Information → competitive intensity
Empirical validation of results	-	-	- / + (examples from real business)	-
Dynamics	Static	Static	Static	Static

In their paper on the value of marketing expertise, Pasa and Shugan 1996 technically equate marketing expertise with information. More precisely, the value of marketing expertise is measured in terms of the ability to identify the underlying state of nature, which is usually the definition of the value of information. However, the difference of both terms consists in their interpretation: marketing expertise includes that firms with the same information arrive at different strategies because they interpret the information differently, according to their respective marketing expertise. Hence, the value of information is considered as a part of the value of marketing expertise, whereas marketing expertise determines the interpretation of the information. Pasa and Shugan 1996 identify market instability (reflected e.g., by new product introductions), market presence, organization size, organization instability, and competition (determined by the number of competitors, profits, and market entry) as factors that influence the value of marketing expertise.

In a meta-analysis comprising several approaches of the value of information, Repo 1989 concludes that those approaches are not overly helpful when it comes to measuring the value of information in practice. E.g., the author posits that the traditional economic concepts (like Hilton 1981's concept) are of limited practical use because they require knowledge of all probabilities of actions, consequences (pay-offs) from those actions, prior probabilities without additional information and information on the information system itself. Also, the evaluation of information as an uncertainty-reducing tool, while abstracting away from its content has been criticized (Glazer 1991).

2.3 Information in the context of market orientation and information processing

Since Kohli and Jaworski's seminal paper in 1990, introducing market orientation as a way to facilitate the implementation of the marketing concept within organizations (Kohli and Jaworski 1990), much attention has been devoted to the construct of market orientation.

Information constitutes an integral part of the market orientation construct (e.g., Kohli and Jaworski 1990; Narver and Slater 1990). The construct's components comprise intelligence generation, its dissemination across departments, and organizationwide responsiveness to it. Intelligence generation describes the development of a market intelligence which includes not only the collection of customer information but also a focus on external factors such as competition and regulation. The dissemination of information requires the participation of all departments or sub-divisions of an organization. It can consist in spreading information via newsletter or informal interdepartmental meetings. Intelligence responsiveness includes the reaction to the collected and disseminated information, for example in the form of selecting target markets, designing a product, or reacting to market trends in general (Kohli and Jaworski 1990). In a subsequent study, Jaworski and Kohli find that "market orientation of a business is an important determinant of its performance, regardless of the market turbulence, competitive intensity, or the technological turbulence of the environment in which it operates" (Jaworski and Kohli 1993, p. 64).

Building on Kohli and Jaworski 1990's study of a rather behavior-oriented approach to market orientation, Narver and Slater 1990 offer a culture-oriented view[12] and definition of market orientation in the same year. Their definition entails that market orientation is composed of (1) a customer orientation, (2) a competitor orientation, and (3) an interfunctional coordination (Narver and Slater 1990). Customer orientation means complete understanding of the target customers to the firm's benefit. This includes customers' present and future preferences and needs. Competitor orientation refers to the understanding of competitors' present and future long-term and short-term abilities and strategies. However, a competitor orientation has also been defined as the pursuing of competitor-related objectives. A competitor orientation in the latter sense has been shown to harm a firm's performance (Armstrong and Collopy 1996). Interfunctional coordination refers to the existence of a network linking the various departments within an organization. This enables all departments within an organization to use common resources, e.g., information about customers or competitors thus making intra-organizational processes more efficient: "A market orientation is valuable because it focuses the organization on (1) continuously collecting information about target-customers' needs and competitors' capabilities and (2) using this information to create continuously superior customer value" (Slater and Narver 1995, p. 63).

Research on market orientation is closely related to research on information processing. The latter is less concerned with a specific strategic orientation (like a market orientation), but focuses on the process of organizational learning and information flows within organizations, e.g., firms. The stream of research on information processing evolves around the idea that a main challenge for (especially large) firms consists not only in the acquisition of information, but also in its dissemination or transmission, and in its use. Many articles are therefore concerned with identifying key determinants of organizational information use to the organization's advantage. Important determinants of information processing are

[12] Narver and Slater 1990's view entails that market orientation is based on a market oriented culture triggering a market oriented behavior.

organizational culture (e.g., Moorman 1995), individual decision makers' characteristics, e.g., prior dispositions (Menon and Varadarajan 1992), intrinsic motivation (Strieter et al. 1999) learning inertia (Adams et al. 1998), etc., and reward systems, i.e., extrinsic motivation (Strieter et al. 1999). Marinova 2004 investigates the impact of market knowledge diffusion within a firm on a firm's performance and innovation effort. She defines market knowledge as the ability to correctly identify customer preferences (customer knowledge) and competitors (competitor knowledge). She finds that market knowledge has only an effect on innovation effort and performance when it is constantly updated and shared among the decision makers within a firm. This relationship is stronger for competitor knowledge than for customer knowledge.

One might argue that the work at hand is related to research on market orientation and information processing. Market oriented firms are supposed to closely examining DRI (e.g., see measurement of customer orientation by Frambach et al. 2003). However, unlike the existing work on market orientation (e.g., Atuahene-Gima 1995; Frambach et al. 2003; Kohli and Jaworski 1990; Lukas and Ferrell 2000; Narver and Slater 1990; Noble et al. 2002), the work at hand does not investigate the effects of certain demand-focused or customer-focused strategies or processes within an organization. Instead, I adopt Glazer et al. 1992's approach and treat information, i.e., its accessibility, explicitly.
More precisely, the correlation between information gathering, sharing, and usage thereof, suggests that information access drives the processing of market information (Ottum and Moore 1997). Thus, I also investigate whether access to DRI affects performance and innovation - like it has been shown for market orientation or its components[13].

2.4 Firm responses to information, decision aids, and forecasting tools

In contrast to the various papers on the impacts of market orientation that often treat information as an implicit component but fail to measure it separately, there is little research that investigates explicitly the effect of information per se. However, information constitutes an important research variable in itself (Glazer 1991). An interesting study on the impact of information on marketing and organizational structure is conducted by Glazer 1991. The author develops several propositions as to how an increase in the quality and quantity of

[13] Components include customer orientation, competitor orientation, and interfunctional coordination (e.g., Narver and Slater 1990).

information[14] can change marketing and organizational structure. Glazer points out the need for empirical research on this issue.
Existing research addresses firm responses to firm-level information revealed primarily to customers, e.g., product or service quality information, information provided by consumer reports, etc. (Foreman and Shea 1999; Moorman 1998; Moorman et al. 2005; Moorman and Slotegraaf 1999). There is very little empirical research on firm and/or market responses to information revealed to firms (for exceptions, see Abramson et al. 2005; Glazer et al. 1992; Huck et al. 1999; Huck et al. 2000). Below I summarize work that addresses the question of how firms are influenced by information. In this context, there is only very little research that investigates the special type of *demand-related* or *customer-related* information. The literature review below includes research on decision aids and decision support systems which can also be considered as information providing tools.

Huck et al. 1999 and Huck et al. 2000 conduct a series of computerized experiments in quadropolistic markets to investigate the effect of information on competition. They find that more information about demand and cost conditions leads to a lower intensity of competition whereas information about competitors increases competitive intensity. However, these papers may raise concerns about external validity since subjects had a largely truncated marketing mix to decide on, i.e., they could only decide on product prices or, alternatively, on quantities. Important marketing variables such as product characteristics, quality, or advertising remained outside those experiments.
Using a similar experimental setting, Abramson et al. 2005 investigate the impact of decision aids (i.e., profit simulations) and the accessibility of competitor-related information on a firm's pricing decisions and profits. The authors use laboratory market experiments comprising eight business periods. Subjects have to make pricing decisions while the information available to them is manipulated. One information manipulation consists in giving firms access to information about competitors' profits. The authors find that firms set lower prices and achieve a higher level of decision quality[15] when provided with such competitor-related information. However, these effects change when firms are additionally given access to a decision aid (see section on decision aids and decision support systems below). However, since, like in Huck et al. 1999's and Huck et al. 2000's experiments,

[14] Glazer defines a firm's information intensity as the degree to which the firm's „products and operations are based on the information collected and processed as part of exchanges along the value-added chain“ (Glazer 1991, p. 5).
[15] In Abramson et al. 2005's paper, decision quality does not necessarily correspond to performance.

Abramson et al. 2005's experimental decision variables are restricted to pricing decisions, one may have concerns about external validity. Another critical aspect is the fact that in Abramson et al. 2005's experimental setting, a firm is represented by one subject only. Thus, firm decisions may be highly sensitive to an individual subject's characteristics and abilities.

Another empirical approach is pursued by Glazer et al. 1992. More precisely, the authors examine the impact of information on marketing decisions using simulated market experiments (using the MARKSTRAT[16] simulation). The information manipulation comprises four different consumer information types, i.e., a consumer survey, a semantic scale, a perceptual mapping, and an advertising experiment. The decisions investigated include advertising spending, sales force expenditures, R&D expenditures for new and existing products, repositioning activities, pricing decisions, and the number of brands marketed. In a pretest, the authors identify those decision variables to which the given information relates the most and the least (e.g., they find that the information addresses strongly the repositioning activity variable due to the perceptual map included).

The authors discover a phenomenon they call "locally rational decision making". This phenomenon entails that firms with access to additional information perform worse, even though they use the information correctly. The authors offer an interesting explanation by arguing that the information leads managers to focus or even limit their decisions to the dimensions addressed by the information provided and, thus, neglect other variables - even those most related to performance. Due to Glazer et al. 1992's experimental setting, the information manipulation varies during the experiment. That is, the provision of information is restricted to some experimental periods. Likewise, the number of firms that are given information access is altered between periods. Consequently, Glazer et al. 1992's experiment does not allow a long-term investigation of information impacts because neither the duration of information access nor the number of firms with information access is stable.

The empirical work of this essay is somewhat related to Glazer et al. 1992's experiments. That is, like Glazer et al., I investigate the impact of information on marketing decisions. Besides from differences in the information type and the decision variables investigated, the experimental design of the current work differs from the one used by Glazer et al. 1992 in that information manipulation in my research is held stable within the experiments. A detailed comparison between Glazer et al.'s experimental design and my experimental design is provided in Table I-5.

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[16] See Larréché and Gatignon 1977.

Another stream of literature related to the work at hand examines the impact of information provided by Marketing Decision Support Systems (MDSS[17]) or decision aids (Abramson et al. 2005; Todd and Benbasat 1992; Wierenga et al. 1999). MDSS and decision aids can support decision makers in many ways, e.g., they can do calculations, support the analysis and diagnosis of a specific situation, offer suggestions, and help frame the important issues and uncertainties associated with a problem (Wierenga et al. 1999). Famous DSS like CALLPLAN (Lodish 1971) are optimization tools. The surplus of an MDSS does not consist in the gathering of additional new information[18] but in interpreting and evaluating the already existing information to support the decision maker in making a good decision (Van Bruggen et al. 1998). In this sense, an MDSS can be seen as a transformer of available information whose output is intended to aid the decision maker. The effectiveness of using a decision aid depends on many factors, e.g., the type of decision maker (intuitive or analytic, risk-averse vs. risk-seeking, experienced vs. unexperienced), the structure of the decision problem, the characteristics of the decision aid, and the decision environment (Van Bruggen et al. 1996). DSS can improve managerial decision quality by preventing managers from using heuristics like anchoring and adjustment mechanisms (Van Bruggen et al. 1998). Improving the quality (i.e., precision) of a decision support system can enhance objective decision performance (measured in terms of market share and profit), although this does not seem to foster managers' subjective decision confidence (Van Bruggen et al. 1996). Also, decision aids have been found to work best when equally combined with managerial judgment (Blattberg and Hoch 1990).

Abramson et al. 2005 investigate the impacts of a decision aid *and* competitor-related information while also taking into account interactions between both information types. The impacts of competitor-related information alone have been detailed above. The authors design the experimental decision aid manipulation by providing firms with a profit simulator. The profit simulator enables firms to conduct "what if" analyses. The authors find that, when all firms have access to a decision aid, firms set lower prices and achieve lower profits. When firms' access to the decision aid is differential (i.e., when only a few firms have access to the decision aid), profits of those firms are increased. Hence, the decision aid seems to pay only

[17] For a definition see Little 1979.

[18] The definition of MDSS does not exclude the gathering of new information (Little 1979). Also, managers seem to consider an MDSS primarily as a device for obtaining new information and not for the upgrading of existing information (Wierenga and Ophuis 1997). However, the problems decision makers are confronted with today are not those of a lack of data but they deal with the difficulity to process all the information available (Ferguson et al. 2005; Van Bruggen et al. 1998). For that reason, I consider an MDSS as a tool that provides insights (or supports decisions) based on already existing information rather than a source of new information.

if it constitutes a competitive advantage. Also, Abramson et al. 2005 find that there are interactions between competitor-related information and the decision aid. When all firms have access to both a decision aid and information about competitors' profits, they will end up making worse decisions. The decision-improving effect of competitor-related information becomes non-significant in the presence of a decision aid. Abramson et al. 2005 argue that subjects may have been distracted (Glazer et al. 1992) by the additional information (i.e., by the additional decision aid).

In this essay, I focus on the question how marketing decisions, performance and competition are affected by the provision of demand-related information presented in the form of a demand forecasting tool. One could argue that this forecasting tool represents some kind of a decision support system (DSS). However, it is important to note the differences between DSS and the DRI I refer to in this essay. In contrast to the DSS addressed in the aforementioned articles, the forecasting tool of the current work contains new, additional information about market mechanisms a manager without this tool would not have. Unlike a DSS which processes and analyses the relevant information without adding new information[19], the DRI addressed in this essay provides access to additional information, i.e., information that could have been purchased from a market research company. Second, the information tool provided in the work at hand differs from a DSS because it restricts itself to providing demand forecasts and allowing "what if" analyses regarding primary demand. It does not support the decision maker in interpreting the results like a DSS does (Little 1979). In contrast, DSS are supposed to guide and support a manager's decision as a whole[20]. This should include several decision aspects, e.g., cost aspects, the financial situation of the company, and, of course, demand aspects.

2.5 Managerial over-action

As there seems to be a lack of research on over-acting, I turned to a special case of over-acting namely over-reacting. Literature on over-reacting includes work by Leeflang and Wittink 1996, Naik et al. 2005, Brodie et al. 1996, and Massey and Wu 2005. Leeflang and

[19] Naturally, the result of a DSS information processing and analysis can be regarded a new piece of information. But for the reasons stated above, I maintain that the focus of MDSS lies primarily on the processing and interpreting of already existing information.

[20] One example of a decision aid is a profit simulator (Abramson et al. 2005). It supports the decision maker by assessing the respective firm profits resulting from different actions. Assuming profits are to be maximized, the profit simulator shows the decision maker which action is optimal.

Wittink (1996) argue that over-reaction represents one form of erroneous reaction. That is, a manager reacts although the reaction is truly unnecessary in the sense that the competitor's action was insufficiently effective to warrant a reaction. The second erroneous reaction includes that a manager may not react although a competitive action will affect his/her consumers' behavior and, thus, his/her bottom line.

Leeflang and Wittink 1996 argue that a market is in equilibrium when market shares remain constant over time. In case a brand's market share is affected by another brand's marketing instrument, the reacting manager is usually interested in restoring his own brand's market share. Hence, given a brand i initiates a marketing activity using marketing instrument h, then it is only necessary for a brand j to react to that move if brand j's market share is affected. Hence, a competitive reaction of brand j should only occur if

$$\frac{\partial ms_j}{\partial u_{hi}} \neq 0$$

with

ms_j : *market share of brand j*

u_{hi} : *marketing instrument h of brand i* $(h = 1, \ldots, k_i)$.

The total effect of brand i's change in marketing instrument h on brand j is composed of the primary impact of brand i's activity on brand j's market share, plus the competitive reaction effect that instrument h of brand i has on brand j's marketing instruments, multiplied by brand j's own market share effect of its marketing instruments:

$$\frac{\partial ms_j^{\,T}}{\partial u_{hi}} = \frac{\partial ms_j}{\partial u_{hi}} + \sum_{l=1}^{k_j} \frac{\partial ms_j}{\partial u_{lj}} \frac{\partial u_{lj}}{\partial u_{hi}}.$$

Thus, if a brand's market share is affected by another brand's marketing activity (i.e., if $\frac{\partial ms_j}{\partial u_{hi}} \neq 0$), the market will revert to equilibrium if

$$\frac{\partial ms_j^{\,T}}{\partial u_{hi}} = 0 \quad or$$

$$\frac{\partial ms_j}{\partial u_{hi}} = -\sum_{l=1}^{k_j} \frac{\partial ms_j}{\partial u_{lj}} \frac{\partial u_{lj}}{\partial u_{hi}}.$$

The above expression can be rewritten as:

$$\frac{\partial ms_j}{\partial u_{hi}} \frac{u_{hi}}{ms_j} = -\sum_{l=1}^{k_j} \frac{\partial ms_j}{\partial u_{lj}} \frac{u_{hi}}{ms_j} \frac{\partial u_{lj}}{\partial u_{hi}} \frac{u_{lj}}{u_{lj}} \quad \textit{which is equal to}$$

$$\frac{\frac{\partial ms_j}{ms_j}}{\frac{\partial u_{hi}}{u_{hi}}} = -\sum_{l=1}^{k_j} \frac{\frac{\partial ms_j}{ms_j}}{\frac{\partial u_{lj}}{u_{lj}}} \frac{\frac{\partial u_{lj}}{u_{lj}}}{\frac{\partial u_{hi}}{u_{hi}}} \quad or$$

$$\eta_{ms_j,u_{hi}} = -\eta_{ms_j,u_{lj}} \rho_{u_{lj},u_{hi}} \quad with$$

$\eta_{ms_j,u_{hi}}$ *: cross market share elasticity for brand j with respect to brand i's instrument h*

$\eta_{ms_j,u_{lj}}$ *: own market share elasticity for brand j with respect to instrument l*

$\rho_{u_{lj},u_{hi}}$ *: reaction elasticity for brand j's instrument l with regard to brand i's instrument h.*

According to Leeflang and Wittink 1996 over-reaction or under-reaction represents an inequality between a brand's cross market share elasticity and the product of the brand's own market share elasticity and the brand's reaction elasticity regarding another brand. More precisely, they define *under*-reaction of a defending brand j if its (absolute) cross market share elasticity exceeds the (absolute) product of own market share elasticity and reaction elasticity. Conversely, a brand *over*-reacts if the (absolute) product of its own market share elasticity and its reaction elasticity exceeds its cross market share elasticity. Using weekly scanner data from a product category Leeflang and Wittink find that over-reaction occurs more frequently than under-reaction.

Brodie et al. 1996 predict similar results as they try to generalize Leeflang and Wittink's 1996-findings.

Using a experimental Markstrat2[21] setting, Clark and Montgomery 1996 investigate competitive reactions and firm performance. The authors compare actual competitive reactions with firms' perceptions of those competitive reactions and relate the congruency between actual and perceived reactions to performance. They find that firms often misperceive competitive reactions (mostly they fail to perceive reactions which can be considered a form of under-reaction). Interestingly, the authors find that under-reaction can hurt performance, while over-reaction[22] (i.e., perceiving competitive reactions that have not taken place) tends to foster performance. Apparently, only under-reaction (and not over-reaction) is sub-optimal in Clark and Montgomery 1996's paper. However, both types originate from managerial misperception, resulting in an unfounded reaction (over-reaction) or a missing reaction (under-reaction).

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[21] See Larréché and Gatignon 1990.
[22] This phenomenon is termed „paranoia“ by the authors.

Recently, over-reaction in the promotional area has been researched by Naik et al. 2005. They investigate the case of over-promoting of certain brands. They find over-reaction in the form of over-promotions of large brands especially. Massey and Wu 2005 argue that over-reactions or under-reactions depend on the nature of a manager's environment. Over-reaction is argued to be more likely if the environment is more stable and if the environment is composed of rather noisy signals. Similarly to Leeflang and Wittink 1996's work, these papers investigate specific forms of over-reacting while the paper at hand takes a broader perspective.

While the term over-reaction (or under-reaction) describes a mostly sub-optimal, overly strong if not unnecessary (or overly weak if not missing) reaction to a competitor's action, the term over-action as it is used in this essay refers to a form of sub-optimal managerial behavior which reduces marketing productivity. Notably, few papers have addressed the issue of over-reacting but not the issue of over-acting[23].

2.6 Information impacts – summary of insights from the literature

Overall, the literature suggests the following: Insights from decision theory suggest that information has performance-increasing benefits (Glazer et al. 1992; Pasa and Shugan 1996). Likewise, the processing of information is an integral part of a market orientation, which, in turn, is found to be positively related to performance (Deshpandé and Farley 2004; Jaworski and Kohli 1993; Narver and Slater 1990; Rodriguez Cano et al. 2004; Slater and Narver 1994), new product performance (Atuahene-Gima 1995; Slater and Narver 1994), innovation (Sandvik and Sandvik 2003), and to indirectly lead to a higher customer satisfaction (Langerak 2001). Notably, a customer orientation which entails the processing of customer-related information has been shown to increase new product activity (Frambach et al. 2003) and innovation (Lukas and Ferrell 2000) while its effects on performance are seen controversial (Dawes 2000; Noble et al. 2002).

As to the effects of information per se, researchers posit that the use of information increases new product success (Ottum and Moore 1997) and the timeliness of new products (Moorman 1995). However, the extant literature reveals also insights on the negative effects of information or market research (Glazer et al. 1992; Hart and Diamantopoulos 1993; Todd and

[23] Gourville and Soman 2005 address a form of over-acting, namely the sub-optimal managerial decision of offering too much variety. Their study shows that a large, „nonalignable" product assortment (i.e., product variants that vary along multiple, noncompensatory dimensions) can negatively impact consumer choice and market share. The authors explain the negative relationship by consumers' cognitive overload and anticipation of regret.

Benbasat 1992). Information is suggested to make firms more cooperative as opposed to competitive (Glazer 1991) and lead to a lower number of brands offered (Glazer et al. 1992). While information regarding demand or costs has been observed to lessen competitive intensity (Huck et al. 1999), the provision of information about competitors leads to more competitive behavior (Abramson et al. 2005; Huck et al. 1999).

Glazer et al. 1992 demonstrate a negative effect of additional information, which they call "local rationality" effect. Using a MARKSTRAT[24] experiment, they show that firms that are given additional information tend to perform worse than firms without this information, even though they use the information correctly. The reason is that the firms that are given the information tend to focus too much on the decision variables addressed by the information and thereby neglect those decision variables that are most related to performance.

Due to a lack of research on over-acting, I refer to the special cases of over-reacting. Over-reacting has been shown to be reflective of misperceiving competitors' moves (Clark and Montgomery 1996), unnecessarily reacting to a competitor's action (Brodie et al. 1996; Leeflang and Wittink 1996), falsely detecting changes in dynamic environments, e.g., changes regarding the market, competitors or technology (Massey and Wu 2005), or over-spending on promotion (Naik et al. 2005).

In summary, I maintain that a lack of research prevails on the important link between demand-related information and marketing productivity. Interestingly, the demand-related information-performance relation points to managerial sub-optimal behavior of over-acting, which is underresearched as well.

The subsequent tables summarize some of the extant literature.

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[24] See Larréché and Gatignon 1977.

Table I-2: Synopsis: Over-reaction and information

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Abramson et al. 2005	Impact of access to decision aids and information regarding competitors' profits on managerial decision quality, prices, and profits	Information regarding competitors' profits, Decision aid (profit simulator), Interaction between decision aid and competitor information, Information provided in public vs. private condition	Laboratory experiments with 224 executive MBA students using a 8-period market simulation (decisions include only pricing decisions)	Relative to the availability of competitive information, the access to a decision aid has a larger effect on lowering prices and profits (thus leading to more intense competition). Decision aids only improve performance when they represent a competitive advantage.
Brodie et al. 1996	Do managers over- or under-react to competitive pricing or promotion strategies? Replication and generalization of Leeflang and Wittink 1996	Over-reaction (under-reaction): see Leeflang and Wittink 1996	Supermarket scanner data, New Zealand	Confirmation of Leeflang and Wittink's conclusions, but no statistical support for some of their specific hypotheses.
Clark and Montgomery 1996	Do firms perceive competitive reactions correctly? How does the accuracy in perception relate to firm performance?	Over-reaction (under-reaction): misperception of competitive reactions	Laboratory experiments with MBA students and executives using the Markstrat2[25] simulation, 7 or 8 periods, respectively	Under-reaction occurs more often than over-reaction. While under-reaction harms performance, over-reaction ("paranoia") leads to a higher performance.

[25] See Larréché and Gatignon 1990.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Dennis 1996	Impact of group support systems (GSS) on group decision quality	Information processing in groups	Experiments with business students	The increased information exchange in GSS does not improve decision quality.
Glazer et al. 1992	Impact of accessibility of information on performance	Different types of information are given to some firms	Laboratory experiments with MBA students using the MARKSTRAT[26] simulation, 9 periods	Evidence of locally rational decision making: Decision makers focus on those components of decision making most clearly addressed by the information, not on those components most tied to performance.
Glazer 1991	Impact of information intensity on marketing strategy and organizational structure	Information intensity, knowledge	--	Information intensity leads to increased cooperation among firms, non-product market mix elements become more important, market definitions shift from product-based to market-based.
Hart and Diamantopoulos 1993	Impact of marketing research activity on performance	Marketing research activity including use (internal vs. commissioned), types (e.g., frequency), and sources (primary vs. secondary) of marketing research	Survey (interviews) using 86 managing directors from different industries including above and below average performing companies	Marketing research activity does not affect performance. Differences in the quality of the research conducted and the effectiveness of its utilization are potentially relevant explanations for the null effects.

[26] See Larréché and Gatignon 1977.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Huck et al. 1999	Impact of different types of information on competition	Firms are given information about demand or competitors	Laboratory experiments with students using a market simulation (including only pricing or quantity decisions)	Information about demand and cost conditions decreases competition, information about competitors increases competition.
Leeflang and Wittink 1996	Correspondence between competitive reaction and consumer response	Over-reaction (under-reaction): managers react overly strong (very little) to competitive actions even though they have only low (very high) impact on consumer response	Weekly scanner data containing sales and promotional activities of a product category (7 brands) sold in the Netherlands	Empirically observed competitive reactions differ from those predicted by economic theory: over-reaction occurs more frequently than under-reaction.
Massey and Wu 2005	Individuals' reaction to regime shifts	Over-reaction (under-reaction): believing a regime shift has (not) occurred before it actually has (when it has)	3 experimental studies, judgment and choice tasks, computerized experiments using students as subjects, several periods	Individuals pay to much attention to the signal and neglect the environment: Individuals over-react to noisy signals in stable environments and under-react to precise signals in unstable environments.
Moorman et al. 2005	Impact of standardized information disclosure to firm survival and pricing decisions	Standardized information about firms is revealed to the public (e.g., consumers). Moderating variable: firm size (market share)	Quasi-experimental field study using longitudinal IRI data from firms operating in the U.S.	Firm responses to standardized information disclosure depend on firm size (market share): small-share firms tend to exit the market when being forced to reveal standardized information while large-share firms increase distribution.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Moorman 1998	Market-level impacts of market information	"Market information", i.e., information about firms, is revealed to the public/ consumers (e.g., in the form of consumer reports)	Field study using brand data, Consumer survey	Consumers react less strongly to market information than predicted. Competitive rivalry is affected by market information.
Moorman 1995	Cultural antecedents of information processes in firms, Impact of those organizational information processes on new product development performance, timeliness, and creativity	Information processing	Survey using 92 marketing managers	Information utilization processes positively impact new product performance and the timeliness of new products. Clan cultures are the most effective at transmitting and using market information.
Naik et al. 2005	Brand promotion and marketing mix strategies	Overspending on promotion	Single-source market data for fast moving consumer products / Lanchester model	There is promotional over-reacting for large brands.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Ottum and Moore 1997	Relationship b/w market information processing (i.e., information gathering, sharing, and utilization) and new product (NP) success	Market information processing (market orientation, see Kohli and Jaworski 1990). Moderators: 4 environmental factors (i.e., product or market newness of the project, technological innovativeness of the product, environmental turbulences)	Survey (questionnaires) of 28 firms, data on 58 new products, half of them failures and half successes. Marketing and R&D managers from computers and medical devices sectors, Utah, U.S.	Strong relationships between market information processing and NP success, with success most closely related to information use. This relationship is independent of environmental factors (e.g., product or market newness of the project, technological innovativeness of the product, environmental turbulences). The three steps of information processing (i.e., information gathering, sharing, using) are correlated.
Todd and Benbasat 1992	Impact of decision aids on information use – do subjects improve decision performance or conserve effort?	Decision aid	Experiments (verbal protocol analysis) using undergraduate business students	Decision makers provided with decision aids do not use more information, instead they conserve effort.

Table I-3: Synopsis: Market orientation, customer orientation, competitor orientation

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Armstrong and Collopy 1996	Impact of competitor orientation (measured in terms of competition-related objectives and information about competitors) on performance	Cometitor-related information (information about competitors' profits), competitor orientation (competitor-oriented goals)	Laboratory experiments with undergraduate and MBA students in the U.S. and Argentina, Field study using data from 20 U.S. firms	Providing firms with competitor-related information leads to decreased firm profits. Firms with competitor-oriented goals achieve lower ROIs.
Atuahene-Gima 1995	Impact of market orientation on new product (NP) performance (market and project performance), impact of market orientation on (seven) new product development (NPD) activities	Market orientation	Survey among 275 Australian manufacturing and service firms, Marketing, R&D and NP managers	Regression analysis reveals strong effects of market orientation on NP performance.
Dawes 2000	Impact of market orientation components on business profitability (isolation of customer and competitor orientation impacts)	Market orientation (see Narver and Slater 1990), customer orientation, competitor orientation	Survey (personal interviews) using CEO's from 93 companies located in South Australia	Competitor orientation has the strongest impact on performance, but customer orientation is also important.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Frambach et al. 2003	Market orientation (consisting of customer and competitor orientation) as a mediator of the relationship between business strategy (i.e., cost leadership, product differentiation, and focus strategies) and new product activity (i.e., number of new products)	Customer orientation, competitor orientation	Survey (questionnaires) using managers of 175 Dutch firms in the manufacturing sector	Focus strategies lead to a lower emphasis on customer orientation. Customer orientation mediates the relationship between business strategy and new product activity. Customer-oriented firms engage more in new product activity than competitor-oriented firms. Customer and competitor orientation are highly correlated.
Jaworski and Kohli 1993	Impact of market orientation on performance Influence of environmental factors as moderators of the market orientation-performance-relationship Market orientation = intelligence generation, intelligence dissemination, responsiveness	Market orientation	Survey using executives, U.S.	Market orientation is related to overall (judgmental) business performance (but not market share), independent of environmental factors.
Kyriakopoulos and Moorman 2004	Impact of market orientation on the profitability to engage in both marketing exploitation and marketing exploration strategies	Market orientation (all major definitions of the construct)	Study using Dutch firms in the packaged food industry	Market oriented firms can efficiently engage in both the improvement of their current expertise and the development of new knowledge and skills.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Lukas and Ferrell 2000	Impact of market orientation on product innovation	Market orientation (measured as in Narver and Slater 1990)	U.S. manufacturing companies	Customer orientation increases new-to-the-world innovations and decreases me-too-product introductions. Competitor orientation enhances me-too products and inhibits new-to-the-world innovations and line-extensions.
Narver and Slater 1990	Impact of market orientation on business profitability / performance Market orientation = customer orientation, competitor orientation, interfunctional coordination (MKTOR)	Market orientation	Survey (questionnaires) using executives from 140 business units, U.S.	Market orientation positively affects performance.
Noble et al. 2002	Comparison of market orientation, i.e., its elements (customer and competitor orientation and interfunctional coordination) and other marketing management philosophies and their impacts on performance	Market orientation (see Narver and Slater 1990), customer orientation, competitor orientation	Data from 8 periods of a single industry, U.S. mass merchandiser	Competitor orientation significantly impacts performance. No significant effect of customer orientation on performance. National brand focus and selling orientation positively impact performance, private label brand focus negatively relates to performance. Only modest support for the mediating effects of learning and innovation on the relationships between strategic orientations and performance.

Citation	*Content of research*	*Focus of investigation / Context of information*	*Data / Method*	*Results*
Sandvik and Sandvik 2003	Impact of market orientation (generation, dissemination of information, responsiveness to it) on new product introductions / innovation	Market orientation (see Kohli and Jaworski 1990)	Survey (telephone interviews) using managers from the Norwegian hotel industry	Market orientation positively impacts new-to-the-market innovations and new-to-the-firm innovations.

Table I-4: Summarizing the literature: What do we know about information and its impacts?

Information and business performance	▪ Expected utility theory / information economics / decision analysis: Information cannot decrease performance when classic assumptions of expected utility theory/information economics hold. I.e., if the information is accurate and processed correctly (no information overload, no capacity constraints on the manager's attention), one cannot lose having additional information (e.g., Glazer et al. 1992; Pasa and Shugan 1996). ▪ Export-related information enhances small- and medium-size firms' export performance (Hart and Tzokas 1999). ▪ Locally rational decision making (see Glazer et al. 1992): In complex decision tasks, individual biases may occur such that managers focus too much on the content of the information while neglecting the performance-relevant decision variables. Hence, firms do not perform better when provided with more information. ▪ Marketing research activity (including several information types and contents) does not increase performance (Hart and Diamantopoulos 1993). ▪ Public access to decision aids leads to lower firm and industry profits, while private access to a decision aid increases the respective firm's profits (Abramson et al. 2005). ▪ Decision aids do not improve decision quality, instead they motivate effort conserving strategies (Todd and Benbasat 1992). ▪ Market orientation (which reflects several information processes) has a positive influence on overall business performance (Jaworski and Kohli 1993; Narver and Slater 1990; Slater and Narver 1994). The impact of competitor orientation as a component of market orientation is not clear: According to Dawes 2000 a competitor orientation has a stronger influence on performance than a customer orientation whereas according to Armstrong and Collopy 1996, a competitor orientation leads to lower profits. ▪ The use of information technology, not the investment in technology itself, increase financial performance (Devaraj and Kohli 2003).
Information and new product success	▪ The accessibility of information yields a lower number of brands (Glazer et al. 1992). ▪ Market orientation positively impacts new product activity success/new product performance (Atuahene-Gima 1995, Slater and Narver 1994). This is especially true for information use (Ottum and Moore 1997). ▪ Information utilization processes, especially the conceptual information processes in organizations increase new product performance and timeliness of new products (Moorman 1995).

Information and innovation	▪ Customer orientation enhances new-to-the-world innovations and inhibits me-too products (Lukas and Ferrell 2000). Customer orientation increases engagement in new product activity whereas competitor orientation is negatively related to new product activity (Frambach et al. 2003). ▪ Competitor orientation increases the number of me-too product introductions and reduces the launching of new-to-the-world innovations and line-extensions (Lukas and Ferrell 2000). ▪ Market orientation positively impacts new-to-the-market innovations and new-to-the-firm innovations (Sandvik and Sandvik 2003). ▪ Information positively impacts new product activity (Ottum and Moore 1997).
Information and competition	▪ Information makes firms more cooperative as opposed to competitive (Glazer 1991). ▪ Information about demand or costs leads to less competitive behavior while information about competitors leads to more competitive behavior (Huck et al. 1999). ▪ Decision aids and competitor-related information enhance competition (Abramson et al. 2005).

3. Information impacts – conceptual framework

3.1 Defining demand-related information (DRI)

The objective of this essay is to investigate the impacts of information on managerial decisions, marketing productivity, and competition. The focus of this work directs to a specific type of information, i.e., information about primary demand or "demand-related information" (DRI). Knowledge of expected primary demand plays a decisive role, not only for the development of new products. E.g., market research companies are most of the time concerned with demand and sales forecasts for their customers' products. The knowledge of future demand, sales and, consequently, profits is crucial to a manager's decision to launch or give up a new product. Further, decisions regarding current products require an idea of future demand for those products. I investigate DRI impacts in a specific experimental setting. The way DRI is designed in this setting aims to simulate a most realistic situation of managerial information access and decision support. I examine the impacts of an information tool providing firms (i.e., decision makers) with demand forecasts. The information's accuracy is perfect up to the manager's uncertainty about competitors' future decisions. The fact that the accuracy of forecasts depends on the correctness of assumptions reflects the reality of forecasters and market researchers. To make assumptions regarding competitors' future decisions, firms usually have to rely on past data while also taking into account the present situation, e.g., the market development etc. This is exactly what subjects in the subsequent experiments have to do.

Research that relates to DRI includes primarily research on information, decision making, and over-acting, but also research on market orientation, information processing, and decision aids. Although there may be similarities between DRI and decision support systems (DSS) in that both support managerial decision making, it is important to note the differences between DSS and DRI. As mentioned earlier, the DRI I refer to in the work at hand represents an access to new, additional information about market mechanisms, i.e., the demand function. DRI is *not* an optimization tool. DRI provides access to additional information, i.e., information that could have been purchased from a market research company. As future demand forecasts depend on assumptions regarding competitors' decisions, firms with DRI access can do "what if" analyses. However, the output of such "what if" analyses is a primary demand forecast[27], which does not include an optimization of the DRI using firm's decision.

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[27] More precisely, firms can access DRI for any business period, including past, present and future periods.

DRI does not support a decision as a whole (i.e., including all decision aspects, e.g., cost aspects, the financial situation of the company, or demand aspects).

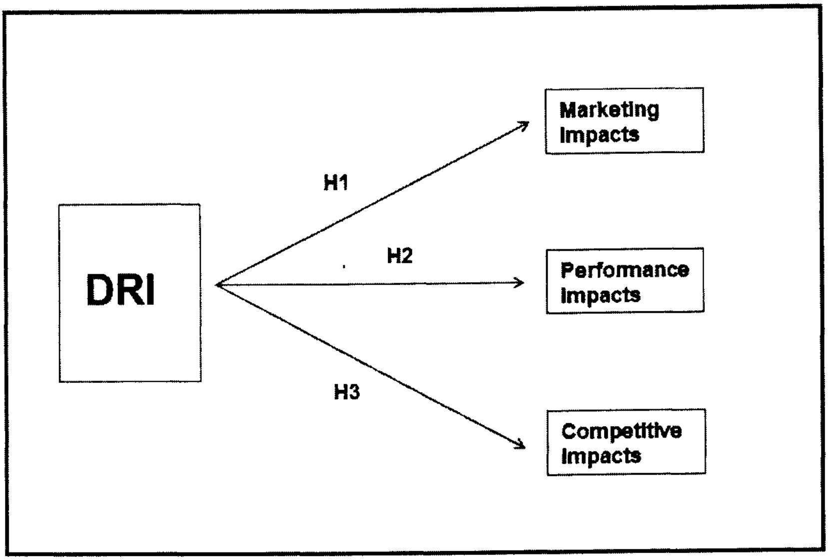
3.2 Conceptual framework

The provision of DRI can influence decision makers in many ways. In this paper, I investigate the impacts of DRI on marketing decisions, subsequent performance and competition. Finally, the findings regarding the link between DRI and marketing productivity may provide new insights into managerial over-acting.

DRI seems to have a direct influence on managerial decisions. These decisions may, in turn, affect firm and industry performance. In oligopolies where firms are competing interactively, there may be no generally valid determinants of performance. Moreover, a firm's action may enhance or deteriorate performance, depending on competitors' actions. Also, firms' decisions and behavior may influence competition. The impacts of DRI I investigate in the work at hand are threefold. The subsequent hypotheses are therefore grouped into three blocks (see Figure I-1). The first block (H1) addresses DRI impacts on marketing decisions, while the second block (H2) relates to the impact of DRI on performance. The third block (H3) addresses the influence of DRI on competition.

Responding to Abramson et al. 2005's suggestions, my experimental study is extended to several important decision variables. Further, my investigation comprises a longer time horizon, notably fifteen business periods.

Figure I-1: Conceptual framework



3.3 Hypotheses

3.3.1 Overview

Overall, the literature suggests the following: Insights from decision theory indicate that information should (at least) not hinder performance. Notably, a customer orientation which entails the processing of customer-related information has been shown to increase new product activity and innovation while its effects on performance are seen controversial. Information use has been found to increase new product success and the timeliness of new products. The literature also offers insights on negative effects of information (or market research). Information could make firms more or too cooperative and less competitive, leading to fewer products marketed. In fact, information regarding demand or costs has been observed to lessen competitive intensity, yet the provision of information about competitors leads to more competitive behavior.

A lack of research on over-acting prompted me to consider one of its special cases, i. e, over-reacting. This stream of research focuses on mistakenly managerial behavior, e.g., in the form of erroneous or unnecessary reaction. Such reactions have been found in the form of over-promoting, especially for large brands and in stable competitive environments that contain noisy signals.

In the following, several hypotheses are developed linking DRI to various measures of marketing variables. These variables include consumer-related variables such as satisfaction of customer preferences, number of products, rate of innovation, primary demand, price-quality correlation, etc. and performance variables (firm profits, industry profits). The third pillar addresses hypotheses about the link between DRI and competition.

3.3.2 Marketing impacts

3.3.2.1 DRI and exhaustion of customer preferences

The value of information has been attributed to its ability to enhance exchanges between the firm and its customers (Glazer 1991). Firms in possession of supplementary information about customers or demand exhibit a better understanding of customer needs[28] and are more able to satisfy those needs. Those firms are expected to know the customers' preferences for products better than firms that do not have DRI. In most markets, there are potential customers who are actually interested in buying a product of the category but who remain non-buyers because they do not like the products offered. For example, a customer might be willing to buy a new pair of shoes but decides against buying because the shoes in the stores are uncomfortable or unfashionable in his opinion. A firm that knows about its customers' preference might try to reach those customers by changing their assortment in a way that more customers buy their products. The shoe producer could offer some especially comfortable shoes and vary the shoe design in a way that a certain customer segment will all of a sudden like their shoes. These product modifications do not necessarily include an enlargement of a firm's assortment, but they imply that the assortment is designed in a certain way to reach a larger part of the potential customers. Provision and usage of DRI is expected to lead to a more precise targeting of consumer preferences and, thus, to a better ability to match those preferences. Therefore, I expect the "exhaustion of customer preferences" (i.e., the percentage of customers whose preferences are covered by the current product assortment) to be higher when firms have DRI than when they do not have DRI. I hypothesize that

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[28] The regular and systematic collection of information about customers is part of a customer orientation (Frambach et al. 2003; Narver and Slater 1990).

Hypothesis 1a: DRI leads to a higher exhaustion of customer preferences.

3.3.2.2 DRI and number of products

I expect that firms having access to DRI will increase their number of products marketed. I argue that the access to DRI will show a manager the potential demand for additional or potential products. For a manager with a strong marketing orientation[29], the tendency towards competitive preemption is likely to dominate the perceived risk of launching a product (Teplensky et al. 1993). When there is sufficient potential demand for a product, the marketing manager's temptation to launch the product and try to preempt competitors will be considerable. This holds especially true if the product as such is profitable. It is hypothesized that

Hypothesis 1b: DRI leads to a larger number of products.

3.3.2.3 DRI and rate of innovation

Information about the market and competitors is key in influencing new product success (Calantone et al. 1996). Research on market orientation has found positive relationships between market orientation and product innovation (Atuahene-Gima 1995; Frambach et al. 2003) and between market orientation and a firm's innovativeness (Han et al. 1998). Lukas and Ferrell 2000 find that one has to analyse components of market orientation, i.e., customer orientation, competitor orientation and interfunctional coordination, separately to isolate their effects on innovation. They find that customer orientation increases the number of new-to-the-world products and reduces the number of me-too products. Sandvik and Sandvik 2003 empirically investigate the hotel industry and find a positive effect of market orientation on both new-to-the-market innovations and new-to-the-firm innovations. Existing research linking information and innovation limits to the aforementioned studies referring specifically to the constructs of market orientation and customer orientation respectively. The above findings might therefore not be transferable to my research setting. That is, I cannot infer that access to DRI will generate the same effects as a firm's customer orientation (in the sense of

[29] Teplensky et al. 1993 argues that a management with a strong financial orientation will be less disposed to competitive preemption „due to a primary focus on sources and uses of funds", while a management with a stronger marketing orientation might be more attracted towards competitive preemption and the reputation gain resulting from a broader market penetration.

Han et al. 1998; Narver and Slater 1990). Directionally, however, I anticipate that DRI may enhance new product activity. In general I expect that firms who are given more information about demand are likely to offer a larger variety of new products than firms without this information. Hence, I propose the following hypothesis:

Hypothesis 1c: DRI leads to a higher rate of innovation.

3.3.2.4 DRI and primary demand

The provision of DRI informs companies and managers about the existence of market segments and market niches. As a result, one can argue that DRI enables firms to determine the drivers of primary demand. This can, in turn, allow for the market to grow as a whole as well as individual companies to grow in size and, some of them, in terms of market share (Arora et al. 1998).

To illustrate, possessing detailed information about a market's heterogeneity will allow firms to fine-tune their product offerings to markets differing needs and wants. More precisely, the resulting better match between market needs and market offerings is likely to translate into several effects. First, existing consumers are likely to consume a higher rate - causing the market's observed primary demand to grow. Next, potential consumers are less likely to fall victim to substitutes - causing the market's primary demand to increase. Finally, others will less often stop consuming the market's product category altogether - causing the market's primary demand to not shrink.

Based on the aforementioned arguments, I offer the following hypothesis linking DRI and primary demand.

Hypothesis 1d: DRI leads to a higher primary demand.

3.3.2.5 DRI and price-quality correlation

I argue a dual base between DRI and the price-quality correlation. More precisely, the relationship entails consumer issues as well as issues pertaining to competition.

Generally, providing all companies with DRI will allow each firm to more precisely address consumers' needs and wants. The provision of DRI can, thus, allow a firm to skim more of the consumers' surplus, approach consumers' willingness to pay, and optimize pricing decisions. This entails tagging a price to a product although that price corresponds rather little to its quality. For example, DRI will allow firms to identify non-quality based USPs[30]. That is, as companies know more about their consumers they also learn about opportunities of intangible product augmentations. By product augmentation I mean changes in products that maintain the product's quality (e.g., a different color of a car) or a firm's identification and exploitation of a new trend (e.g., that Perrier water is very low in calorie and, as a result, is in line with a calorie-conscious trend). Thus, DRI will facilitate that the price-quality correlation can decline.

DRI will also facilitate and accelerate firms' learning about competitive strategies and preferences of their rival firms. As a further result, precise knowledge of demand or the demand function can allow a company to position its offerings more precisely to prevent its products from entering a competitor's turf. This will not only lead to a more crisp positioning but also holds the promise of less of a head-to-head competition and competitive misunderstandings that have been viewed as one cause for price wars (Heil and Helsen 2001). Along these lines, it is important to note that this decline in the price-quality relationship is totally market driven (Day 1994). That is, it is not related to any type of tacit collusion (e.g., Chamberlin 1929, Heil and Langvardt 1994).

The aforementioned arguments combine into the following hypothesis linking DRI to the price-quality correlation.

Hypothesis 1e: DRI leads to a decline in the correlation between product quality and product price.

3.3.3 Performance impacts

Naturally, the effect of DRI on a firm's or industry's performance is nothing short of fundamental. The distillation of this effect is, however, not straightforward as two arguments can be put forth: In the literature of information economics, information is seen as an observable signal dependent on an unobservable underlying state of nature (e.g., Nelson and Winter Jr. 1964). If the signal is useful, it can help the decision maker to identify the underlying state of nature with a higher probability. If the signal is not useful, the decision

[30] USP: Unique Selling Proposition

maker is free to ignore it. Consequently, information from the information economics' perspective is never harmful and often ameliorates the decision maker's situation[31].

In industries with asymmetrically informed firms, the better informed firms enjoy a greater flexibility to adapt to the state of nature while the worse informed firms can benefit from a higher commitment (Einy et al. 2002; Gal-Or 1987; Gal-Or 1988[32]). Under certain conditions (e.g., in a Cournot oligopoly with non-constant marginal costs, see Einy et al. 2002) the benefit gained from commitment can dominate the flexibility benefit, i.e., the worse informed firm can be better off than the better informed firm. However, when all firms have access to information, no firm can take advantage of its lack of information thus restricting my view to the informational flexibility benefit.

The processing of information is an integral part of a market orientation, which, in turn, is found to be positively related to performance (Deshpandé and Farley 2004; Jaworski and Kohli 1993; Narver and Slater 1990; Rodriguez Cano et al. 2004; Slater and Narver 1994). The performance impacts of a customer orientation which entails the processing of customer-related information are seen controversial (Dawes 2000; Noble et al. 2002). The use of information tools (i.e., decision aids) has been found to foster profits and market share (Van Bruggen et al. 1996).

I hypothesize the provision of DRI to direct managers' attention toward making consumer issues more "prominent" within management's mind set. Taking a more precise and even intense consideration of the customers' point of view, firms should, for example be more able to avoid marketing efforts that are not rewarded by the customers (Francese 1995). Thus, DRI should enhance total industry profits.

Furthermore, one might assume that the positive effect of information on performance is derived from the information constituting a competitive advantage (Francese 1995) that other competitors do not have. This effect should not exist per se if every firm gets the same market research information. However, firms are likely to differ as to their willingness and ability to process, evaluate, and utilize DRI. Thus, I expect competition and competitive interaction to provide additional sources for an increase in firm profits, at least for certain firms.[33]

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[31] However, decision theory usually assumes independence of strategies and states of nature. Consequently, the advantage of additional information is often contingent on the fact that competitors do not know about the informational advantage (Ponssard 1976).

[32] However, Gal-Or's findings refer to the case of Stackelberg competition.

[33] Although a large part of the literature posits a positive effect of information on performance, there is also contrary evidence. Decision makers may not benefit from their information access by retrieving more information but by effort saving (Todd and Benbasat 1992). In a survey on the effects of market research

Overall, DRI should positively affect industry and firm profits. As a result, I propose the following hypotheses:

Hypothesis 2a. DRI increases total industry profits.
Hypothesis 2b. DRI increases firm profits.

3.3.4 Competitive impacts

Competitive intensity is regarded to directly impact profits but, if competitive intensity is too high, disastrous competition can result (Heil and Helsen 2001). As DRI allows companies to position their products, I expect that firms will utilize this information to avoid being overly close to competitive offerings. Thus, high competitive intensity, for example in the form of head-to-head competition will occur less often as a result of the provision of DRI. Notably, under more intense competition, total industry profits may turn out to be smaller than in markets with a low competitive intensity. Boone 2001 points out that this is only true if the firms face equal costs. Otherwise, profits can also increase when competition becomes more intense. This is due to the fact that, according to Boone, in markets where firms have different cost levels, the most efficient firms become more powerful when competition increases whereas the least efficient firms lose and may eventually have to leave the market (Boone 2000, Boone 2001). Please note that more details on the peculiarities of competitive intensity will be discussed as part of the measurement section.

Generally, competitors learn about their rivals, develop competitive attitudes, and tend to adjust their market conduct accordingly. It has been argued that a rather limited number for interaction suffices for such reputation-building (Fombrun 1996). Thus, I expect that competition will rather soon converge to a competitive interaction that can be dubbed as rather stable. This notion is consistent with conceptual and empirical work on price wars that suggests a rather stable competitive interaction and intensity after a price war has been terminated (Heil and Helsen 2001).

A growing number of products often implies that more products enjoy a unique positioning. As a result, head-to-head competition can occur less frequently. As a straightforward consequence, competitive intensity is expected to decline in the case of frequent new product introduction.

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activity, Hart and Diamantopoulos 1993 find a null effect on performance. Furthermore, additional information can even harm performance (Glazer et al. 1992).

According to findings by Huck et al. 1999 and Huck et al. 2000 for the quadropoly case, I should expect lower quantities and higher prices when firms get additional information about demand. As Huck and Oechssler and Bonanno and Haworth 1998 consider these two variables as indicators of competitive intensity, they conclude competition is less intense when firms have more information about customers or demand.

Meagher and Zauner 2004 found that for the duopolistic linear market case with quadratic transportation costs, firms tend to differentiate more when they are uncertain about the location of demand or the consumers' preferences, respectively. Using this line of argumentation I should expect products to be more differentiated when firms have less information about demand. However, a market with more differentiated (i.e., less substitutable) products is generally considered less competitive. Hence, this would contradict the aforementioned idea of DRI's decreasing effect on competition.

Based on the aforementioned, I propose the following hypotheses on competitive intensity:

Hypothesis 3a. DRI decreases competitive intensity.

Hypothesis 3b. Competitive intensity will be stable after it peaked.

Hypothesis 3c. As more products are introduced, competitive intensity will decline.

4. Empirical investigation using the simulation "SINTO Market"

4.1 Research method and choice of subjects

To test my hypotheses, I collected primary data using the simulation "SINTO Market". In general, simulations provide many opportunities traditional research methods, e.g., surveys, interviews, or laboratory experiments, cannot provide. A simulation provides the environment while people provide the behaviors and decisions (Lant and Montgomery 1992). Lant and Montgomery 1992 state that "simulation games provide a more controlled research setting than the field" and "a much more realistic setting than a laboratory". Compared to real-world observations, quasi-field experiments like the SINTO simulation game enable me to isolate the effects of information by holding everything else constant, which would not be possible for real market data. Similar simulations, like the MARKSTRAT and Markstrat2 environments (Larréché and Gatignon 1977; Larréché and Gatignon 1990), have been widely acknowledged and used for studying marketing decision making (e.g., Clark and Montgomery 1999; Glazer et al. 1989; Glazer et al. 1992; Van Bruggen et al. 1996; Van Bruggen et al. 1998). SINTO provides access to all firms within an industry and allows the researcher to observe the effects of information over a time frame of *fifteen* business periods, which is longer than the one offered by other simulations (e.g., MARKSTRAT). The experiments were conducted using graduate business students at the Johannes Gutenberg-Universität at Mainz and at the University of Applied Sciences (Fachhochschule) at Mainz, Germany.

Students majoring in business were select as ideal candidates. Although managers are frequently viewed as ideal subjects for research on competition, they seemed to be less suited for my experiment. This is since I am inquiring rather basic market phenomena, ideal subjects should have a certain "sufficient" knowledge about markets, prices, products, etc. yet such subjects should not be burdened by too much experience, recollection of war stories, and the like.[34] Since homogenous experimental groups always implicate some limitations to generalizability, the use of students offers the same limited potential for generalizations as does the use of "real world" subjects (Greenberg 1987). Notably, using a homogenous group of subjects like graduate business students is generally preferable to using heterogenous groups (Greenberg 1987). Thus, business students appeared as preferred subjects.[35]

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[34] For example, the use of information is supposed to be affected by a manager's prior knowledge as well as by a predisposition towards or against the information (Menon and Varadarajan 1992).

[35] As a matter of fact, the use of student subjects in management research is widespread (e.g., Armstrong and Collopy 1996; Glazer et al. 1989; Marinova 2004; Van Bruggen et al. 1996; Van Bruggen et al. 1998).

The subjects that participated in the experiment were attendants of marketing seminars offered to graduate business students. Receiving the credits for the seminar required participation in the experiments. As an incentive, the subjects were informed that their performance in the experiment[36] would affect their final grade in the seminar.

4.2 Description of the simulation "SINTO Market"

My experiment used a 2 (information) by 15 (period) mixed factorial design. Information was a between-subjects factor (Scenario 1: no information; Scenario 2: information) and period was a repeated within-subjects factor (period 1 to 15).

To test my hypotheses, I employed the "SINTO Market" simulation (Becker and Selten 1970).[37] This game simulates an oligopolistic market with three symmetric firms. The firms compete with each other for 15 business periods, periodically making simultaneous decisions. The term "SINTO" refers to a newly developed technology adopted by all three firms.[38] Every firm can market up to ten different variants/brands.

The firms have symmetric starting conditions, i.e., capacities, financial situation, cost functions etc. This enables me to control for possible firm size effects (Moorman et al. 2005). The brands are characterized by two main product attributes[39] as well as quality[40] (all three variables can adopt levels on a discrete scale from 0 to 9). While a higher quality incurs higher production costs, the choice of the two main attributes does not affect costs. The competitive effect of one product on another one increases with increasing similarity of their main attributes. A higher number of brands incurs higher fix costs. Customers do not pay attention to the firm that produced the brand when making a purchase decision. Advertising decisions are typically made on the product level as opposed to the firm level. Consequently, all products are potential competitors.

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36 The performance in the experiment was measured in terms of absolute firm equity and relative firm equity compared to competitors (see also subsequent section).

37 See also Becker 1972; Becker et al. 2003; Fischer 1972; Leopold-Wildburger and Lind-Braucher 2001; Reinfeldt 1972; Selten 2002 for more applications of the SINTO simulation.

38 Hence, the term „SINTO“ can be interpreted as the technical platform from which firms can start to produce their products.

39 The main product attributes entail the tartness (mild to bitter taste) and grainedness (fine-grained to coarse-grained) of SINTO products.

40 A product's quality is measured as its package quality (very simple to very luxurious package). Importantly, this does not mean that quality is generally equated with package luxuriousness. Moreover, in this specific simulated market setting, all consumers prefer, ceteris paribus, higher levels of package luxuriousness. That is, package is not a question of taste or individual preferences, but a higher package level is unambiguously better than a lower level. As such, package constitutes a variable for vertical differentiation as is the case with quality (e.g., like the cleaning-effectiveness of a household cleaner, see Besanko et al. 2004, p. 214; Lancaster 1990). Therefore, the package variable in the SINTO market can be interpreted as product quality.

In every period, the firms can develop new products, eliminate existing products, modify their existing products' attributes, quality, prices, advertising expenditures and quantities, and invest in or reduce capacity. The demand for products in the SINTO market is a function of product attributes, quality, prices, advertising expenditures, competitors' decisions, prior product decisions and market development (see Appendix for details about the demand function). The market potential increases during initial periods of the game, then flattens and stays constant until the end of the game. The firms have to optimize their marketing mix and other decision variables and come up with conjectures about their competitors' more or less likely moves.

At the end of every period the firms receive print-outs containing their results. I.e., every firm gets a result sheet containing its own business situation: a balance sheet, a profit and loss statement, a breakeven analysis of its products, a ranking of the three firms with respect to their equity capital (e.g., "firm 2 better than firm 3 and firm 3 better than firm 1"), and a market analysis showing all products marketed in the current period including product attributes, quality levels, prices, advertising expenditures and units sold. The market analysis also contains a two-dimensional visualization of the products in the market according to their two main attributes. Decisions in subsequent periods are made after analyzing previous periods' results. The decision time per period is limited to approximately 40 minutes.

To prepare for the game, the subjects are given a written explanation of the SINTO rules in advance. At the beginning of the game the rules are explained a second time. The subjects are told that the goal of the game is to maximize their firm's profits and equity.

In both experimental conditions conducted, the firms had complete information about the cost situation of the game. This was not the case for information about demand.

4.3 Experimental design

4.3.1 Repeated measures factorial design

My experiment used a 2 (information) by 15 (period) mixed factorial design. Information was a between-subjects factor (Scenario 1: no information; Scenario 2: information) and period was a repeated within-subjects factor (period 1 to 15). Keppel 1991 describes this form of design as a "mixed within-subjects factorial design" using the term "mixed" to point out that both between-subjects and within-subjects factors are employed.

My experimental design differs[41] from the MARKSTRAT[42] design used by Glazer et al. 1992 (see also later sections for a detailed comparison). Therefore, it will be interesting to find out whether Glazer et al. 1992's results regarding performance and the number of products will replicate in my research setting.

Table I-5: Comparison of present experimental setting to Glazer et al. 1992's experimental setting

	Glazer et al. 1992's MARKSTRAT experiment	*This SINTO experiment*
Subjects	44 MBA students	216 graduate business students of the Johannes Gutenberg Universität at Mainz & the University of Applied Sciences at Mainz
Number of firms	Oligopolies with 5 firms (5 firms= 1 industry)	Oligopolies with 3 firms (3 firms= 1 industry)
Group size	2-3 students per firm/team	3-4 students per firm/team
Firm symmetry	Firms have different competitive starting conditions (asymmetric)	Firms have equal starting conditions (symmetric)
Sample size	Sample of 4 industries	Sample of 22 industries (11 without DRI + 11 with DRI)
Time frame	9 periods	15 periods
Number of brands at the beginning	Each firm has to start with 2 brands.	Firms can start with 1 to 10 brands.
Number of brands limit	Number of brands is limited to 5 per firm.	Number of brands is limited to 10 per firm.
Competitive context	Firms are not aware of whether their competitors do or do not possess information.	Firms are aware of their competitors possessing the same information.

[41] Glazer et al. 1992 point out that it would be interesting to examine the local rationality effect in a different competitive context (p. 224). Acting on this suggestion, I use a different competitive context insofar as, in my experiments, all firms of an industry have access to the same type of information and are aware of this fact. Hence, I investigate whether information enhances (or, with in line with Glazer et al. 1992, rather inhibits) industry performance even if the same information is given to all competitors and, thus, does not constitute a competitive advantage for a segment of firms. Furthermore, my experimental design enables me to investigate the long-run effects of information accessibility.

[42] See Larréché and Gatignon 1977.

	Glazer et al. 1992's MARKSTRAT experiment	*This SINTO experiment*
Information manipulation	Period 1-2: all firms receive 4 types of information (consumer survey, semantic scale, perceptual mapping, and advertising experiment) Period 3-7: a firm either has to or cannot purchase all of the aforementioned types of information. The firms are free to purchase or not purchase any or all of the remaining 11 types of information (overall, there are 15 market research studies available in MARKSTRAT, 4 of which are part of the manipulation). In every period, the firms that receive the information are chosen randomly. Either 1, 3 or 5 firms receive information in a period at a time. The information manipulation changes in every period, i.e., a firm does not have information access in every period.	Period 1-15: SCENARIO 1: None of the firms receive additional information. Period 1-15: SCENARIO 2: All firms in an industry receive the same type of information (information about potential demand for specific products). The information manipulation is constant over time and across firms. I.e., there is no switching in firms that receive information, nor do I alter the number of firms that receive information. To be able to observe the long-run effects of information accessibility, I do not alter the information manipulation over time periods.
Type of information	4 market research studies (see above).	Primary demand (DRI): firms are given a program which enables them to forecast primary demand for any product, given the firm's conjectures about their competitors' decisions.
Information costs	Firms have to purchase information.	Information is costless.

4.3.2 Information manipulation

In both experimental conditions conducted, the firms had complete information about the cost situation of the game. This was not the case for information about demand.

To examine the influence of DRI, I played the game in two different scenarios. In scenario 1 (NO INFO group), subjects were given only qualitative and fundamental information about demand (see Appendix for a more detailed description of the experimental conditions). More precisely, subjects were only told that low prices, high quality and high advertising expenditures increase demand and that most customers prefer medium levels of the two main product characteristics while some customers prefer extreme levels. Subjects were informed that demand for a brand decreased when many brands with similar attributes were offered.

In scenario 2 (INFO group), all firms were given the same information as in Scenario 1 plus additional precisely calibrated information in terms of the exact demand function[43] (see Appendix for details). I decided against providing the firms with the mathematical demand function for two reasons: first, I wanted the information to be somewhat realistic. The pieces of information about demand firms get from market research companies do usually not have a functional form. Moreover demand forecasts are often conveyed in the form of numerical estimators or tools firms can use to generate demand forecasts depending on some input variables. Secondly, I wanted to make sure that the information provided is easy to use by the firms. Due to its complexity, the demand function presented as a mathematical function would probably have confused the subjects thus putting an unintentional restriction on the use of the information. To facilitate things, I decided to convey the information in the form of a spreadsheet enabling the firms to input their own product decisions and their conjectures about their competitors' decisions for the respective time period. Then, the demand forecast was instantly generated for all products. The firms were free to compute forecasts not only for the upcoming but also for later periods of the game. However, as the firms had to conjecture their competitors' decisions, it was necessary to adapt assumptions periodically in order to get exact demand forecasts for later periods. Consequently, all firms used the information tool in every period. As soon as they were informed about the results of the former period, they corrected their assumptions and planned the next periods based on the adapted parameters. The information tool could help the firms to decide on new products, changes on existing products, pricing, advertising, capacity planning, and competitive strategies in general. There was no constraint on how many forecasts firms were allowed to generate, but there was a time constraint limiting the decision time per period.

To capture the long-term effects of DRI I did not alter the information manipulation across time periods (this is different from the experiments conducted by Glazer et al. 1992). Besides, my experimental time horizon comprised fifteen business periods. This exceeds the one used by previous research (Abramson et al. 2005; Glazer et al. 1992) by up to 90%.

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[43] The DRI provided in this scenario accounts for competitors' actions, thus referring to a competitive setting (see Abramson et al. 2005).

I note that I broadened the conceptual base as used by Glazer et al. 1992. More precisely, all firms were aware of their competitors' information access.[44] Yet, as expectations about competitors' actions determined the quality of the demand forecast, the information given to the firms was inherently differential.

4.3.3 Data

I conducted SINTO experiments using a total of 216 graduate business students. Among these students, 111 were assigned to games (i.e., industries) under scenario 1 condition, while 105 students were assigned to industries under scenario 2 condition. Every experimental unit, i.e., every industry, comprised nine to twelve students. Within industries, students were divided into three teams, with each team representing one firm (thus, each firm was represented by three to four students). All students were randomly assigned to firms and experimental conditions. In every industry, SINTO was played over fifteen business periods. The subsequent data analysis is based upon eleven scenario 1 industries and eleven scenario 2 industries.

4.3.4 Dependent variables

The dependent variables were measured periodically for each of the conducted SINTO runs. That is, for a given dependent variable, the SINTO simulation recorded 15 periodical measures for every SINTO run.

The satisfaction of customer preferences was defined as the degree to which existing customer preferences (i.e., preferences for the two main product attributes) were covered by the products offered (see Appendix for details). The measure is termed "exhaustion of customer preferences" since it assesses the degree to which products correspond to customer preferences.

The number of products was extracted as the total number of offered products in a Sinto market. The rate of innovation was measured in terms of the number of new product introductions (NPIs) in a period. Primary demand was assessed by measuring the quantity of customers willing to buy the products offered by the firms. To investigate the price-quality correlation, I calculated the correlation coefficient (Pearson) of product prices and the corresponding quality levels (0 to 9) in a period.

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[44] The question of how firms would behave if they suspected that their competitors had the same information is considered an interesting research topic for future research (Glazer et al 1992).

To investigate industry and firm performance, I assessed two alternative variables: Total industry profits were measured by aggregating the individual profits of all three firms within an industry. The same was conducted for firms' financial equities. To investigate individual firm performance, I ranked the firms within an industry according to their individual profits and financial equity in every period (like this, rank one belonged to the best firm, rank two to the second-best and rank three to the worst firm). Then, I compared absolute profits and financial equity of the best firms (max), the second-best firms (med) and the worst firms (min) of both information treatments.

The measurement of competitive intensity is described in the measurement section (see below).

4.4 Measurement

4.4.1 Measurement of competition

The measurement of competition has been somewhat lacking for a considerable period of time (Weitz 1985, Heil and Montgomery 2001). This may be since the construct of competitive intensity proves rather complex. Also, no generally accepted definition of this term exists.

Due to different definitions of competition, the literature offers several measures for this construct - which I use as a platform. In the economics discipline, the intensity of competition is often measured by comparing Cournot and Bertrand competition equilibria (e.g., Huck et al. 1999; Huck et al. 2000). Since Cournot competition leads to higher prices and lower output than Bertrand competition, it is considered a regime of less intense competition (e.g., Bonanno and Haworth 1998). Following this intuition, competitive intensity may be measured in terms of prices and/or output (i.e., quantities, capacities) while lower prices and higher output will be associated with a more intense competition. Raju and Roy 2000 adopt the Cournot-Bertrand concept to measure competition but argue that it is not the only possible alternative to measure competitive intensity. As a second alternative, they incorporate the substitutability of products. Another measure offered by economists entails the number and the concentration of competitors in a market. The higher the concentration the lower competition is said to be. This idea is refuted by Boone 2001 who provides four axioms a measure of competition should have. He states that increasing competition becomes obvious in (1) declining total industry profits, (2) a larger discrepancy between the profits of the most and the least efficient firm, (3) increasing total industry output and (4) a smaller output level of firms that feature much higher costs than the leader. Product substitutability meets the four abovementioned axioms which gives further support for it as a measure of competitive intensity. Boone 2001 finds also support for travel costs and market transparency. Another measure that is often used are industry profits. If all firms face equal costs, a more intense competition goes along with decreasing total industry profits (Boone 2001; Pasa and Shugan 1996). If firms have different cost conditions, the most efficient firms become more powerful whereas the least efficient firms lose market shares and may eventually have to leave the market. In the latter case, a more intense competition may be accompanied by higher total industry profits (Boone 2001).

In an interesting approach, Gatignon 1984 uses competitive reactivity to measure competition. More specifically, he focuses on reaction elasticities and attributes a higher competitive intensity to markets where firms are more apt to react to their competitors' moves. However, Gatignon acknowledges that other measures of competition exist and claims that alternative measures can roughly be summarized by measuring the number of competitors in a market (e.g., for a small number of competitors, the Herfindahl index is highly correlated with the number of competitors). Other researchers use surveys to assess competitive intensity in a market. E.g., Ottum and Moore 1997 use the term "environmental turbulences" to measure changes of customers, competitors, and technology over time. Atuahene-Gima 1995 assesses "environmental hostility" via questionnaires given to managers. Ali 2000 measures competitive intensity by asking managers questions about aggressive competitive activity and the number and relative strength of competitors in the marketplace.

Due to the aforementioned various measures of competition provided by the extant literature, the problem of measuring competitive intensity was solved as follows. Instead of deciding for one measure of competition while neglecting other alternatives, I considered several important measures of competitive intensity from the literature that were applicable to my experimental data. As an initial approach, I restricted the measurement of competition to applying and comparing the following measures:

- Aggregate profits: Under certain conditions, aggregate industry profits tend to decline when competition becomes more intense (Boone 2001; Pasa and Shugan 1996).
- Individual performance differences: With increasing competition, the most efficient firms become more profitable whereas the least efficient firms become even less powerful (Boone 2001).

- Average prices: We usually observe falling prices when competition becomes more intense (e.g., Abramson et al. 2005; Huck et al. 1999; Huck et al. 2000; Raju and Roy 2000).
- Aggregate capacities: With increasing capacities, firms supply higher quantities which come along with lower prices (Huck et al. 1999; Huck et al. 2000; Raju and Roy 2000).
- Product substitutability (measured as the inverse of product differentiation): Increasing product substitutability (decreasing product differentiation) indicates increasing competition (Raju and Roy 2000) and product interlacing reveals a higher competitive intensity than product segmentation (Brander and Eaton 1984).
- Advertising spending: More advertising activity indicates more intense competition when it reflects a rivalry between the firms and when it makes customers more price-sensitive. When advertising makes customers less price-sensitive, increases a certain firm's market power, or leads to an overall growth of the industry by attracting new customers it can rather be considered as an indicator of a decreased competitive intensity (e.g., Comanor and Wilson 1979; Soberman 2004).

To measure competitive intensity defined in terms of prices and quantities, I extracted the average prices across all products as well as the firms' aggregate capacities. The performance gap (i.e., individual performance differences) between the most efficient and the least efficient firm was measured by calculating the ratio of their financial equities (i.e., the lowest financial equity in a specific period was divided by the highest financial equity in that period). To account for competitive intensity defined as product substitutability, I measured product differentiation as a negative analogon of product substitutability using nearest neighbor analysis (the average nearest neighbor distance in a market was divided by the expected nearest neighbor distance for the given number of products). Advertising was measured in terms of the average total advertising expenditures of the three firms as well as the advertising expenditures per product.

4.4.2 Measurement of product substitutability or product differentiation

Product substitutability is used as an indicator of competitive intensity (e.g., Raju and Roy 2000). In a market with highly substitutable (i.e., similar) products, the degree of competitive intensity is considered to be high, while, in the contrary case, when products are rather dissimilar, competition is supposably less intense. The degree of product differentiation is reflective of the dissimilarity of products in a market. Therefore, product differentiation can be considered an inverse analogon of product substitutability.

(Horizontal) product differentiation is the SINTO market takes place with respect to the two main product attributes (i.e., tartness and grainedness, denoted as r and s). [45] These two attributes span a two-dimensional characteristics space. A product's location is determined by its attribute levels for r and s.[46] For both attributes, products can adopt integer values between 0 and 9 indicating the level of tartness (mild to bitter taste) and grainedness (coarse-grained to fine-grained) respectively. To measure horizontal product differentiation in the SINTO market, it seems therefore appropriate to take into account the location of all products on the two-dimensional quadratic r-s-field (see also Dickson and Ginter 1987). The degree of product differentiation is thus reflected by the proximity of products within the two-dimensional characteristics space. That is, if products are close substitutes, they will be located close to each other. Highly differentiated products will be located at larger distances to each other. In the following I present two ways of measuring product differentiation in a spatial market as described above.

The first measure constitutes a transformation of Weitzman's measure of diversity (Weitzman 1992). That is, I measure the degree of diversity generated by each product on average:

$$V(S)^T = \frac{V(S)}{N}$$

with

$V(S)$: *Weitzman's measure of diversity*

N : *number of products.*

If products are located close to each other, they provide a low level of diversity. The normalization by the number of products accounts for the fact that the degree of diversity cannot decline when additional products enter the market. Transforming $V(S)$ into a measure

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[45] The degree of product differentiation should describe the similarity or dissimilarity of products regardless of their superiority. By superiority I mean that all customers prefer one product to another given everything else (e.g., price) is equal. These products would be called vertically differentiated. In the SINTO game, quality (denoted as q) represents such a variable of vertical differentiation, because, ceteris paribus, all customers prefer a higher quality. The quality variable is consequently not included in the measurement of product differentiation. The main product attributes tartness and grainedness (denoted as r and s) represent variables of horizontal differentiation, because, ceteris paribus, two products with different levels of r and s will both face positive demand. That is, none of the products is unambigously superior to another product only because it has different levels of tartness and grainedness.

[46] Therefore, the form of product differentiation in the work at hand is somewhat similar to the address models of differentiation examining location decisions and spatial competition (Hotelling 1929; Lancaster 1975). The market space can thus be interpreted as a characteristics space in which the location of products is determined by their corresponding product characteristics (Eaton and Lipsey 1975).

on a per-product basis enables me to compare product differentiation across markets that differ with respect to the number of products.

The second measure of product differentiation is taken from spatial statistics. It is used to investigate point patterns in multidimensional or geographical spaces. In this context, is common to distinguish three general patterns: a regular pattern, a random pattern, and a clustered pattern. The measure, termed „Nearest Neighbor Index" (NNI), is equal to (see Clark and Evans 1954):

$$NNI = \frac{d(NN)}{Exp(NN)}$$

with

$d(NN)$: *average nearest neighbor distance of all products*

Product i's nearest neighbor distance is the (euclidean) distance to the product located the closest to i.

$Exp(NN)$: *expected average nearest neighbor distance if products were located at random.*

If products are clustered, nearest neighbor distances will be small, thus leading to a small NNI (NNI=0 in the extreme case). If products follow a random distribution, the observed d(NN) will be about equal to Exp(NN). Consequently, NNI will be close to 1. If product locations exhibit a regular pattern, nearest neighbor distances will be larger than expected distances under randomness, thus leading to an NNI above 1.

Highly clustered products can be associated with a lower degree of product differentiation, while regularly located products indicate a higher degree of product differentiation. In this sense, NNI can be interpreted as a measure of the degree of product clustering within a market space and be used as an indicator of product differentiation.[47]

[47] In the SINTO environment, I do not use an edge-correction of NNI (see Donnelly 1978) for the following reason: The study area of the SINTO product market does not constitute a sampling area. Consequently, an event located close to the edge of the market area cannot have a nearest neighbor outside the study area. Also, for the ease of computation, the calculation of product differentiation in the work at hand is not based on higher order nearest neighbor distances.

4.5 Method

4.5.1 On the analysis of repeated measurements

The analysis of the SINTO data is rather complex. The reason lies in my experimental design involving several observations on the same experimental unit (here: game) over fifteen time points. Independent variables involving repeated (and therefore often correlated) observations, e.g., observations over several time points like in a longitudinal setting, are usually known as "within-subjects" (Littell et al. 1996) or "repeated measures factors" (e.g., Latour and Miniard 1983). Experimental designs, including both a between-subjects and a within-subjects factor, are also referred to as split-plot designs (Bock 1985, p. 447).

Typically, applying a univariate analysis of variance (ANOVA) including conventional F tests of main and interaction effects is not appropriate in the context of studies with repeated measurements. The reason is that critical assumptions made in classic univariate ANOVA are violated when within-subjects factors are involved: Apart from the assumption of normally distributed and independent errors, the so-called assumption of "multisample sphericity[48]" causes difficulties. Typically, repeated observations are nonspherical, i.e., do not have equal variances and covariances at all times[49]. Moreover, measurements closer in time tend to be more correlated than measurements farther apart in time, and variances tend to increase with time. While the F test is robust to covariance heterogeneity in between-subjects factors[50], a violation of the sphericity assumption in the within-subjects factor[51] leads to highly inflated Type I errors[52] when the within-subjects factor has more than two levels (Latour and Miniard 1983; Max and Onghena 1999). Hence, a violation of the spherity assumption yields invalid F tests of the within-subjects factor including interactions involving the within-subjects factor. The Greenhouse and Geisser 1959 index measures the degree of departure from sphericity and can - like the correction by Huynh and Feldt 1976 - be used to adjust the F test degrees of

[48] The assumption of equal covariance matrices across all levels of the between-subjects factor and all levels of the within-subjects factor is also referred to as multisample sphericity.

[49] The assumption of variance and covariance homogeneity across all levels of the within-subjects factor is also known as sphericity assumption (see e.g., Keselman et al. 2002) or circularity assumption. Huynh and Feldt 1970 have specified this assumption and identified equality of variances of differences for all pairs of treatment measures (in the repeated factor) as a necessary and sufficient condition under which the F test is valid in a repeated measurements analysis of variance (Huynh-Feldt condition).

[50] Between-subject heterogeneity occurs when different groups of subjects display different variance patterns but are homogeneous within groups (Littell et al. 1996, p.267).

[51] Within-subject heterogeneity occurs when variance varies across different levels of the within-subjects factor, e.g., when variance changes over time (Littell et al. 1996, p. 267).

[52] A Type I error is the probability of falsely rejecting a true null hypothesis.

freedom. An approach by Huynh 1978 corrects for violations of multisample sphericity, employing the conventional F test (Keselman et al. 1999).
The literature suggests several univariate and multivariate approaches to deal with repeated measures data (e.g., see Keselman et al. 2001 for a review). The appropriateness of those approaches depends on the sample size, group sizes (balanced vs. unbalanced designs), the distribution of observations (normally vs. nonnormally distributed), the number of factors and factor levels and the existence of missing data and so on. Basically, the difference between univariate and multivariate repeated measurements approaches consists in the following: Univariate approaches assume that there is only one dependent variable whose values belong to different levels of a repeated independent factor. The multivariate approach, however, creates a separate dependent variable for every level of the repeated factor (e.g., for 15 time periods like in the SINTO experiment, the multivariate approach assumes 15 dependent variables each belonging to a single period). Multivariate repeated measurements approaches, e.g., those using Hotelling's T^2 test statistic[53], do not require sphericity. Instead they require covariance homogeneity in the between-subjects factor.

A mixed model analysis is the most recent approach to the analysis of repeated measurements (Keselman et al. 2002; Keselman et al. 1999). It is favorable to other repeated measures approaches (Keselman et al. 2001) since the user can explicitly model the data's covariance structure (prior to testing for treatment effects) thus making it possible to account for time-related correlations of observations within an experimental unit (Kowalchuk et al. 2004; Littell et al. 1998; Keselman et al. 1999). Technically, one can examine the data's covariance structure and then select the correct structure of the model among a set of possible alternatives (e.g., compound symmetric, spherical, autoregressive, heterogeneous autoregressive, unstructured, variance components, etc.). One can use an autoregressive covariance structure when observations closer in time are more correlated than observations farther apart in time (Keselman et al. 2000). This is especially important for the SINTO data at hand since we have autocorrelated measurements in many of the dependent variables. In the SINTO market, all experimental units face equal starting conditions, which often leads to a low variance between games in the first periods of the experiment and an increased variance in later periods. The mixed model procedure can be considered "midway between" univariate and

[53] There are four alternative test statistics to be used for multivariate repeated measures anova, but when the between-subjects factor has only two levels they are all equivalent to Hotelling's T^2 statistic (Keselman et al. 2001).

multivariate approaches (Max and Onghena 1999). Unlike other univariate approaches, the mixed model analysis does not require spherical data, but neither does it leave complete freedom in estimating covariances, as in the multivariate analysis of variance (Max and Onghena 1999). Contrary to the multivariate approaches, the mixed model allows modeling heterogeneity in the between-subjects factor (Keselman et al. 2001).

A viable alternative to the mixed model procedure is a multivariate extension of the Welch and James approach (James 1951; Johansen 1980; Welch 1951). It is robust to heterogeneity of the between-groups covariance matrices, even when group sizes are unequal (unbalanced). However, sufficiently large sample sizes are required for the test of main and interaction effects being valid (Keselman et al. 2001; Kowalchuk et al. 2004).

The mixed model gains additional power from the fact that the covariance structure of the model can be explicitly specified. Naturally, this can only be achieved in case the structure to be specified is correct. The freedom of choosing the data's covariance structure implies leaving the user alone with the difficult task of selecting the structure that provides the best fit to the data. Researchers generally recommend the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) to support this decision. Both criteria are based on the log-likelihood function and a penalty according to the number of parameters estimated (whereas the SBC penalty is more severe than the AIC penalty). However, studies have shown that neither AIC nor the Schwarz criterion are able to detect reliably the correct covariance structure (Keselman et al. 1999). Therefore, researchers have been looking for a heuristic that leads to better results.

4.5.2 Mixed model analysis using the SAS PROC MIXED procedure

To apply a mixed model analysis to my primary data, I used the PROC MIXED procedure of the SAS System (SAS Institute Inc.). The covariance structure to be modeled in the PROC MIXED procedure refers to variances at individual times and to correlation between measures at different times on the same experimental unit (Littell et al. 1998).

In general, the mixed model underlying structure has the following form (Verbeke and Molenberghs 2000; Kowalchuk et al. 2004):

$Y = XB + ZU + E$.

Y is a vector of response scores, X and Z are known design matrices, B is a vector of unknown fixed-effect parameters, U is a vector of unknown random effects, and E is a vector of random errors. The model requires that U and E are normally distributed with

$$E\begin{bmatrix} U \\ E \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \text{ and } V\begin{bmatrix} U \\ E \end{bmatrix} = \begin{bmatrix} G & 0 \\ 0 & R \end{bmatrix}.$$

Thus, the variance of the response scores is given by $V(Y) = ZGZ'+R$.

The variation between experimental units is specified by a RANDOM statement which models the G matrix, whereas the covariation within experimental units is specified by a REPEATED statement which models the R matrix.

Applying the mixed model to the SINTO data, we arrive at the following (see also Bock 1985, p. 470f.):

$$Y_{ijk} = \mu + scen_i + period_j + scen * period_{(ij)} + game\_no(scen)_{(ki)} + e_{ijk}$$

with

Y_{ijk} : *observation of game number k in scenario i and period j*

μ : *grand mean*

$scen_i$: *effect of scenario i*

$period_j$: *effect of period j*

$scen * period_{(ij)}$: *interaction between scenario i and period j*

$game\_no(scen)_{(ki)}$: *individual component of game number k in scenario i*

e_{ijk} : *error in game number k in scenario i and period j*

$game\_no(scen) \sim N(0, \sigma_\pi)$

$e_{ijk} \sim N(0, \sigma_e^2)$.

The design matrix X consists of the effects μ, *scen, period, and scen * period*.

The design matrix Z consists of the *game_no(scen)* effects.

The error term E is defined by *game_no(scen) * period*.

4.5.3 Model specification

After checking the data plots I find no variance differences between subjects except for subject-related differences. Notably, there seem to be no major variance differences between the two info treatment groups (i.e., the two scenarios). However, for many of the dependent variables there is considerable variance heterogeneity in the within-subjects factor (i.e., the period factor). Therefore I do not specify a RANDOM statement in the SAS mixed data analysis but specify a REPEATED statement and choose three different covariance structures to be checked for the best fit to the model: an autoregressive structure (AR), a heterogeneous autoregressive structure (ARH), and an unstructured covariance matrix (UN) (see below). Since no random effects are specifies, the model reduces to (Rao 1997, p. 32)

$$Y_{ijk} = \mu + scen_i + period_j + scen * period_{(ij)} + e_{ijk}$$

or

$$R = \begin{bmatrix} R_1 & & 0 \\ & \ddots & \\ 0 & & R_{22} \end{bmatrix}.$$

Y is assumed normally distributed with mean XB. Its variance-covariance matrix of Y is $V(Y) = R$. E is a vector of random errors. It is assumed normally distributed with zero mean. Its variance-covariance matrix (termed R) is block-diagonal (see below).

The model's fixed effects contain a constant, a scenario effect, a period effect, and a scenario* period interaction effect. The fixed effects regressor matrix X and the fixed coefficient B have the following form:

$$X = \begin{bmatrix} 1 & 1 & & 1 & & & 1 & & & & \\ \vdots & \vdots & & & \ddots & & & \ddots & & & \\ \vdots & 1 & & & & 1 & & & \ddots & & \\ \vdots & & 1 & 1 & & & & & & \ddots & \\ \vdots & & \vdots & & \ddots & & & & & & \ddots \\ 1 & & 1 & & & 1 & & & & & 1 \end{bmatrix} \quad B = \begin{bmatrix} const \\ scenario\ 1 \\ scenario\ 2 \\ period\ 1 \\ \vdots \\ period\ 15 \\ scenario\ 1 * period\ 1 \\ \vdots \\ scenario\ 2 * period\ 15 \end{bmatrix}.$$

The R matrix can be explicitly specified thus allowing for correlation among the observations from the same experimental unit (i.e., game number/SINTO industry) or variance heterogeneity in the period factor. R consists of identical, diagonal blocks $R_1, R_2, \ldots, R_{22}$. Each block corresponds to an experimental unit ($R_1, R_2, \ldots, R_{22}$).

$$R = \begin{bmatrix} R_1 & & 0 \\ & \ddots & \\ 0 & & R_{22} \end{bmatrix}.$$

To model the structure of R, one has to specify the structure within the blocks $R_1, R_2, ..., R_{22}$. Please note that the structure is the same for all blocks. $R_1, R_2, ..., R_{22}$ can be designed using a variety of alternative structures:

If observations from an experimental unit are correlated over time (as can be the case for repeated measurements on the same subject), it is advisable to specify a covariance matrix with an autocorrelated structure (AR(1))[54]:

$$AR(1): \quad R_k = \sigma^2 \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{15} \\ \rho & \ddots & \rho & \cdots & \rho^{14} \\ \rho^2 & \rho & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho \\ \rho^{15} & \rho^{14} & \cdots & \rho & 1 \end{bmatrix} \qquad for\ k = 1,\ldots,22.$$

The blocks are identical for all experimental units thus yielding a total of two parameters (σ^2, ρ) to be estimated.

A heterogenous autoregressive structure (ARH(1)) not only allows for autocorrelated observations within the same experimental unit, but it also accounts for variance heterogeneity in the repeated factor (i.e., the period factor).

$$UN: \quad R_k = \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & & \cdots & \sigma_{1,15} \\ \sigma_{1,2} & \ddots & & & \\ & & \ddots & & \vdots \\ \vdots & & & \ddots & \\ \sigma_{1,15} & \sigma_{1,14} & \cdots & & \sigma_{15}^2 \end{bmatrix} \qquad for\ k = 1,\ldots,22.$$

The number of parameters to be estimated is 16 ($\sigma_1^2, \ldots, \sigma_{15}^2, \rho$).

An unstructured covariance structure (UN) leaves complete freedom regarding the structure within the blocks of the R matrix.

$$UN: \quad R_k = \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & & \cdots & \sigma_{1,15} \\ \sigma_{1,2} & \ddots & & & \\ & & \ddots & & \vdots \\ \vdots & & & \ddots & \\ \sigma_{1,15} & \sigma_{1,14} & \cdots & & \sigma_{15}^2 \end{bmatrix} \qquad for\ k = 1,\ldots,22.$$

Due to the fact that UN makes no pre-assumptions regarding the blocks of R, the number of parameters to be estimated goes up to 120 ($\sigma_1^2, \sigma_{1,2}, \sigma_{1,3}, \ldots, \sigma_{1,15}, \sigma_2^2, \sigma_{2,3}, \ldots, \sigma_{2,15}, \ldots, \sigma_{15}^2$).

[54] The structure allows for autocorrelation of lag 1.

4.5.4 Normality assumption

An important issue is the normality assumption made by the mixed approach. With small samples and experimental data, one cannot be sure that this assumption is correct. Therefore, the literature provides several approaches to correct the degrees of freedom of the F test. The Kenward-Roger approximation (Kenward and Roger 1997) involves inflating the estimated variance-covariance matrix of the fixed and random effects. Consequently, Satterthwaite-type degrees of freedom[55] are then computed based on this adjustment (SAS Institute Inc. 2005). Keselman et al. 2002 (referring to work by Kowalchuk and Keselman) state that PROC MIXED tests perform quite well (i.e., good Type I error control) with a Kenward-Roger degrees of freedom correction when data are both nonnormal and heterogeneous and when the Akaike or Schwarz information criteria are used to select the most parsimonious covariance structure of the data. These positive results hold especially for small samples, e.g., for 10 subjects per group (Kowalchuk et al. 2004). Compared to the multivariate Welch-James procedure, the mixed model analysis with a Kenward-Roger corrected F test and a heterogeneous unstructured covariance structure have a superior Type I error control in small sample setting while the two approaches have almost the same power (Kowalchuk et al. 2004).

In line with these results, I specify the appropriate covariance structure of the model according to the Akaike information criterion and use a Kenward-Roger correction of the F test degrees of freedom. For estimation I use restricted/residual maximum likelihood estimation (REML) recommended for simulation studies by Kowalchuk et al. 2004.

4.5.5 Nonparametric approaches – rank transformed data

All parametric approaches require normally distributed errors and independent observations across subjects. Although the F test used in the parametric ANOVA is quite robust to normality violations, alternative approaches for nonnormal data should be searched, especially when sample sizes are small. An alternative to the parametric techniques is the use of nonparametric statistics that do not assume a specific distribution of the data (distribution-free methods). In general, nonparametric tests transform the raw data into rank scores thus

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[55] The use of the Satterthwaite degrees of freedom correction is recommended when the default F test of the mixed model analysis are not robust to multisample sphericity violations.

creating valid tests for at least ordinal data. The use of ranks instead of the original quantitative values avoids the normality assumption.

The Kruskal-Wallis test is an alternative to the F test[56] and can be considered an extension of the Wilcoxon rank sum test for more than two samples. Both the Wilcoxon and the Kruskal-Wallis test are applicable in a one-way ANOVA. In a two-way ANOVA, they can only be used to test the significance of the between-subjects factor, and one has to average the data across the within-subjects factor.

A nonparametric test replacing a two-way ANOVA is the Friedman test (Friedman 1937) which is an extension of the sign test for more than two treatments (Iman et al. 1984). The Friedman test requires only one observation per cell and assumes no existence of interaction effects[57]. For more than one observation per cell, one usually averages the values belonging to one cell thereby neglecting the additional information (Schlittgen 1993). The Friedman test is also applicable in a repeated measures one-way ANOVA. The application in a two-factorial design can be done taking the following steps: Starting from a two-way table (representing the two factors), the data is ranked for each row separately. Next, the columns are compared with respect to their average rank scores. The distribution of those mean rank scores tends to be distributed according to a chi-squared distribution when the ranking is random, i.e., the factor tested has no influence (Friedman 1937). In case different rows (instead of columns) are to be compared, ranks and columns can be switched, or the ranking can be done column-wise. To conduct a Friedman test in a split-plot design, ranks are computed for each block (i.e., each subject, experimental unit). Consequently, the test uses only within-block information (i.e., information within experimental units). The information loss due to the fact that metric observations are replaced by ordinal ranks assures the test's independence from the normalitiy assumption. Due to the ignorance of interaction effects, the applicability of the Friedman test is rather limited. Applying the Friedman test to the present SINTO data would require me to compute ranks across all 15 periods for every game/industry separately and then compare the sum of ranks across different periods. If there was no time effect, all rank sums would be about equal, i.e., the sum of ranks belonging to period one would equal the sum of ranks belonging to period ten, for example. The between-subjects effect in a repeated measures design can only be tested with the Friedman test when all games belonging to the same scenario are averaged such that there is only one observation per cell

[56] The Kruskal-Wallis test statistic is approximated with a chi-squared distribution (e.g., Conover 1999, p. 289). If the number of observations is small or the frequency of ties is large, this approximation is not very good since the chi-squared distribution overestimates the variance of the test statistic (Kruskal and Wallis 1952).

[57] Conover 1999 admits that there are no good, exact nonparametric tests for interaction.

(that way, the scenario levels would form the rows of the two-way table while the period levels would compose the columns).[58] Therefore, the Friedman test is described as a nonparametric equivalent of the one-way repeated measures or within-subjects ANOVA (while the Kruskal-Wallis H test is considered the nonparametric equivalent of a between-subjects ANOVA).

Unfortunately, many statistical programs like SAS or SPSS do only support basic nonparametric procedures whereas more complex tests, e.g., a nonparametric repeated measures analysis of variance involving two or more factors, are not supported (SAS has acknowledged this fact by email). However, as a bridge between parametric and nonparametric techniques, some researchers recommend the application of parametric procedures on rank-transformed data (Conover 1999; Conover and Iman 1981). The result is a conditionally distribution-free procedure (Conover 1999, p. 419).

To conduct a rank transformation, the data is ranked without regard to block membership (Thompson and Ammann 1990). The SAS Institute recommends using parametric techniques on rank-transformed data (SAS Institute Inc. 2005). However, studies have demonstrated that this approach fails to detect interactions when both main treatment and block effects are present.

Another approach is the aligned rank transform procedure. Before being ranked, observations are aligned by subtracting estimates of group means depending on what effects (main or interaction effects) are to be tested (Richter and Payton 1999).

For experimental designs, Conover 1999 recommends using the usual ANOVA on the data and then using the same procedure on the rank transformed data: "If the two procedures give nearly identical results the assumptions underlying the usual analysis of variance are likely to be reasonable and the regular parametric analysis valid" (Conover 1999, p. 419f.).

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[58] There do exist extensions of Friedman's rank transformation for the case of several observations for each treatment in each block (Conover 1999, p. 383). However, the suggested extension is only applicable when all experimental units receive all treatments (which is not the case for the information treatment in the SINTO experiments).

4.6 Empirical results

4.6.1 Overview

As an initial and conservative approach, I used nonparametric analyses to test the data for general differences between the NO INFO (scenario 1) games and the INFO (scenario 2) games. Therefore I averaged the data across all 15 periods and conducted Mann-Whitney-U tests as well as Wilcoxon rank sum tests for independent samples. Both tests are based on rank-transformed data thus avoiding biases caused by outliers. To detect time-related differences between the games with and without information, I used a repeated measures analysis of variance (RM ANOVA). To do so, I used the SAS PROC MIXED procedure with a REPEATED statement which enabled me to explicitly model the covariance structure within subjects (Littell et al. 1996) thus accounting for possible over-time correlation and within-subject heterogeneity. I modeled three different covariance structures, i.e., an autoregressive (AR1), a heterogeneous autoregressive (ARH1) and an unstructured (UN) structure; the best fitting structure was selected according to Akaike's Information Criterion (AIC). To make sure that the F tests were sufficiently robust against normality violations, I adjusted the degrees of freedom by the Kenward Roger correction (Kenward and Roger 1997) recommended especially for small samples (e.g., 10 subjects per group) by Kowalchuk et al. 2004. Except from investigating main DRI and period effects, I tested the data for DRI effects on linear, quadratic, and cubic trends. To further validate my findings, I applied the RM ANOVA to the ranked observations. I used the rank transform approach[59] suggested by Conover and Iman 1981 as well as a Friedman-type rank transformation[60] (Friedman 1937). The results of all tests are summarized in the subsequent tables. The unit of analysis for the subsequent results is industry thus leading to a sample size of 22 (11 + 11). Table I-8 summarizes the tests for main DRI effects while Table I-9 contains results from tests for DRI-by-period interaction effects. Table I-10 summarizes and interprets results concerning the hypothesized relationships.

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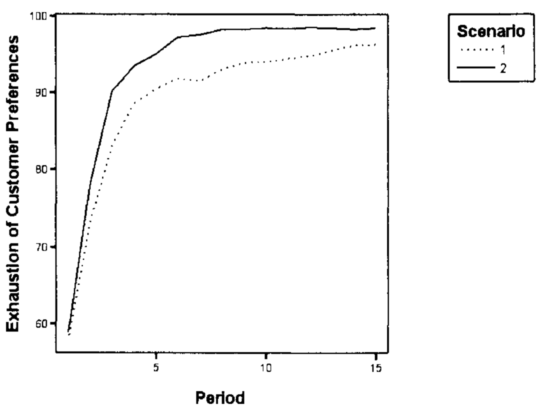
[59] The Conover-type rank transformation transforms the original observations into ranks across games and periods. This rank-transform method assures that the analysis is robust to outliers in general.

[60] The Friedman-type rank transformation implies that the data are ranked block-wise, i.e., for every game separately. This rank transformation assures that I can compare the relative development over time within a game across different games. For example, I can detect directional (i.e., rank-based) similarities across games even if the absolute values vary strongly across games. Of course, the rank ordering within games prevents the testing of main information effects (as all games average out at the same mean rank).

4.6.2 DRI and exhaustion of customer preferences

The mixed factorial analysis found a significant general effect of information. That is, overall, the INFO group had a significantly higher exhaustion of customer preferences than the NO INFO group. The exhaustion of customer preferences increased significantly over time in all games. The linear trend, the quadratic trend and the cubic trend were significant. The trends did not differ significantly between the INFO and the NO INFO group. This indicates that the effect of information remained constant over time. The Mann-Whitney-U test and the Wilcoxon test gave further support for the overall effect of DRI on the exhaustion of customer preferences. Overall, the INFO treatment exhibits a higher satisfaction of customers across all periods of the game (see Figure I-2). These results support hypothesis 1a.

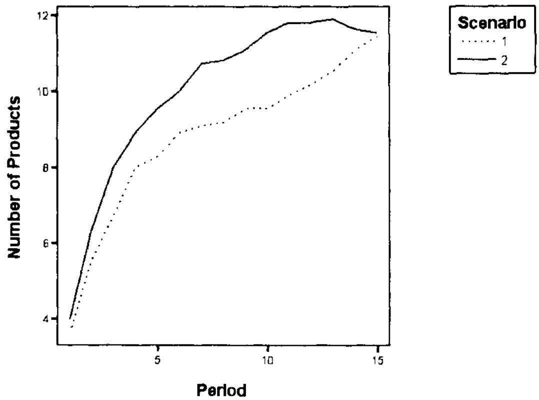
Figure I-2: Exhaustion of customer preferences



4.6.3 DRI and number of products

All games revealed a significant increase of the number of products over time. The linear trend, the quadratic trend and the cubic trend were significant. The results of the repeated measures ANOVA indicated a significant information effect (p=0.015). The number of products was significantly higher in the INFO treatment. I further found slightly significant differences in the quadratic trends between scenario 1 and scenario 2. The Mann-Whitney-U test and the Wilcoxon test gave further support for the significant general effect of DRI on the number of products offered (p=0.0150 and p=0.0165). Notably, firms with DRI offered more products than firms without DRI (Figure I-3). These results support hypothesis 1b.

Figure I-3: Number of products

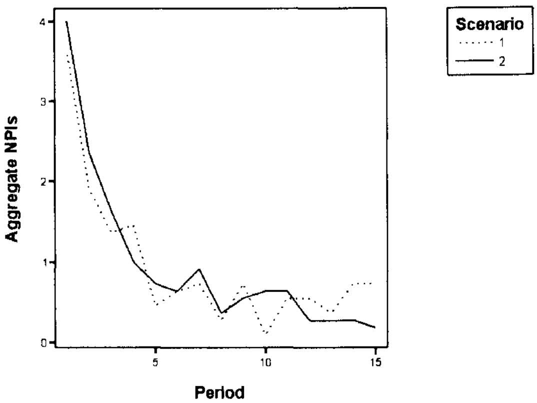


4.6.4 DRI and rate of innovation

The Mann-Whitney-U test did not detect a significant main effect of DRI on the number of new product introductions (NPIs) per period.

The results of the RM ANOVA indicated a modest information effect on the linear trend for the number of NPIs per period (p=0.0403). The linear trend interaction on the number of NPIs was also detected using RM ANOVA on ranked observations (Conover-type and Friedman-type ranks). This difference between the two information treatments with respect to their linear trends indicates that more products were introduced at early stages of the game when DRI was provided. Over time, the number of new product introductions assimilated in both information treatment groups. These results provide directional support for hypothesis 1c.

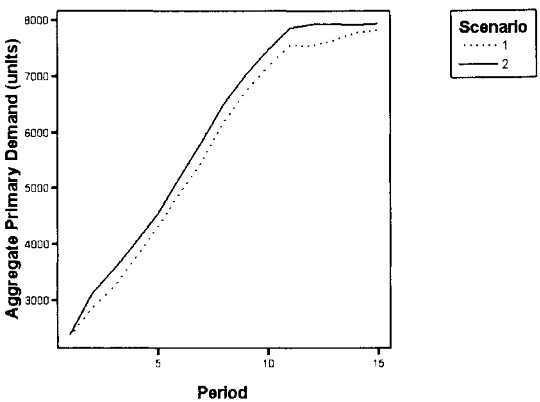
Figure I-4: Aggregate number of new product introductions (NPIs)



4.6.5 DRI and primary demand

The Mann-Whitney-U test showed that the quantity of primary demand was higher in the games with DRI (p=0.04). Also the repeated measures ANOVA found a significant main effect of information (p=0.0262). This supports hypothesis 1d.

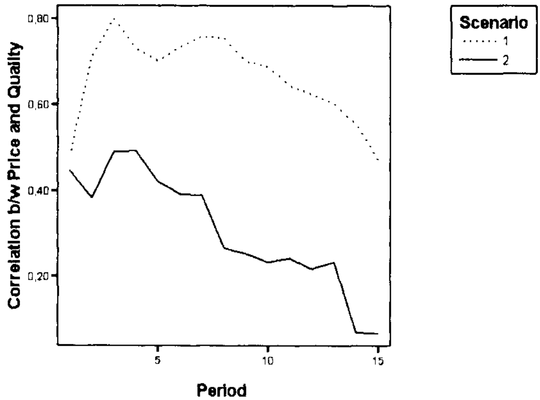
Figure I-5: Aggregate primary demand



4.6.6 DRI and price-quality correlation

Both the Mann-Whitney-U test and the Wilcoxon test revealed a highly significant DRI effect ($p < 0.01$) on the price-quality correlation. The RM ANOVA applied to the original and Conover-ranked data arrived at the same result (p=0.0031 and p=0.0016). There were no significant trend interactions of DRI. In the games with DRI the price-quality correlation was significantly lower than in games without DRI (see Figure I-6). This supports hypothesis 1e.

Figure I-6: Price-quality correlation



4.6.7 DRI and industry and firm performance

In both scenarios, the total industry performance increased over time. The average aggregate financial equity level and average industry profits were numerically higher in the INFO treatment. However, the Mann-Whitney-U test and the Wilcoxon test did not find significant main effects of DRI on total industry performance (i.e., aggregate financial equity and aggregate profits). The RM ANOVA arrived at the same result. Further, there were no significant trend differences between the NO INFO and the INFO treatments. The results for the individual firm performances (max, med and min individual financial equity and max, med, and min individual profits) were likewise non-significant. Thus, hypotheses 2a and 2b are not supported.

Figure I-7: Aggregate profits

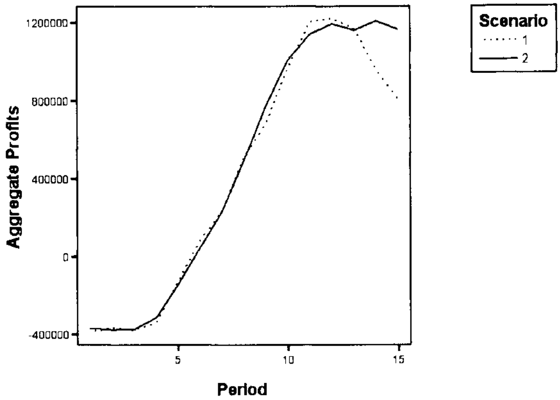
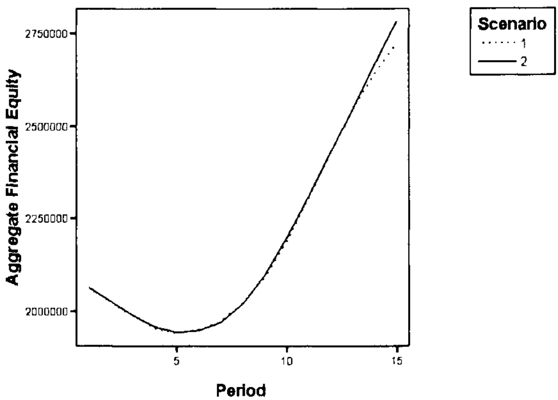


Figure I-8: Aggregate financial equity



4.6.8 DRI and competitive intensity

There were no significant main effects of DRI on aggregate capacities, average prices, and performance differences between the best and the weakest firm (see Figure I-9, Figure I-10, Figure I-11). There was a significant main effect of DRI on average advertising spending per product ($p<0.05$). Firms with access to DRI spent less on advertising on a per-product-basis than firms that did not have DRI (see Figure I-13). However, the DRI effect on (total) average advertising spending was non-significant (see Figure I-12). This indicates that firms have about equal advertising budgets, but firms in scenario 2 distribute their budgets across a larger number of products.

Figure I-9: Aggregate capacity

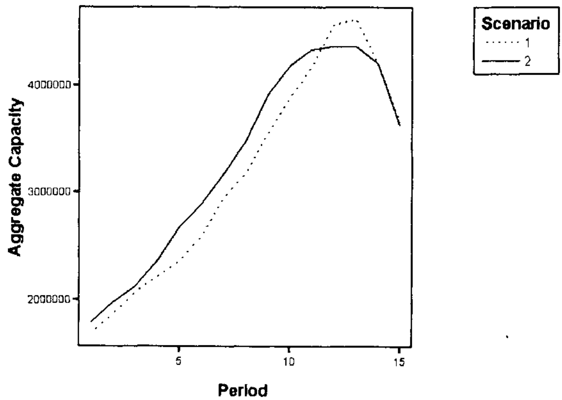


Figure I-10: Average prices

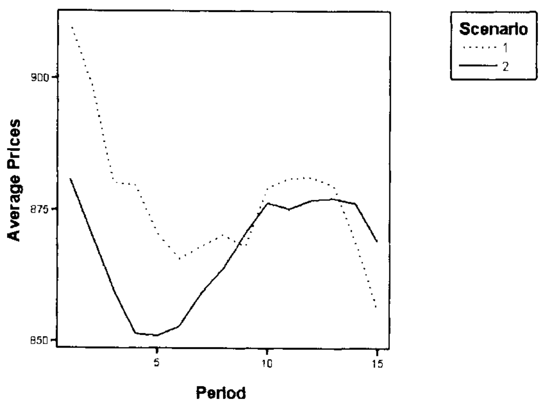


Figure I-11: Relative performance gap between the best and the worst firm[61]

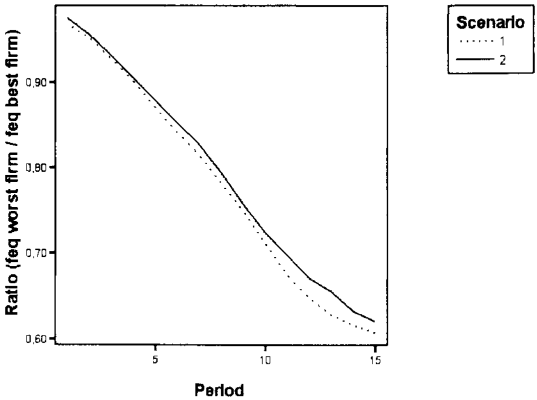
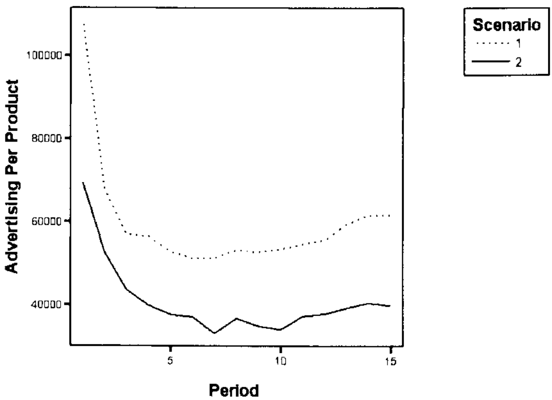
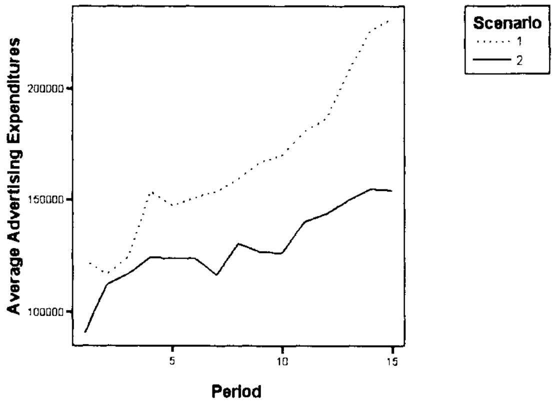


Figure I-12: Average advertising expenditures



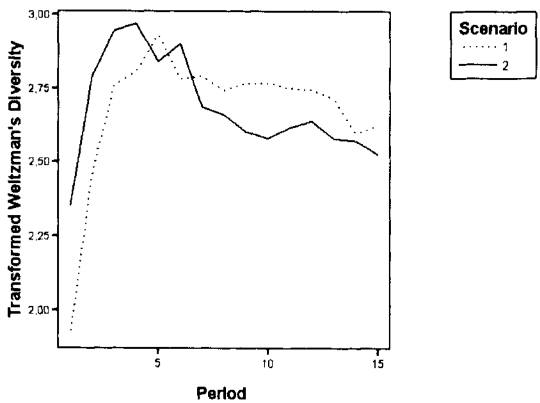
[61] The weakest firm's financial equity (feq) is divided by the strongest firm's financial equity, whereas the weakest firm is defined as the firm with the lowest feq and the strongest firm has the largest feq within an industry and period.

Figure I-13: Average advertising expenditures per product



In all games, the average degree of diversity per product (measured in terms of a transformation of Weitzman's diversity measure, see Weitzman 1992) increased in initial periods of the game and slowly declined in later periods (see Figure I-14). Both the Mann-Whitney-U test and the Wilcoxon test failed to detect a main effect of DRI on the average diverstiy per product. RM ANOVA confirmed the null results.

Figure I-14: Diversity per product (Transformation of Weitzman's diversity)



The second measure of product differentiation, the degree of product clustering (measured in terms of the Nearest Neighbor Index), showed a similar pattern as the above diversity per product measure. That is, overall, the degree of product clustering went up in the first time periods and slowly declined in the course of the remaining periods (see Figure I-15). That is, the clustering of products declined in the first periods and increased later on during the games. DRI did not have a significant effect on product clustering.

Figure I-15: Product clustering (Nearest Neighbor Index)[62]

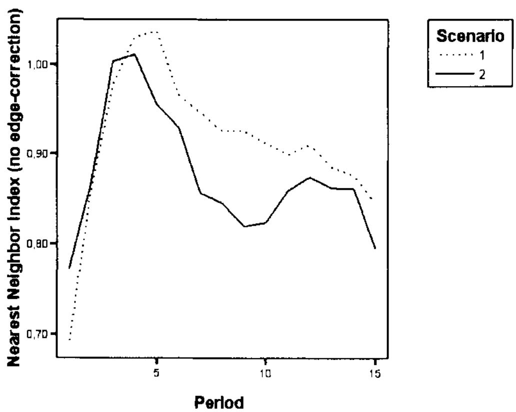


Table I-6: Mann-Whitney-U test results for DRI effect on competitive intensity

Indicator of Competitive Intensity	*Main DRI effect (tendency)*
Prices	n.s.[63] (rather lower with DRI)
Capacities	n.s. (rather higher with DRI)
Total industry profits	n.s. (rather higher with DRI)
Performance gap between the best and the weakest firm	n.s. (no difference)
Average advertising expenditures	n.s. (rather lower with DRI)

[62] Low absolute values indicate a high degree of product clustering.
[63] n.s.: not significant

Indicator of Competitive Intensity	*Main DRI effect (tendency)*
Advertising expenditures per product	p=0.04 (lower with DRI)
Product clustering: Nearest Neighbor Index (NNI)	n.s. (no difference in initial periods, rather lower in later periods with DRI)
Average diversity per product (transformation of Weitzman's diversity)	n.s. (rather higher in initial periods, rather lower in later periods with DRI)

Overall, there seems to be no significant effect of DRI on competitive intensity. Also, the different indicators of competitive intensity do not point in the same direction. The direction of the effect of DRI on competitive intensity is rather positive, negative or zero, depending on the way competitive intensity is measured (see Table I-7).

Table I-7: DRI effects on competitive intensity – direction of effect

Indicator of Competitive Intensity (CI)	*Direction of effect (DRI – CI relationship)*
Prices	Directionally *not as hypothesized* (higher CI)
Capacities	Directionally *not as hypothesized* (higher CI)
Total industry profits	Directionally *as hypothesized* (lower CI)
Performance gap between the best and the weakest firm	Directionally *not as hypothesized* (no difference)
Advertising	Depends on interpretation of advertising as an indicator of CI: If more advertising means more intense competition: *as hypothesized* (lower CI) If more advertising means less intense competition: *not as hypothesized* (higher CI)
Product differentiation	Directionally *not as hypothesized* (in later periods higher CI)

4.6.9 Summary of results

The experimental results are summarized in the subsequent tables.

Table I-8: Main effects of DRI – results from nonparametric and parametric analyses (p-values, two-tailed)

Hypothesis	*Relationship*	*Measure*	*Mann-Whitney-U test (asymptotic significance)*	*Wilcoxon test (normal approxi-mation)*	*RM ANOVA with K-R ddfm*	*RM ANOVA with K-R ddfm, applied to Conover's rank trans-formed data*	*Direction of effect*
H1a	DRI – exhaustion of customer preferences	Exhaustion of customer preferences	**0.0053**	**0.0058**	**0.0028**	**0.0014**	**As hypothesized**
H1b	DRI – number of products	Total number of products	**0.0151**	**0.0165**	**0.0295**	**0.0291**	**As hypothesized**
H1c	DRI – rate of innovation	Aggr. number of NPIs	n.s.	n.s.	n.s.	n.s.	**As hypothesized**
H1d	DRI – primary demand	Primary demand	**0.0386**[64]	**0.0418**	**0.0262**	**0.0548**	**As hypothesized**
H1e	DRI – price-quality correlation	Price-quality correlation coefficient	**0.0035**	**0.0039**	**0.0031**	**0.0016**	**As hypothesized**
H2a	DRI – industry performance	Aggr. feq[65], Aggr. profits	n.s.	n.s.	n.s.	n.s.	**Null effect**

[64] Exact significance, no tie correction
[65] Feq: financial equity

Hypothesis	*Relationship*	*Measure*	*Mann-Whitney-U test (asymptotic significance)*	*Wilcoxon test (normal approximation)*	*RM ANOVA with K-R ddfm*	*RM ANOVA with K-R ddfm, applied to Conover's rank transformed data*	*Direction of effect*
H2b	DRI – firm performance	Max indiv. feq Med indiv. feq Min indiv. feq	n.s.	n.s.	n.s.	n.s.	**Null effect**
		Max indiv. profits Med indiv. profits Min indiv. profits	n.s.	n.s.	n.s.	n.s.	**Null effect**
H3	DRI – competition	Advertising per product	**0.0418**	**0.0386**	**0.0386**	**0.0483**	**See Table I-7**
		Advertising	n.s.	n.s.	n.s.	n.s.	
		Prices	n.s.	n.s.	n.s.	n.s.	
		Capacities	n.s.	n.s.	n.s.	n.s.	
		Weakest/best firm performance ratio	n.s.	n.s.	n.s.	n.s.	
		Product clustering	n.s.	n.s.	n.s.	n.s.	
		Diversity per product	n.s.	n.s.	n.s.	n.s.	

Table I-9: Time-related DRI effects – results from nonparametric and parametric analyses (p-values, two-tailed)

Hypothesis	*Relationship*	*Measure*	*RM ANOVA with K-R ddfm (two-tailed)*	*RM ANOVA with K-R ddfm, applied to Conover's rank transformed data (two-tailed)*	*RM ANOVA with K-R ddfm, applied to Friedman-type rank transformed data (two-tailed)*	*Interpretation*
H1b	DRI – number of products	Total number of products	**Quadratic: 0.0398**	**Quadratic: 0.0331**	--	Number of products raises faster and decals slower when DRI is provided
H1c	DRI – rate of innovation	Aggr. number of NPIs	**Linear: 0.0403**	**Linear: 0.0223**	**Linear: 0.0467** **Quadratic: 0.0236**	More NPIs during initial business periods when DRI is provided

Table I-10: Overall summary of results

Hypothesis	*Relationship*	*Result*	*Significant findings*	*Interpretation*
H1a	DRI – exhaustion of customer preferences	✓	Main DRI effect	DRI increases exhaustion of customer preferences.
H1b	DRI – number of products	✓	Main DRI effect, Quadratic trend interaction	In games with DRI, the number of products is higher, raises faster and decays more slowly.
H1c	DRI – rate of innovation	(✓)	Linear trend interaction	No overall (main) DRI effect, but more NPIs during initial periods when DRI is provided.
H1d	DRI – primary demand	✓	Main DRI effect	Primary demand is higher in games with DRI.
H1e	DRI – price-quality correlation	✓	Main DRI effect	Price-quality correlation is lower when DRI is provided.
H2a	DRI – industry performance	--	n.s.	DRI does not increase industry performance.
H2b	DRI – firm performance	--	n.s.	DRI does not increase firm performance.
H3	DRI – competition	--/✓/?	Main DRI effect on average advertising expenditures per product, n.s. for remaining indicators of competitive intensity	DRI does not seem to affect most indicators of competitive intensity. DRI-competition relationship should be further investigated when there is more clarity about how to assess competitive intensity.

5. Conclusions

5.1 Discussion of results

Contrary to predominant belief, I do not find a significant performance benefit of DRI. At the same time, I find that the provision of DRI to all firms in a market leads to a higher number of products offered. Notably, this finding differs from Glazer et al.'s 1992 results. Very surprisingly, a higher exhaustion of customer preferences, a higher rate of innovation during initial business periods, and a higher primary demand fail to enhance firm performance. The provision of DRI leads to a decline of correlation between a product's price and its quality which indicates that the firms adapted pricing decision due to aspects other than quality.

To investigate whether the firms in the INFO group offered a larger number of unprofitable products[66] than the NO INFO group, I conducted the following test: I selected two periods in which the total number of products differed the most between the two treatment groups[67]. Next, I compared the number of unprofitable products using a Mann-Whitney-U test.
For both periods, the U test did not reveal significant differences between the games with and without DRI regarding the number of unprofitable products ($p=0.69$ for period 7 and $p=0.55$ for period 10).[68] Thus, the fact that the number of unprofitable products was equal in both groups suggests that over-acting does not provide a veil for new product failure.

Another reason for my findings may rest in a phenomenon called "locally rational decision making" (Glazer et al. 1992) implying that firms focus too much on decision variables addressed by the information instead of concentrating on the most performance-relevant decisions.
My findings over a fifteen-period timeframe indicate that this phenomenon may persist in the medium-term or even long-term. As a result, one could conjecture that the firms with DRI tend to neglect especially cost-related decision variables.

I found only little support for the influence of demand-related information on competition. Notably, the relationship between demand-related information and competitive intensity cannot be detected without an operationalizable definition and measurement of competitive

[66] I.e., products with negative profits on a per product basis.
[67] These periods were period seven and period ten.
[68] I also compared the relative percentage of unprofitable products in both scenarios and arrived at the same conclusion ($p=0.53$ for period 7 and $p=0.77$ for period 10).

intensity. The current work reveals that demand-related information affects the indicators of competition in alternate ways thus making it impossible to draw a clear-cut conclusion on the DRI effect on competition. For nearly all indicators, these effects were non-significant. This insignificance may be explained by the fact that all firms were in possession of DRI. That is, since firms were equally "privileged" by having information, the striving for profits and market share was possibly comparable to the situation in which none of the firms was in possession of information.

5.2 Managerial implications

My findings provide useful implications for marketing managers. First, my results indicate that there are companies that do "everything right." These firms listen to the consumers, segment the market, develop interesting products, innovate, stimulate primary demand and so on. Yet, these companies seem to fall victim of doing too much of a good thing: They loose sight of profitability and reduce the productivity of their marketing efforts. Notably, the aforementioned phenomenon occurred across firms and industries[69]. As a result, managers should be careful not to fall victim to a new kind of myopia: Namely, managers should avoid focusing too much on consumers and loose sight of overall profitability.

These comments appear to be in line with concerns voiced recently albeit conceptually. As has been pointed out, managers should be careful to simply pursue consumer-based marketing opportunities (Day 1999). More precisely, the null effect of information on industry profits that goes along with more products, a better matching of customer preferences and a higher primary demand lends support to the idea that managers may over-act.

As a result, over-acting poses a most serious threat to marketing productivity. Noteworthy is also that the number of unprofitable products (i.e., products with negative profits per product) did not differ significantly between the games with and without DRI.

Second, managers should rethink some of their pricing behavior. Interestingly, once being better informed about demand, managers tend to set prices that correlate less with quality. It is intuitively appealing that extra information opens avenues to price along attributes other than quality. However, such pricing seem to have been conducted to a degree such that profits have not been nurtured sufficiently. Managers should, therefore, carefully monitor the

[69] I note that in my experiments market research information was cost free which may inflate the observed effect between DRI and profits. However, this inflation should not be significant as typical costs for DRI are relatively low.

evolving price-quality relationship of their products. If necessary, pricing should obviously be adopted such that the resulting price/quality ratio fails to damage profits.

Third, if, after all, the reason for the lack of a performance effect of DRI can be explained using Glazer et al. 1992's phenomenon of "locally rational decision making", one would, most likely, arrive at a different conclusion: In this case, managers should be trained to use information without getting distracted from the most performance-relevant decision variables. Specifically, the use of information about customers or demand should not distract managers from cost and profitability aspects.

5.3 Research implications

Although the price-quality unit of analysis has been related to market efficiency (e.g., Moorman 1998), there is evidence that a low price-quality correlation is not diagnostic of a market's inefficiency (Ratchford and Gupta 1990). I do not know exactly what the cause for the firms' pricing behavior may be. One explanation may entail that managers benefit from their knowledge about demand and/or customers' willingness to pay enabling managers to set prices somewhat more independently from product quality. Obviously, more research is needed on the issue.

Furthermore, my findings may, in part, be due to concerns about competitive interaction within an industry. More precisely, competitive preemption may provide a rationale for over-acting. That is, over-acting in terms of new product introduction may be justified by a manager's fear that a competitor will otherwise occupy a certain competitive space. Thus, a manager may act even though he/she knows that the action itself is sub-optimal from the perspective of maximizing current profits.
To which degree managerial over-acting is in fact - and should be - reflective of the desire to preempt competitors marks a very important and challenging research endeavor. A major challenge in this context will be to obtain data of reasonable quality. Among other things, managers are understandably reluctant to reveal such objectives as these data may be viewed to be indicative of antitrust violations.

Furthermore, DRI may increase performance depending on the degree to which such information constitutes a competitive advantage. By constituting a competitive advantage I mean that DRI won't be available for all firms. This could be investigated more closely in an experiment with asymmetric information. For example, a third simulation could be run concurrently.

In such a set-up I would expect a performance increase for the firms that have access to DRI. At the same time, I should observe a null effect or a decrease of performance for those firms that do not have access to the information.

To summarize, the phenomenon of over-acting is reflective of too-much-of-a-good-thing. Notably, while the manager does everything "right" in the consumer-domain, a firm's profitability and marketing productivity declines.

As has been shown, over-acting harms firm profits and marketing productivity. Importantly, as indicated, the often applauded ideal of "segment size one" may turn out to be a myth as managers may over-segment and, thus, cause marketing's productivity to decline. In short, over-acting amounts to sub-optimal marketing management.

The measurement of competition deserves also some attention in the future. The current findings suggest that the various indicators of competitive intensity do not correlate. Moreover, it seems as if the effects on competitive intensity depend on how the construct is measured. Obviously, more research on the issue of competitive intensity and its measurement is needed.

5.4 Limitations

In some variables, I found strong differences between the SINTO games. That is, every game had a certain individual dynamic which could not be explained by the factors of the analysis. Another limitation consists in the number of firms which was fixed and limited to three. One can think of oligopolistic games with more than three firms where it would be interesting to check if the results still hold. Further, firms could only advertise for specific products instead of advertising for the company (i.e., no corporate identity).

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Appendix

A.1 Information manipulation

In Scenario 1, firms were given the only qualitative information about the demand function. I.e., they were told that demand for a brand/product is increased by higher advertising expenditures for the brand, a higher package quality, or lower prices. They were also told that most customers prefer products with medium levels of grainedness (r) and tartness (s) while some customers prefer extreme levels of either attribute. Firms were informed that customers do not like frequent changes of a product's attributes or price. Roughly speaking, the firms in Scenario 1 had the following idea of the demand function:

$$D = f(P_{own}, P_{comp}, Ad_{own}, Ad_{comp}, r_{own}, r_{comp}, s_{own}, s_{comp}, q_{own}, q_{comp}, t, Past)$$

where P_{own} denotes a firm's own price, P_{comp} its competitors' prices, Ad denotes advertising expenditures. r and s stand for the product characteristics tartness and grainedness, and q stands for the package quality. t relates to the market potential while $Past$ refers to prior decisions.

Scenario 2 comprised the same information as Scenario 1. Additionally, subjects in Scenario 2 were told that all firms were in possession of a market research tool enabling them to forecast demand. To generate forecasts, every firm was supplied with a notebook containing the programmed demand function.

A.2 Demand function of the SINTO simulation

The demand function that was revealed in the form of a demand forecast program to the three firms in the Scenario 2 condition is the following:

$$x_j = f(t)(\Gamma_j - \frac{.32}{n} p_j - .32(p_j - \bar{p}) + \frac{Q_j}{n} + Q_j - \bar{Q}) + .165062\sqrt{f(t)(\frac{\hat{M}_j}{n} + \hat{M}_j - \overline{M})^{sign}}$$

$$X = \sum_j x_j$$

with

x_j : *primary demand for product j (units)*

X : *total primary demand for all products (units)*

$f(t)$: *function of time period* ($t = 1,2,\ldots,15$)

Γ_j : *function of number of products, location of product j and existence of similar products,*

with : $\Gamma_j = \frac{305}{n} + Z_j$ *(for a definition of* Z_j *see section on ECP below)*

Q_j : *function of quality of product j relative to quality of other products*

$\hat{M}_j$: *function of past and present Ad, P, r, s, q.*

Ceteris paribus, primary demand is higher for moderate values of r and s and lower for extreme values of r and s (see also the term $h(r,s)$ in the section on the exhaustion of customer preferences).[70]

In the scenario 2 condition of my experiments, the firms had to enter their own decisions regarding products, product attributes (tartness, grainedness), quality, price, and advertising expenditures as well as – from their firm's point of view – the most likely decisions of their competitors. The forecast was automatically generated when input variables were set (see also section A.3). In the first period, firms could only guess their competitors' most likely decisions since there was no past to base any assumptions on. After the first period was played and the firms were aware of what their competitors had decided for, they could correct their assumptions and plan the following period. This procedure was repeated for every period.

[70] The distribution of customers is similar to a two-dimensional normal distribution which has its maximum at (r=7, s=6).

A.3 Representation of DRI in scenario 2 condition

DRI was presented to the subjects in scenario 2 condition in the following form:

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A	B	C	D	E	F	G	H	I	J	K	L	M	N	C
t		agio	erao	gemo	mevo	orbo	tono	mano	rimo	gamo	aldo	bona	inda	fan
1	im Markt	ja	ja	nein	nein	nein	nein	nein	nein	nein	nein	ja	nein	
	Neu?	ja	ja	nein	nein	nein	nein					ja		
	r	7	4									7		
	s	6	4									7		
	q	7	4									2		
	p	900	870									799		
	W	80000	20000									50000		
	Erstnachfrage	-428,78058	-490,33	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	-396,50808	#WERT!	#WE
2	im Markt	ja	ja	nein	nein	nein	nein	nein	nein	nein	nein	ja	ja	
	Neu?	nein	nein									nein	ja	
	r	7	4									7	2	
	s	6	4									7	7	
	q	7	5									2	5	
	p	900	700									799	870	
	W	70000	60000									40000	20000	
	Erstnachfrage	-236,53208	-149,57	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	-213,98693	-283,5	#WE
3	im Markt	ja	ja	ja								ja	ja	
	Neu?	nein	nein	ja								nein	nein	
	r	7	7	4								7	8	
	s	6	6	4								7	1	
	q	8	7	5								2	4	
	p	900	900	700								830	870	
	W	50000	70000	60000								35000	5000	
	Erstnachfrage	464,57327	253,896	822,522	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	#WERT!	513,67373	400,98	#WE

A.4 Exhaustion of customer preferences

The exhaustion of customer preferences (ECP) tells us what percentage of the potential customers is covered by the current product assortment. ECP is only determined by the product characteristics of the existing products and the customers' preferences for r-s combinations. It is independent of prices, quantities, advertising, or quality. The assumption is that a customer with preferences (r_o, s_o) for the attributes tartness (r) and grainedness (s) would also buy a product at a location different from his preferred one if it is not too far away from his ideal location. I.e., a customer with preference (r_o, s_o) would buy any product with characteristics (r_j, s_j) if $|r_0 - r_j| < 3$ and $|s_0 - s_j| < 3$.

$$ECP = \frac{\sum_j Z_j}{6.95}$$

$$Z_j = \sum_{r=0}^{9} \sum_{s=0}^{9} \frac{z_j(r,s)}{z(r,s)} \cdot h(r,s)$$

$$z_j(r,s) = \max(0;3 - \max(|r - r_j|;|s - s_j|))$$

$$z(r,s) = \max(1;\sum_{j=1}^{n} z_j(r,s))$$

$h(r,s)$ denotes the attractivity of location (r,s) for customers. For each (r,s), $h(r,s)$ can adopt values between 4 (for any (r,s) with r=0) and 11 (for (r,s) with r=7 and s=6). The sum of $h(r,s)$ over all r and s is 695.

$z_j(r,s)$ defines the ability of product j to attract customers with preferences (r,s). It can adopt values from 0 (if product j is too far away from (r,s)) to 3 (if product j is exactly located at (r,s)). By "too far", I mean that $\max\{|r - r_j|;|s - s_j|\} > 2$. That is, a customer who likes products with characteristics r_0 and s_0 would not buy a product p with characteristics r_p and s_p if $|r_0 - r_p| \geq 3$ or $|s_0 - s_p| \geq 3$. The ability of product j to attract customers located at (r,s) increases with decreasing distance between j and (r,s) (measured as $\max\{|r - r_j|;|s - s_j|\} > 2$).

$z(r,s)$ can be interpreted as the overall ability of all existing products to attract demand centered at (r,s). By definition, its minimum value is 1 (if all products are far away from (r,s), or, if $z_j(r,s)$ is 0 for every product j and a specific (r,s)). The maximum value is 3n, if all n products are located exactly at (r,s) so $z_j(r,s)$=3 for every product j=1,...,n.

The ratio of $z_j(r,s)$ and $z(r,s)$ is the ability of product j relative to all products to attract customers at (r,s).

The ratio can adopt the value "1" if product j is located exactly at (r,s) and the no other products are located nearby. It adopts 3/3n = 1/n if all products are located at (r,s) or if all products are located at the same point somewhere close to (r,s). If product j is far away from (r,s), the ratio is 0 no matter where other products are located. If product j is close to (r,s) and some (but not all) other products are also located close to (r,s), the ratio will adopt any value between 0 and 1, relative to the distances of the products to (r,s).

The ratio of $z_j(r,s)$ and $z(r,s)$ is weighted by $h(r,s)$. The weight $h(r,s)$ is higher when the location is close to (r=7,s=6). In other words, extreme product characteristics have lower weights than moderate product characteristics. The ratio of $z_j(r,s)$ and $z(r,s)$ multiplied by $h(r,s)$ can adopt a maximum value of 11 (for (r=7,s=6) if only one product is located there and no competing products are close), and a minimum value of 0.

Z_j denotes the sum of $[z_j(r,s)\ /\ z(r,s)]^*\ h(r,s)$ across all *r* and *s*. It can be interpreted as the ability of product *j* to attract customers relative to other products at any location in the whole market. The attractivity of a location (r,s) depends on customers' preferences for the product characteristics r and s. The maximum value that any Z_j can have is 235 (if *j* is located at (r=7,s=6) and the only product in the market).

When two products *j* and *k* are located at the same spot, the sum of Z_j and Z_k equals the value of Z_j if *j* is a monopolist.

The sum of Z_j for all products j=1,…,n can achieve a maximum of 695 which is the sum of $h(r,s)$ across all r and s. That is, if the products are located in a way that all customers will find a product close to their personal preferences, the sum of Z_j (j=1,…,n) will be 695. Hence, the exhaustion of customer preferences is defined as the sum of Z_j (j=1,…,n) divided by 6,95. The result tells us what percentage of the potential customers is covered by the current product assortment. In the following, this percentage will be called "exhaustion of customer preferences (ECP)". Please note that ECP is only determined by the product characteristics of the existing products and the customers' preferences for r-s combinations. It is independent of prices, quantities, advertising, and quality.

A.5 SAS PROC MIXED data analysis (SAS program code)

```
proc mixed data=&d covtest maxiter=1200 method=REML;
title 'proc mixed' &y ' ';
class scenario period game_no;
model &y = scenario | period / outp=predicted s ddfm=kenwardroger ;
repeated period / type=ar(1) subject=game_no ;
contrast 'overall linear' period -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 ;
contrast 'scenario x linear' scenario*period
-7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7
7 6 5 4 3 2 1 0 -1 -2 -3 -4 -5 -6 -7;
contrast 'overall quadratic' period
0.4722703 0.2698678 0.0986059 -0.041518 -0.150504 -0.22835 -0.275059 -0.290628 -
0.275059 -0.22835 -0.150504 -0.041518 0.0986059 0.2698687 0.4722703;
contrast 'scenario x quadratic' scenario*period
0.4722703 0.2698678 0.0986059 -0.041518 -0.150504 -0.22835 -0.275059 -0.290628 -
0.275059 -0.22835 -0.150504 -0.041518 0.0986059 0.2698687 0.4722703
-0.4722703 -0.2698678 -0.0986059 0.041518 0.150504 0.22835 0.275059 0.290628 0.275059
0.22835 0.150504 0.041518 -0.0986059 -0.2698687 -0.4722703;
contrast 'overall cubic' period
-0.456256 -0.065179 0.1754832 0.2908008 0.3058422 0.2456765 0.1353728 0.0 -0.135373 -
0.245677 -0.305842 -0.290801 -0.175483 0.0651795 0.4562564;
contrast 'scenario x cubic' scenario*period
-0.456256 -0.065179 0.1754832 0.2908008 0.3058422 0.2456765 0.1353728 0.0 -0.135373 -
0.245677 -0.305842 -0.290801 -0.175483 0.0651795 0.4562564
0.456256 0.065179 -0.1754832 -0.2908008 -0.3058422 -0.2456765 -0.1353728 0.0 0.135373
0.245677 0.305842 0.290801 0.175483 -0.0651795 -0.4562564;
run;
```

ESSAY II: Spatial Product Differentiation

Abstract

The degree of product differentiation of a market is diagnostic of the similarity or dissimilarity of products. It indicates whether products are substitutable or differentiated and therefore constitutes a useful measure of a market's competitive intensity. The substitutability of products appears to be an appropriate measure of product differentiation. However, its operationalization proves rather complex, especially when it comes to the comparison of product differentiation over time or across markets.

In the present paper, I discuss and develop measures of product differentiation in a multidimensional characteristics space (or in a Hotelling-type market). After specifying the requirements a measure of product differentiation should satisfy, I investigate a number of avenues to measure product differentiation. Interestingly, I am able to illustrate that popular distance measurement functions such as the sum of Euclidean distances or the sum of City Block distances contradict basic notions of product differentiation and therefore contradict the above requirements. Further, I discuss the potential of Weitzman's measure of diversity to validly measure product differentiation. I offer a transformation of Weitzman's diversity measure which may turn it into a useful measure of product differentiation. Further, I apply spatial pattern analysis, a technique frequently used in botany, geostatistics, forestry and other research disciplines. From this starting point, I present several indices, functions and statistics based on nearest neighbor distances and discuss their ability to describe product differentiation in the marketing discipline.

1. Introduction

1.1 Motivation

A market's product differentiation is reflective of the similarity or dissimilarity of products marketed. If product differentiation takes place along spatial dimensions, e.g., geographical dimensions or product characteristics, the degree of product differentiation results from products' spatial locations. Classic and recent research investigates equilibria due to differentiation (e.g., Eaton and Lipsey 1975; Hotelling 1929). Existing research indicates that a generally valid equilibrium of product differentiation does not exist. Further, equilibria represent long term solutions, which do not have to be met in the short run. Therefore, an important task consists in investigating the actual degree of product differentiation of a market, apart from showing what would be optimal in the long run.

Assessing the degree of product differentiation can prove complex, especially when the number of dimensions along which products are differentiated is large. The substitutability of products appears to be an appropriate measure of product differentiation. However, its operationalization in a spatial market context is not straightforward. Lancaster 1975 notes that "the greatest single obstacle in the path of formal analysis of product differentiation is that of making quantitative comparisons between goods which are not identical".

In the present paper I aim to develop a measure of product differentiation that enables comparisons over time and across industries. Starting from a Hotelling/Lancaster-type market, I investigate a number of avenues to assess the degree of product differentiation in a multidimensional characteristics space. For reasons of parsimonious modelling, I compare basic and intuitively appealing product locations in spatial markets in terms of their degree of product differentiation. Interestingly, I am able to show that popular distance measurement functions such as the sum of Euclidean distances or the sum of City Block distances contradict basic notions of product differentiation. Next, I aim to develop a measure of the degree of product differentiation. The measure should permit to assess the actual product differentiation in a given market and compare its level of product differentiation across time and industries. The current paper discusses the potential of Weitzman's diversity measure (Weitzman 1992) and spatial pattern analysis to validly measure product differentiation.

1.2 Course of analysis

The remainder of the paper is organized as follows: Section two briefly reviews parts of the literature on product differentiation. Section three addresses the issue of measuring product differentiation in a multidimensional characteristics space. In section four I postulate some requirements a measure of product differentiation should satisfy. Section five contains an investigation of measures of product differentiation. I investigate measurement functions such as the sum of Euclidean distances or the sum of City Block distances and show that they contradict basic notions of product differentiation. Next, I present Weitzman's measure of diversity and point out why it is inappropriate for measuring product differentiation. As a potential solution to the problem, I offer a transformation of Weitzman's measure. Further, I review the area of spatial pattern analysis, introduce nearest neighbor measures applied in other research fields (botany, forestry, geostatistics etc.), and discuss their ability to measure product differentiation in marketing. A conclusion and a discussion of results in section six conclude the paper.

2. On the concept of product differentiation

2.1 Defining product differentiation

The degree of product differentiation of a market is diagnostic of the similarity or dissimilarity of products. It indicates whether products are substitutable versus differentiated and therefore constitutes a useful measure of a market's competitive intensity (see Raju and Roy 2000; Smith 1995). Products can be considered more substitutable with increasing similarity. Hence, product dissimilarity or product differentiation can be seen as an inverse analogon of product substitutability.

According to Lancaster 1975, product differentiation exists when there is a variety of similar but not identical goods within a product class. This definition clarifies the difference between the terms "differentiation" and "diversification". While differentiation takes place within a product class (Lancaster 1975), the term diversification includes activities in more than one product class, business segment or geographic segment (e.g., Hoopes 1999).[71] Similarly, Dickson and Ginter 1987 define product differentiation as "a state in which all products are not perceived as equal on each of the product characteristics, including price" (Dickson and Ginter 1987, p. 5). At the same time, product differentiation can be used to describe a management strategy (Dickson and Ginter 1987; Smith 1956; Smith 1995) which is pursued by "offering a product that is perceived to differ from the competing products on at least one element of the vector of physical and nonphysical product characteristics. [...] [T]his strategy may be pursued through product design in specification of actual product characteristics and/or through advertising directed at establishing perceptions of both physical and nonphysical product characteristics" (Dickson and Ginter 1987, p. 6). Hence, the dimension(s) along which products are differentiated can entail observable or perceived, intangible attributes (e.g., Anderson et al. 1992; Dickson and Ginter 1987), even meaningless attributes (Carpenter et al. 1994). Chamberlin 1962 notes that "virtually all products are differentiated, at least slightly, and that over a wide range of economic activity differentiation is of considerable importance" (p. 57). The consequences of a product differentiation strategy consist in separating between the customers you want and the customers you do not want (Soberman 2003). The benefits from a product differentiation strategy consist in the establishment of a firm's market position and/or the protection against price competition (Smith 1995). Dickson and Ginter 1987 comment on the difference between product

[71] The diversification across business segments is considered the "unrelated" component of diversification, whereas the diversification within a segment is the "related" component (e.g., Palepu 1985).

differentiation and segmentation, arguing that product differentiation is a necessary requirement for a market segmentation strategy, while a strategy of product differentiation does not need the existence of market segments.

Products can be *horizontally* and *vertically* differentiated (e.g., Anderson et al. 1992). Horizontal differentiation implies that none of the differentiated products is objectively better than competing products. Moreover, it depends on the individual consumer's preference which product he/she prefers. Consequently, two horizontally differentiated products with equal prices both enjoy positive demand (e.g., Bonanno and Haworth 1998). In the contrary case, a product is vertically differentiated when it is clearly better than other products (Besanko et al. 2004). The latter holds especially true for product quality (Lancaster 1990) since all consumers prefer a higher quality (although the willingness to pay may differ across consumers). Thus, given equal prices, only one of two vertically differentiated products will enjoy positive demand – the product with the higher quality (e.g., Bonanno and Haworth 1998). The following work refers to the form of horizontal differentiation.

2.2 Spatial and non-spatial models of product differentiation

The two most important streams of research comprise (spatial) address models (Hotelling 1929; Lancaster 1975) and (non-spatial) non-address models (Chamberlin 1962[72]) of product differentiation.[73] Address models assume that every product can be described by its "address" in a characteristics space, i. e., every product is a bundle of attributes and levels thereof. Consumers can likewise be described by their locations (addresses) within the characteristics space. Consumers' locations represent their ideal points in the characteristics space. Ideal points are usually assumed to differ across consumers because, if all consumers had the same ideal point, there would be no product differentiation. The closer two products are within the space the more substitutable they are.

Non-address models assume that consumers have a subset of preferred goods within the product space (instead of an address representing their ideal point). This can be interpreted by consumers' variety seeking behavior which applies mostly for fast moving consumer goods (as opposed to durables).

[72] The definition of product differentiation by Chamberlin 1962 entails that consumers consider more factors than just price when making a product choice. Consequently, in a market with many competitors, a single competitor's price cut will not force other sellers to cut prices either.

[73] See also Anderson et al. 1992 for a detailed comparison of address and non-address models of product differentiation.

The focus of the current investigation directs to the group of spatial models because they seem the most appropriate to assessing product differentiation in a characteristics space.

In a seminal work, Hotelling 1929 models product differentiation as an endogenous market process. Hotelling's market is represented by a straight line (e.g., the main street of a city). Products can be located along this line while their degree of differentiation is measured by their distance. Consumers are uniformly distributed along the line. A customer's preference for a product is determined by its price and the customer's transportation costs[74] only. The transportation costs depend on the distance between the customer's location and the product. Transportation costs determine whether a single firm can serve the whole market (Gupta et al. 2004). Contingent on transportation costs, firms will prefer to offer more similar products i.e., to move close to each other, or to differentiate more. Originally, Hotelling assumed linear transportation costs and arrived at a solution of minimal differentiation. Eaton and Lipsey 1975 examine the robustness of Hotelling's result and identify five assumptions that seem critical to the result of minimal differentiation: The nature of consumers' demand, the number of firms (restricted to two), a zero conjectural variation, i.e., the absence of conjectures of a firm with respect to the behavior of the other firm, the nature of the market (linear with boundaries), and the even distribution of customers thoughout the market. There are several pieces of research that alter some of Hotelling's assumptions (e.g., transportation costs, sequence of firm decisions, demand uncertainty, distribution of customers, dimensionality and shape of competitive space). According to Brenner 2001, firms can influence consumers' transportation costs by offering more general products (e.g., "all in one" products). Gupta et al. 2004 find for a circular market with linear transport costs and Cournot (quantity) competition that all firms never agglomerate at the same location. Furthermore, they find that various combinations of spatial agglomeration and dispersion are possible.

The above literature focuses primarily on deriving equilibria of firm or product location. Existing research suggests that equilibrium differentiation changes with changing conditions, and something like a general "principle or differentiation" does not seem to exist (Brenner 2001). Most work of spatial product differentiation is limited to one dimension of differentiation.[75] The measurement of the degree of product differentiation, allowing

[74] In a geographical sense, transportation costs reflect the customer's effort to walk to the store (i.e., to the product's location). In the sense of product characteristics, transportation costs reflect the fact that the product does not exactly correspond to a customer's taste. The larger the distance between customer and product, the higher are the customer's transportation costs.

[75] This dimension usually refers to (one-dimensional) geographic differentiation. As far as differentiation along product characteristics is concerned, dimensionality is reduced to one by defining a product by its ratio of characteristics (e.g., Lancaster 1975; Lancaster 1990).

comparisons across time and industries, irrespective of equilibria considerations, has gained less attention so far.

3. Product differentiation in a multidimensional characteristics space

Product differentiation can take place along any observable product attributes or other dimensions. Those attributes may entail characteristics of the product itself, e.g., such as the percentage of cocoa and milk for the market of chocolate bars, but dimensions can also include the positioning through promotional activity[76]. The product space is determined by the dimensions or attributes along which consumers distinguish the products (this may also include perceptual dimensions of an MDS map). Every product's location in the space is, in turn, determined by its levels on each of the aforementioned attributes. Therefore, whenever a product market can be represented by an attribute or perceptual space, it is possible to apply address-type approaches of differentiation examining location decisions and spatial competition, e.g., the Hotelling-type approaches. Following Eaton and Lipsey 1975 and Lancaster 1975, the market space can be interpreted as a characteristic(s) space in which products are located according to their product characteristics. Consequently, the distribution of customers (customer density function) reflects the preference of customers for certain attribute levels or combinations thereof. Nevo 2000 has found for the ready-to-eat cereal industry that substitution patterns across brands are driven by product characteristics.

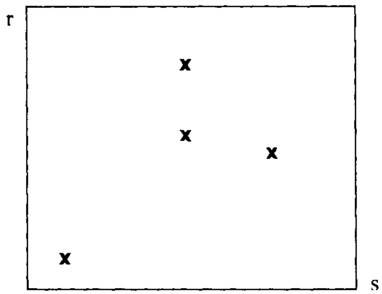
Naturally, customers' preferences for attribute combinations affect essentially where firms locate their products. Consequently, optimal product differentiation cannot be judged without considering customer preferences or segmentation issues. However, this paper will not touch optimality questions arising in the context of product differentiation. Instead, the paper at hand addresses measurement aspects of product differentiation. The location of products in the characteristics space will be taken as given.

The subsequent examples and the discussion of measures of product differentiation will be conducted on the basis of a two-dimensional, rectangular market space[77] with dimensions r and s. An example of a possible product configuration is depicted on Figure II-1. A product's location is marked by an "x" in the characteristics space.

[76] See also Nevo 2000 and Berry et al. 1995 for examples of product characteristics of the ready-to-eat cereal industry and the automobile industry, respectively.

[77] For simplicity, later calculations are based on a market space (area) of unit length and unit height. In the following, the terms market space, product space, and characteristics space will be used synonymously.

Figure II-1: Example of a two-dimensional characteristics space with four products



Although a glance at the figure above offers a first insight into the extent of product differentiation of the corresponding market, it only allows a qualitative evaluation based on visual impression. In order to quantify the degree of a market's product differentiation, investigate its development over time or compare product differentiation across industries, one needs a precise, quantitative measure of product differentiation.

4. Measuring product differentiation - requirements

The goal of the current paper is to find a measure of product differentiation providing a single number that can be interpreted as the degree of product differentiation of products in a multidimensional characteristics space. The measure should allow differentiation comparisons across industries and assess changes in differentiation over time. To decide whether a measure is useful for this purpose, we need verifiable criteria along which a measure can be evaluated. In the following, I present some requirements a measure of product differentiation should satisfy.

1. The measure should adopt its minimum when products are minimally differentiated. This would be the case when all products are agglomerated at the same spot, while it is irrelevant where in the market the cluster of products occurs.
2. The measure should increase with increasing dissimilarity (i.e., differentiation) of products. Put differently, the measure should decrease with increasing substitutability of products.
3. The measure should be somewhat "normalized", thus enabling the comparison of product differentiation across industries (i. e., different characteristics spaces), and evaluate the development of differentiation over time. This includes that the measure be scale-invariant and can be calculated for market spaces of any shape and dimensionality.
4. The measure should take into account the number of products marketed. That is, in a market with a large number of products, the products are more likely to be located closer to each other than in markets with a smaller number of products. Therefore, the total number of products in a market plays an important role for the interpretation of the value of product differentiation. When the number of products is large, a certain similarity of products is inevitable. Still, product differentiation can be high when those products avoid being overly close to each other and occupy many different areas of the characteristics space. In this case, we might assume that competition is not very aggressive. On the other hand, when the number of products is small, the products should have much room for differentiation. Yet, if those products are located rather close to each other, this indicates a low product differentiation and, possibly, a high rivalry between those products. The measure of product differentiation should enable comparisons across markets that differ with respect to their number of products. Therefore, it is necessary that the above considerations are taken into account.

The question whether the measure of product differentiation should have a defined maximum or an upper bound is not easy to answer. Moreover, it depends on boundary existence in the market or the characteristics space. The case of products being maximally differentiated implies that there is no room for further dissimilarity. In an attribute space, it is not always possible to define boundaries. Therefore, I do not suggest requiring a measure of product differentiation to have a pre-defined maximum.

To summarize, a valid differentiation measure (in the sense of this paper) that allows inter-industry and over-time comparison should be strictly monotonic in product differentiation and be minimal when all products are perfect substitutes. Further, it should not depend on scale, dimensionality, or shape of the characteristics space and take into account the number of products.

Given a market setting as depicted in Figure II-1, a measure of product differentiation should incorporate, in some way, the spatial product-to-product distances (here: the r-s-distances between all products). The intuition rests on the fact that two products are more similar to each other when their distance is smaller and more dissimilar when their distance is larger. Consequently, the product differentiation measure has to be any function that is based on product-to-product distances in the characteristics space.

5. Measuring product differentiation

5.1 Existing and new approaches to measuring product differentiation

To my knowledge, there is no measure of product differentiation in a spatial market context. Existing measures of product differentiation count the number of variants (e.g., products, brands) in business, geographic or customer segments although the existence of those segments is not required per se (Dickson and Ginter 1987). Further, counting variants leads to the ignorance of actual or perceived similarity in a characteristics space. Other non-spatial measures of product differentiation use cross-price elasticities which do not have to be reflective of the actual proximity of products in a market space.[78] A cross-price elasticity can at most describe the substitutability of two products. The degree of product differentiation of all products in a market can only be assessed by looking at the matrix of cross-price elasticities (see, e.g., Berry et al. 1995), but this does not provide more insight than looking at an MDS map or the location of products in a characteristics space. Notably, the cross-price elasticities could even be used as input data to generate an MDS map.

To develop a new measure of product differentiation, the most straightforward approach consists in computing a function of distances between products which increases with increasing product differentiation and adopts its minimum when all products are close substitutes. There are several possibilities of measuring distances between products. A well-known family of distance measures is the Minkowski distance metric comprising the Euclidean metric (2nd order) and the City Block metric (1st order) as special cases. The Minkowski distance (MD) is specified by the following family of functions:

$$MD = \left[\sum_{k=1}^{K} | x_{ik} - x_{jk} |^r \right]^{1/r}$$

with

x_{ik} : *value of dimension* k *for product* i

K : *number of dimensions*

r is a constant. $r = 1$ leads to the City Block distance metric while for $r = 2$ the metric equals the Euclidean distance metric.

The Euclidean and the City Block metric have been the two most preeminent spatial models in psychology and marketing (see Glazer and Nakamoto 1991). In the following, I discuss a few functions based on the aforementioned distances.

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[78] For example, consumers may buy orange juice instead of Pepsi cola when the Coca Cola company raises the price of Coca Cola.

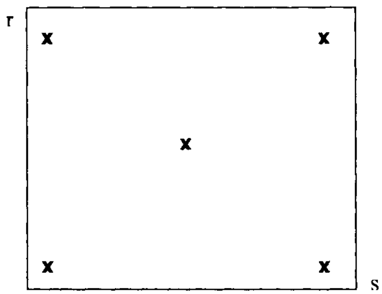
5.2 Sum of Euclidean distances

As a start, the sum of Euclidean distances was tested for its ability to validly measure product differentiation in a multidimensional market space. The sum of Euclidean distances (SED) is a function of distances of the following form:

$$SED = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j>i}}^{N} \sqrt{(r_i - r_j)^2 + (s_i - s_j)^2}$$

The results indicate that SED does not increase with increasing dissimilarity of products. That is, for an exemplary number of five products, the configuration with the maximum SED is not characterized by a large product differentiation (see Figure II-2 and Figure II-3). Moreover, SED's maximum for five products is met in a market where two products are located at the same spot in one of the corners of the characteristics space, while the other three products are located in the remaining corners (see Figure II-3). This does not correspond to our intuition of product differentiation which implies that with increasing differentiation, products are more diversified and less similar to each other.

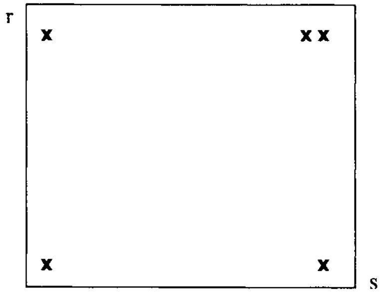
Figure II-2: Market with five products – highly differentiated[79]



$$SED(ex1) = 1.000 + 1.000 + 1.414 + 0.707 + 1.414 + 1.000 + 0.707 + 1.000 + 0.707 + 0.707 = 9.657.$$

[79] All calculations are based on the fact that the market space has unit lenght and unit height. For a better illustration, products located at the corners of the market space are supposed to be located at 0 or 1 along the dimensions r and s.

Figure II-3: Market with five products – less differentiated[80]



$SED(ex2) = 1.000 + 1.000 + 1.414 + 1.414 + 1.414 + 1.000 + 1.000 + 1.000 + 1.000 + 0 = 10.243$.

As discussed above, SED does not satisfy the requirements of a measure of product differentiation. SED does not correspond to the common intuition of product differentiation which implies that the degree of product differentiation is higher when products are less substitutable or more dissimilar, respectively.

5.3 Sum of City Block distances

The sum of City Block distance (SCD) was also tested for its ability to measure product differentiation in a multidimensional market space. For the exemplary two-dimensional market space, the function is defined by the following formula:

$$SCD = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j>i}}^{N} (| r_i - r_j | + | s_i - s_j |)$$

For the exemplary market with five products (see Figure II-2 and Figure II-3), the SCD value of the first (highly differentiated) market equals the SCD value of the second (less differentiated) market. That is, the SCD value of the market in Figure II-2 is $SCD(ex1) = 1 + 1 + 2 + 1 + 2 + 1 + 1 + 1 + 1 + 1 = 12$ which equals the SCD value for the market in Figure II-3:

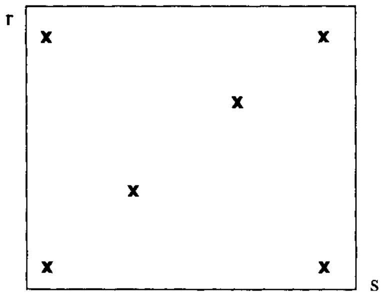
$SCD(ex2) = 1 + 1 + 2 + 2 + 2 + 1 + 1 + 1 + 1 + 0 = 12$.

The above example indicates that SCD is unable to differentiate between markets with more and less differentiated products.

[80] For a better illustration, the two x's located close to each other are not put on top of each other although they are supposed to have exactly the same coordinates on the r-s-market space.

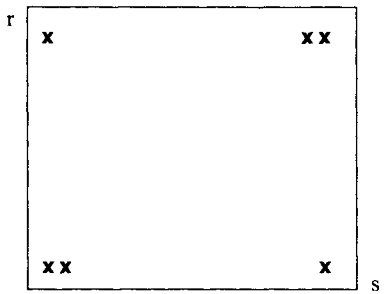
Further, SCD was computed for two exemplary markets with six products (see Figure II-4 and Figure II-5). For the case of six products, the product configuration producing a maximum value of SCD is depicted in Figure II-5. Although the market in Figure II-4 clearly exhibits a higher degree of product differentiation, its SCD is smaller than the SCD computed for the market in Figure II-5.

Figure II-4: Market with six products – highly differentiated



$$SCD(ex3) = 1+1+2+1.4+0.6+2+1+1+1+1+1+1+0.6+1.4+0.8 = 16.8$$

Figure II-5: Market with six products – less differentiated



$$SCD(ex4) = 1+1+2+2+0+2+1+1+1+1+1+1+0+2+2 = 18$$

To summarize, the sum of City Block distances is not appropriate as a measure of product differentiation because it does not differentiate between markets with more and less differentiated products. As the six-products example shows, SCD does not increase with increasing dissimilarity of products.

5.4 A measure of diversity and its transformation into a measure of product differentiation

5.4.1 Weitzman's measure of diversity

Weitzman 1992 introduces a cluster-based measure of spatial diversity. The idea behind this measure is to draw a maximum likelihood tree (Nguyen et al. 2004) or a rooted directed tree[81] (Weitzman 1992) linking all points in the space (or products in the market). The diversity function equals the sum of branch lengths of the tree. The data needed to calculate the measure is the pairwise spatial distances between products in the market space, e.g., in form of a distance matrix (for an example see Nguyen et al. 2004). Weitzman's diversity function, denoted by $V(S)$, is inductively defined on a set S of N products. Hence, $V(S)$ is computed recursively, starting from the two points with the closest distance (nearest neighbors):

$$V(S) = \max_{i \in S}\{V(S \setminus i) + d(i, S \setminus i)\}$$

$$\text{with}$$

$$V(i) \equiv d_0 \quad \forall i$$

$$d(i,Q) = \min_{j \in Q}\{d(i,j)\}.$$

d_0 can be any constant, usually one normalizes d_0 by setting it equal to zero. $d(i, S \setminus i)$ denotes the minimum distance between i and S. It is derived by computing the distance[82] between i and the element in S that is closest to i.

Weitzman provides a fundamental representation theorem guiding through the computation process. The diversity measure is computed recursively, taking the following steps (for more details see Weitzman 1992, p. 384ff.):

1. include all products in S
2. seek for the products in S with the smallest distances $d(i, j)$
3. exclude the product i from S for which $V(S \setminus i) > V(S \setminus j)$ or $d(i, S \setminus \{i,j\}) > d(j, S \setminus \{i,j\})$ holds. i can be termed a "link species" linking the "representative species" j to the remaining points/products in S.

[81] A tree is a graph with no cycles. A directed tree is a digraph whose underlying graph is a tree and which has no loops and no pairs of vertices joined in both directions. In a rooted directed tree every point has exactly one root which it is connected to. See also http://www.math.utk.edu/~rdavis/Math504/Lecture08.doc.

[82] It is not clear which distance should be used here. However, it is common practice to use the Euclidean distance.

4. define $S = S \setminus i$
5. go to 1. until $|S| = 1$
6. $V(S)$ is the sum of all $d(i, j)$ from all iterations.

The calculation process can be programmed e.g., using Visual Basic (VBA) (I provide the code in the appendix) or FORTRAN (Garcia et al. 2005). However, computation time can become extensive when many products are involved since computation time grows exponentially with the number of products (Garcia et al. 2005).

The mathematical properties of $V(S)$ include the monotonicity property, the link property, and the twin property. Monotonicity implies that the adding an element to a set will increase the set's diversity by at least the distance between the new element and the element within the set that is closest to the new element: $V(Q \cup j) \geq V(Q) + d(j,Q), \quad \forall Q, \ \forall j \notin Q$.

The link property requires that *for all S, with* $|S| \geq 2$, there exists at least one[83] element $j \in S$ that satisfies $V(S) \geq d(j, S \setminus j) + V(S \setminus j)$.

The twin property entails that adding an element k outside a set S to S does not affect the set's diversity if k is identical to an element j belonging to S. That is, if $d(j,k) = 0$ and $d(j,i) = d(k,i)$ *for all i in* S, then $V(S \cup k) = V(S)$.

Weitzman's diversity measure adopts its minimum when all products are clustered at a single spot in the market space. In this case, all distances between products are zero which results in $V(S) = 0$.

For the market in Figure II-2, the measure adopts a value of

$V(S, ex1) = 0.707 + 1.000 + 1.000 + 1.414 = 4.121$.

For the market in Figure II-3, the measure arrives at the following result:

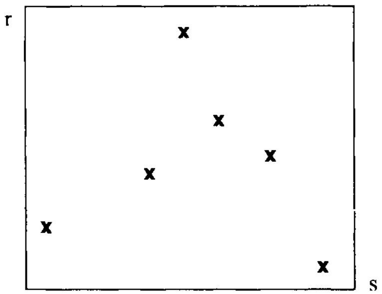
$V(S, ex2) = 0 + 1.000 + 1.000 + 1.414 = 3.414$.

Hence, Weitzman's measure seems to overcome the shortcomings of the aforementioned measures SED and SCD.

However, Weitzman's measure suffers from a disadvantage caused by the mathematical twin property (see above). The twin property leads to the following result:

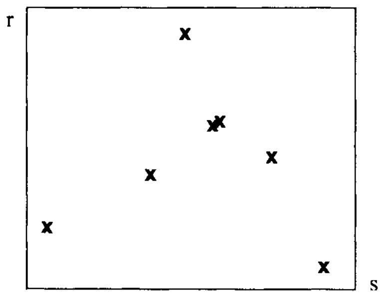
[83] This statement hold for all j in S in the case of ultrametric distances (Weitzman 1992).

Figure II-6: Market with six products – no clusters



$V(S, ex5) = 0.224 + 0.412 + 0.539 + 0.943 + 1.118 = 3.236$

Figure II-7: Market with seven products - clustered



$V(S, ex6) = 0 + 0.224 + 0.412 + 0.539 + 0.943 + 1.118 = 3.236$

Due to the twin property, the diversification $V(S)$ does not change when a product that has the same properties (i. e., the same location in the attribute space) as an existing product is added.

The two figures above (see Figure II-6 and Figure II-7) have the same value of Weitzman's diversity: $V(S5) = V(S6) = 3.236$. However, the degree of product differentiation is obviously not the same in both figures. In the market in Figure II-7, two products located at the same spot are perfect substitutes. The degree of product differentiation in this market should therefore be lower than product differentiation in the market in Figure II-6. Weitzman's diversity measure does apparently not detect slight changes in product differentiation as has been illustrated in the two market examples above.

To summarize, while Weitzman's V is a very powerful measure of the diversity of products, it fails to validly measure the degree of product differentiation. The reason is due to the fact that, ceteris paribus, the number of elements (i.e., products/points) is not explicitly taken into account in Weitzman's measure. While the mathematical twin property may prove reasonable for a diversity measure this does not hold for a measure of product differentiation. Notably, the degree of product differentiation is not independent of the number of products.

5.4.2 Transformation of Weitzman's measure

To overcome this disadvantage, one could think of normalizing Weitzman's measure by dividing it by the number of products. Hence, the new, normalized measure might have the following form:

$$V(S)^T = \frac{V(S)}{N}$$

with N *: number of products.*

$V(S)^T$ may be interpreted as the average diversity contribution per product. It could tell us how much diversity on average we gain by each product. If products are very similar, we gain only a little diversity by the respective products. If products are highly differentiated, the average diversity per product will be high. The number of products is explicitly taken into account thus leading to different values of $V(S)^T$ when two markets have the same degree of diversity $V(S)$ but a different number of products. More precisely, there could be several products at the same spot in one of the two markets while in the other market there are fewer products such that only one product occupies a certain spot. If the occupied spots are the same, the degree of differentiation is the same in both markets, but due to the clustering of products in one of the markets, the levels of product differentiation are different. That is, the degree of product differentiation is higher in the market with fewer products and lower in the market with clustered products. $V(S)^T$ would correspond to this intuition of product differentiation and detect the aforementioned difference. $V(S)^T$ is not scale-invariant, but this problem could be overcome by normalizing the characteristics space before calculating the measure.

5.5 Spatial pattern analysis

5.5.1 Overview and origins of spatial pattern analysis

Spatial pattern analysis originates from biology, forestry, ecology, geostatistics, botany, astrology, meteorology, archeology and many other research disciplines where point patterns are to be analyzed. Examples entail the detection of distribution patterns of trees in a forest, or the distribution of accidents, crimes or rare diseases on a geographical map (e.g., a country or a city). Hence, the raw data to conduct a spatial pattern analysis is a geographical map or a two- or three-dimensional study area with points marking the occurrence of certain events (e.g., trees, accidents, crimes, etc.). As we will see later on, the study area can have any number of dimensions.

In the marketing discipline, spatial data analysis may have the potential to describe the pattern of products (= events) located in a market space (= map or study area). The market space can be determined by product attributes, perceptual dimensions (e.g., like an MDS map) or geographical dimensions.

Notably, the use of spatial pattern analysis to assess the degree of product differentiation or product substitutability seems promising. The reason is that, in a spatial context, product differentiation is reflected in the appearance of specific patterns, e.g., a very low degree of product differentiation implies the formation of clusters, while a high differentiation will rather entail a regular product pattern in the market space (or characteristics space).

Surprisingly, spatial data analysis, although widely used in a wide variety of scientific disciplines, has never been applied in the marketing discipline. It seems interesting to investigate the appropriateness of spatial data analysis as an approach to measure the differentiation vs. substitutability of products or brands in a market.

5.5.2 Nearest neighbor methods

Nearest neighbor methods constitute a popular family of methods to detect or describe spatial point patterns. They are frequently used in the context of spatial analysis to describe spatial distributions, e.g., positioning, mixture, and differentiation of forest stands (Kint et al. 2003), and detect point agglomerations or regular point patterns. Apart from their application in ecology, forestry and geography, nearest neighbor methods are a popular instrument in meteorology, marine science, biology, archaeology, or psychology (Sinclair 1985).

Nearest neighbor methods are based on distances between events[84], especially nearest neighbor distances. An event's nearest neighbor is located closest to that event. More precisely, event k is the nearest neighbor of event i if

$$d(i,k) = \min_{j}\{d(i,j)\}$$

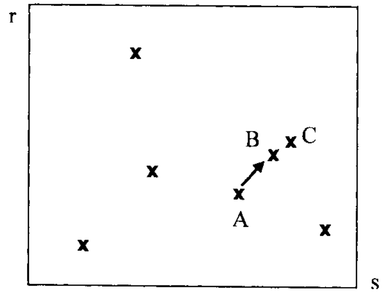
$$with\ d(i,j) : distance\ between\ event\ i\ and\ event\ j.$$

The nearest neighbor distance of event i is termed $d(NN)_i$.

The nearest neighbor concept does not specify which distance function should be used when calculating $d(i,j)$. However, it is common practice to use the Euclidean distance function, which will be done as well in the subsequent calculations.

Figure II-8 illustrates a nearest neighbor relationship: Here, A's nearest neighbor is B (see arrow). Every event has a nearest neighbor. For example, B's nearest neighbor is C and C's nearest neighbor is B, and so on.

Figure II-8: Nearest neighbor events



A simple example of a nearest neighbor search is the selection of an emergency vehicle closest to the scene of an accident.[85] In classification tasks, one can use the classification of an unknown object's nearest neighbor as the most likely classification. In botany, for example, nearest neighbor analysis can tell the researcher whether a plant tends to attract other plants or whether there is a repulsion effect between plants.

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[84] For clarity, I use the term "event" and not "point" because, in spatial analysis, the term "point" is often referred to as any spot in the space while an event marks the occurrence of a focal object, e.g., a product, a tree, an accident etc. In this context, there are measures that focus on event-event distances while others calculate distances between randomly selected points and an event (e.g., the event that is closest to that point).

[85] Here, the accident and the emergency vehicle mark two different types of events.

The average nearest neighbor distance for all events $d(NN)$ is defined by

$$d(NN) = \frac{1}{N}\sum_{i=1}^{N} d(NN)_i$$

with

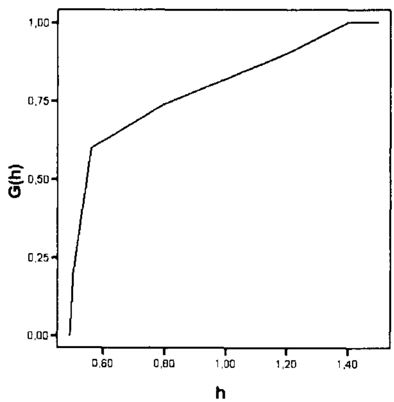
$d(NN)_i$: *nearest neighbor distance of event i*

N : *number of events within the study area.*

Given all nearest neighbor distances, the empirical cumulative distribution function $G(h)$ is derived by the following:

$$G(h) = \frac{\#\{i \mid d(NN)_i \le h\}}{N}.$$

Figure II-9: Empirical nearest neighbor distance cumulative distribution function G(h)



Viewing the cumulative distribution function (see Figure II-9) provides information on the size and distribution of nearest neighbor distances. A fast rising function indicates a rather clustered pattern of events, while a late sharply rising function reflects a rather regular pattern.

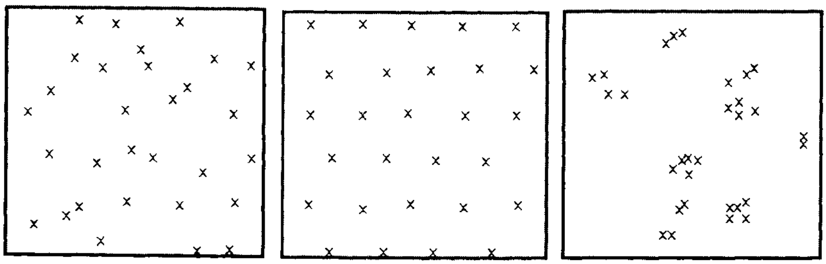
The Nearest Neighbor Index (NNI), also known as positioning index, is a "measure of nonrandomness" first described by Clark and Evans 1954 and edge-corrected[86] by Donnelly 1978. NNI has good power for detecting departures from spatial randomness (Sinclair

[86] The edge correction is supposed to remove this bias caused by the border of the space. This issue will be addressed later.

1985). It measures "the manner and degree to which the distribution of individuals in a population on a given area departs from that of a random distribution" (Clark and Evans 1954). A "random distribution" in this sense is characterized by the fact that every spot in the space has the same probability of receiving an event and that the location of an event is independent of the location of any other events (Clark and Evans 1954). This state is also termed "complete spatial randomness" (csr).

The NNI is based on the following idea: The average distance between an event and its nearest neighbor is compared against the expected mean distance if events were randomly positioned. Basically, three general spatial patterns can be distinguished: a random distribution[87], a uniform (or regular) distribution, and a clustered (or aggregated) pattern (Clark and Evans 1954). These patterns are illustrated in Figure II-10.

Figure II-10: Event patterns: Random/csr (left), Regular/uniform (middle), clustered/aggregated (right)



The original NNI developed by Clark and Evans 1954 relates the observed average nearest neighbor distance, $d(NN)$, to the expected nearest neighbor distance under a random distribution, $Exp(NN)$:

$$Exp(NN) = \frac{1}{2\sqrt{\lambda}} = \frac{1}{2}\sqrt{\frac{A}{N}}$$

with

λ *: density of area A*

A *: study area*

N *: number of events within area A.*

The nearest neighbor statistic NNI is derived by the ratio of observed and expected average distance (Clark and Evans 1954):

[87] A random distribution, also termed complete spatial randomness (csr), implies that events are realizations of a homogenous Poisson process with intensity λ.

$$NNI = \frac{d(NN)}{Exp(NN)} \qquad with\ 0 \le NNI \le 2.1491.$$

If all events are clustered at the same spot, all nearest neighbor distances will be zero, which results in $d(NN) = 0$. Consequently, NNI will adopt a minimum of zero. If the events are distributed at random, the observed average nearest neighbor distance, $d(NN)$, will equal more or less the expected average nearest neighbor distance under a random distribution, $Exp(NN)$, thus leading to $NNI = 1$. If the pattern of events equals a regular pattern[88], NNI will adopt its maximum of 2.1491 (Clark and Evans 1954).

Clark and Evans 1954 also offer a statistic that allows the statistical testing for spatial randomness:

$$Z_{NN} = \frac{d(NN) - Exp(NN)}{\sqrt{Var[d(NN)]}}$$

$$with\ Var[d(NN)] \approx \frac{(4-\pi)A}{4\pi N^2} \approx 0.0683\frac{A}{N^2}.$$

As the nearest neighbor distances are not independent[89], the asymptotic distribution of $d(NN)$ does not follow the Central Limit Theorem (see Ripley 1981, p. 153). However, the distribution of $d(NN)$ has been shown to be normal for $N > 6$ (Donnelly 1978).

If the study area represents a sample from a larger area, the above NNI does not produce very precise results. Moreover, some events within the sampled study region are closer to the border of the area than to their nearest neighbor. Due to the fact that an event's nearest neighbor may be outside the study area, the NNI has a tendency to overestimate actual nearest neighbor distances. To resolve this problem, Donnelly 1978 suggested an edge correction. Donnelly's correction changes $Exp(NN)$ into the following form $Exp(NN)^c$:

$$Exp(NN)^c = \frac{1}{2}\sqrt{\frac{A}{N}} + 0.0514\frac{P}{N} + 0.0412\frac{P}{N^{3/2}} = Exp(NN) + 0.0514\frac{P}{N} + 0.0412\frac{P}{N^{3/2}}$$

with P : circumference of area A.

The edge-corrected index, NNI^c, is thus given by

[88] A regular pattern is characterized by an even, hexagonal pattern in which every event is equidistant from six other events (Clark and Evans 1954).

[89] The limited independence of nearest neighbor distances is caused by the existence of reflexive nearest neighbors. However, the correlations between nearest neighbor distances have been found to be small (Ripley 1981, p. 153).

$$NNI^c = \frac{d(NN)}{Exp(NN)^c}.$$

An edge-correction of $Var[d(NN)]$ is given by (Ripley 1981, p. 153):

$$Var[d(NN)]^c \approx 0.0683\frac{A}{N^2} + 0.037\frac{P\sqrt{A}}{N^{5/2}} = Var[d(NN)] + 0.037\frac{P\sqrt{A}}{N^{5/2}}.$$

5.5.3 Appropriateness of nearest neighbor methods in product differentiation measurement

In the following I am going to transfer nearest neighbor analysis to the marketing discipline and discuss its appropriateness when it comes to measuring product differentiation. It is straightforward that the term "events" can be replaced by "products" or "brands", while the "multidimensional characteristics space" replaces the former "study area". Importantly, nearest neighbor methods can be applied for any number of spatial dimensions. Nearest neighbor distances are derived by calculating Euclidean distances, which can be computed for an arbitrary number of dimensions. The expected average nearest neighbor distance, $Exp(NN)$, does not put restrictions on dimensionality either, for the density of the study area can also be calculated in a multidimensional context. Further, nearest neighbor methods can be calculated for differently shaped spaces.

When applying the NNI to the measurement of product differentiation in a multidimensional characteristics space, an edge-correction is not necessary because the study area (i. e., the market space) does not constitute a sample from a larger area. Consequently, a product located close to the edge of the market space cannot have a nearest neighbor outside the market space.

For the market in Figure II-2, NNI arrives at the following result

$$NNI(ex1) = \frac{\frac{1}{5}(0.707 + 0.707 + 0.707 + 0.707 + 0.707)}{\frac{1}{2}\sqrt{\frac{1}{5}}} = \frac{0.707}{0.224} = 3.16.$$

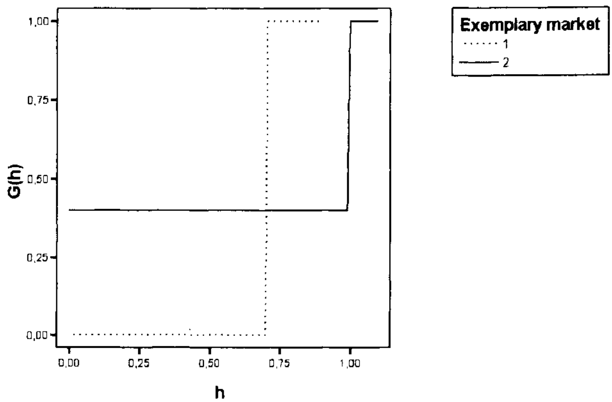
For the market in Figure II-3, NNI is given by the following:

$$NNI(ex2) = \frac{\frac{1}{5}(1 + 1 + 1 + 0 + 0)}{\frac{1}{2}\sqrt{\frac{1}{5}}} = \frac{0.6}{0.224} = 2.68.$$

$NNI(ex1)$ exceeds $NNI(ex2)$, which indicates that, in this example, NNI is able to detect differences between a market with more differentiated products and one with less differentiated products.

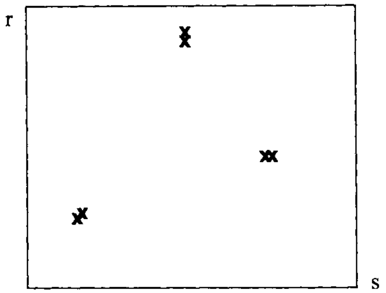
Figure II-11 shows the empirical cumulative distribution functions of the two exemplary markets in Figure II-2 (market number one, see line 1) and Figure II-3 (market number two, see line 2). The two functions illustrate that the number of small nearest neighbor distances is higher in market number two, while in market number one, all nearest neighbor distances are equal at 0.707.

Figure II-11: Nearest neighbor empirical cumulative distribution functions



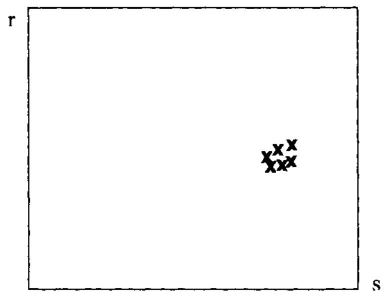
Unfortunately, NNI cannot distinguish between different types of clustered patterns. That is, the market in Figure II-12 has the same NNI value as the market depicted in Figure II-13, although in the first, products are grouped into three differentiated clusters, while in the latter, all products belong to the same cluster. Product differentiation is higher in the first market since products are less similar, but NNI does not detect the difference.

Figure II-12: Market with three product clusters



$$NNI(ex11) = \frac{0}{\frac{1}{2}\sqrt{\frac{1}{6}}} = 0$$

Figure II-13: Market with one product cluster



$$NNI(ex12) = \frac{0}{\frac{1}{2}\sqrt{\frac{1}{6}}} = 0$$

The empirical cumulative distribution functions of both exemplary markets have the same shape. Since, in both cases, all nearest neighbor distances are zero, both cumulative distribution functions rise sharply at $h = 0$ and then stay flat at the level of $G(h) = 1$. Like the NNI, $G(h)$ is unable to detect the difference between a market with several small product clusters and a market with one large cluster.

Hence, NNI does not meet the requirements of a measure of product differentiation postulated in section IV because it does not increase with increasing dissimilarity of products.

Likewise, $G(h)$ does not detect different degrees of product differentiation within clustered product patterns.

NNI detects product patterns and allows the comparison of patterns across markets even if they differ with respect to the number of products, shape of area, or number of dimensions of the market space. The number of products is explicitly taken into account, since $Exp(NN)$ is calculated for the observed number of products. Since NNI is scale-invariant, distances do not have to be normalized before the index is calculated. NNI does not provide information on individual patterns within the market area. E.g., two markets can have the same NNI indicating the same level of clustering although products are concentrated in totally different areas of the market. However, this does not seem to be a problem in the context of product differentiation measurement in marketing, since the definition of product differentiation does not include information on where products are located.

Although NNI has many advantages (e.g., an easy computation and interpretation), it also suffers from a considerable loss of information caused by the averaging of several nearest neighbor distance to one single number (Cressie 1993, p. 611). Also, the fact that second, third and higher order nearest neighbors are not considered is arbitrary (Cressie 1993, p. 611). For this reason, Cressie (1993) does not generally recommend nearest neighbor statistics for mapped[90] data; moreover he points out that they were originally intended for field data.

5.5.4 Extensions of nearest neighbor analysis

To gain a more accurate impression of the degree of product differentiation, nearest neighbor analysis should be extended to investigating second, third, ... and K*th* nearest neighbor distances. The expected average k*th* order nearest neighbor distance is given by (Cressie 1993, p. 611f.):

$$Exp(NN_k) = \frac{k(2k)!}{(2^k k!)^2\sqrt{\lambda}} = \frac{k(2k)!}{(2^k k!)^2\sqrt{\frac{N}{A}}} \qquad k = 1,2,...$$

Consequently, it is possible to extend the NNI to k*th* nearest neighbor distances. The numerator of the index is derived by computing the average k*th* nearest neighbor distance of all products:

$$d(NN_k) = \frac{1}{N}\sum_{i=1}^{N} d(NN_k)_i \qquad k = 1,2,....$$

[90] The term mapped data describes a situation where all the location of events within an area is known.

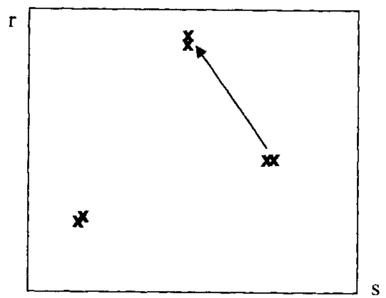
Consequently, the k*th* order Nearest Neighbor Index, NNI_k, is obtained by

$$NNI_k = \frac{d(NN_k)}{Exp(NN_k)} \qquad k = 1,2,\ldots$$

Extending nearest neighbor analysis to higher order nearest neighbors leads to a more exhausting use of available information, and thereby, to a more accurate description of the data. Eventually, it may complement product differentiation measurement by adding aspects to the existing analysis.

To illustrate the additional descriptive power gained by higher order nearest neighbor analysis, I refer to the exemplary markets with three product clusters (see Figure II-12) and one product cluster (see Figure II-13). As we know, the first order NNI arrives at the same value for both markets. The second nearest neighbors of the market with one product cluster (Figure II-13) all equal zero, since all six products are located at the same spot. In the market with three clusters, however, the second nearest neighbors of all products are greater than zero (Figure II-12 and Figure II-14), because only two products at a time are located at the same spot, while the second nearest neighbor products are always located somewhere at a distance from the respective first products (one second nearest neighbor distance is marked by an arrow in Figure II-14).

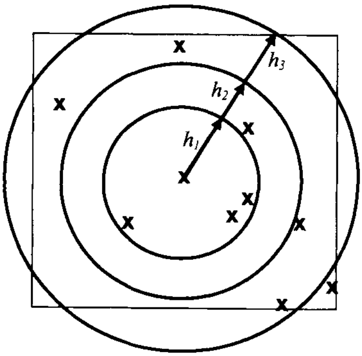
Figure II-14: Second order nearest neighbor distance



This example shows that the second order Nearest Neighbor Index, NNI_2, can detect differences in product differentiation that have not been detected by NNI_1 (i.e., the original first order NNI).

Another extension and refinement of nearest neighbor analysis is the K function (Ripley 1981, p. 158ff.; Cressie 1993). It considers nearest neighbor distances of any order. It is based upon the idea of counting, from a randomly selected event/product, all events within a given distance from that point. This leads to a measure that is more sensitive and powerful in distinguishing complete spatial randomness from spatially regular or clustered patterns at a multitude of scales (Cressie 1993, p. 579). However, it also proves more complex with respect to computation. The basic idea of the K function is illustrated in Figure II-15.

Figure II-15: Higher order nearest neighbors – the K function



The empirical K function is given by

$$K(h) = \frac{1}{\lambda}\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} I_h(d_{ij}) = \frac{A}{N^2}\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} I_h(d_{ij})$$ [91]

with

$I_h(d_{ij}) = 1 \; if \; d_{ij} \leq h \; and \; 0 \; otherwise$

$h \geq 0.$

Under complete spatial randomness in a two-dimensional space, we expect $K(h) = \pi \cdot h^2$. Under regularity, $K(h)$ tends to be less than $\pi \cdot h^2$, whereas under clustering $K(h)$ tends to be greater than $\pi \cdot h^2$ (Cressie 1993, p. 616).

[91] Edge corrections of the K function are provided by e.g., Cressie 1993.

6. Conclusion and discussion

This paper has presented and developed several approaches to measuring product differentiation in a multidimensional characteristics space. Interestingly, the marketing discipline does not offer valid concepts for this purpose. This paper demonstrates that a measure that simply averages or sums up the distances between products does not meet intuitive requirements of a measure of product differentiation. That is, intuitively appealing distance functions (i.e., functions based on Minkowski distances like the sum of Euclidean distances or the sum of City Block distances) do not transfer the general notion of product differentiation. This paper shows that these functions adopt high values when products are clustered in the edges of the characteristics space.

Weitzman's measure of diversity is very accurate as to diversity measurement, but does not meet the necessary requirements of a measure of product differentiation. The reason is that Weitzman's V does not discriminate between markets with the same degree of diversity but different levels of product differentiation. The case of equal diversity but unequal product differentiation can arise when product locations are the same but the number of products differs, such that in one of the markets more than one product occupies the same spot (see Figure II-6 and Figure II-7). Therefore, it is important for a measure of product differentiation to account for the total number of products marketed. In the paper at hand, I suggest a transformation of Weitzman's measure to overcome the aforementioned shortcomings. The interpretation of the thus transformed measure would be something like an "average degree of diversification per product". It seems that this interpretation has much in common with the common intuition of product differentiation. However, future research will have to further investigate the adequacy of using the transformation of Weitzman's diversity measure as a measure of product differentiation in a spatial market context.

The research area of spatial statistics seems to be an interesting and promising source of research for measures of spatial product differentiation in marketing. The Nearest Neighbor Index (NNI) presented in this paper has good power to detect spatial product patterns. The three patterns to be distinguished entail a regular pattern, a random pattern, and a clustered pattern. While a clustered pattern meets the common intuition of a low degree of product differentiation (all products within a cluster are similar), a regular pattern reflects our notion of a high degree of product differentiation (distances between products are large which indicates rather dissimilar products). However, a clustered pattern can have many faces – depending on the number of clusters. Within different clustered product patterns, the degree of product differentiation can vary significantly. In this line of argument, the work at hand reveals that the first order NNI does not sufficiently discriminate between different levels of product differentiation. A more accurate summary of data is obtained by including higher order nearest neighbor distances in the analysis. An example given in this paper illustrates that even using only first and second order nearest neighbor distances can already achieve a much better discriminatory power. Hence, nearest neighbor analysis should always start with investigating the first order NNI. Like this, one gains a helpful first impression regarding the location pattern of products in the market. For markets with equal first order NNI's, the second, third, and higher order NNI's should be taken into account. This enables the researcher to gain insights into the degree of product differentiation. Including several higher order nearest neighbor distances in the analysis assures that all available information is used. This increases descriptive power and leads to a better product differentiation measurement. The K function combines nearest neighbor distances of any order.

To summarize, the measurement of product differentiation is an area that needs to be researched more extensively. Spatial analysis provides a number of opportunities to describe and summarize spatial data. The number of dimensions to be considered in this context is not restricted in general. This may open the opportunity to assess the degree of product differentiation of products in a multidimensional characteristics space.

Additionally, a transformation of Weitzman's measure of diversity may be used to assess the degree of product differentiation. It constitutes a measure of "the degree of diversity generated by each product on average" and can be applied to any number of dimensions. Further research will have to investigate whether the transformed diversity measure is able to validly measure product differentiation.

The above measures may be applied to a variety of spatial market representations. In the work at hand, I focused on a multidimensional characteristics space. However, the scope of applications goes much further. The measures apply to any kind of space, including the perceptual space given by an MDS map, a geographical space, an attribute space, or a space whose dimensions are determined for example by cross-price elasticities between products.

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Appendix

Visual Basic (VBA) code for computation of Weitzman's diversity measure

```
Sub Weitzman()

' The distance matrix has to be inserted in Cell A2 (=left upper corner of distance matrix)
' The distance matrix has to be in form of a triangle representing the lower left half
' of the distance matrix exclusive the diagonal.
' The program writes the final solution of V(S) in cell B1.
' Also, the process provides several provisional results (see the message boxes).

Dim Datarange As Range
Dim Datacell As Range
Dim n As Integer  'n denotes the number of products
n = 6  'please insert here the number of products
Set Datarange = ActiveSheet.Range(Cells(1, 1), Cells(n, n))
Dim V As Double
V = 0
Dim i As Integer
Dim minvalue As Double
Do Until minvalue = 9999
minvalue = Application.WorksheetFunction.min(Datarange)
If minvalue = 9999 Then
Exit Do
End If
V = V + minvalue
For Each Datacell In Datarange 'replace empty cells in Datarange by 9999
If IsEmpty(Datacell) Then
Datacell.Value = "9999"
End If
If Datacell.Value = minvalue Then
Datacell.Select
MsgBox "The minimum value is " & minvalue & " in cell " & Selection.Address
Dim a As Integer
```

```
Dim b As Integer
a = ActiveCell.Row
b = ActiveCell.Column
'MsgBox "The minimum is in row " & a
'MsgBox "The minimum is is column " & b
ActiveCell.Value = "9999"
Exit For
End If
Next Datacell
Dim Range2 As Range
Set Range2 = ActiveSheet.Range(Cells(a, 1), Cells(a, a))
Dim Range3 As Range
Set Range3 = ActiveSheet.Range(Cells(a, a), Cells(n, a))
Dim Totalrange1 As Range
Set Totalrange1 = Union(Range2, Range3)
Totalrange1.Select
Dim min1 As Double
min1 = WorksheetFunction.min(Totalrange1)
Dim Range4 As Range
Set Range4 = ActiveSheet.Range(Cells(b, 1), Cells(b, b))
Dim Range5 As Range
Set Range5 = ActiveSheet.Range(Cells(b, b), Cells(n, b))
Dim Totalrange2 As Range
Set Totalrange2 = Union(Range4, Range5)
Totalrange2.Select
Dim min2 As Double
min2 = WorksheetFunction.min(Totalrange2)
'MsgBox "min1 = " & min1 & " min2 = " & min2
If min1 < min2 Then
Totalrange1.Value = "9999"
Else
Totalrange2.Value = "9999"
End If
MsgBox "V(S) is equal to " & V
```

```
Loop
Range("B1").Value = V
End Sub
```