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A decision-support tool for recommending promising categories for targeted promotions

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A decision-support tool for recommending promising categories for targeted promotions

Abstract

When making marketing mix decisions, marketing managers of companies that offer a broad range of product categories, such as traditional offline and online retailers, mail-order companies, or financial service providers, often need to select one or a few focal categories out of all the possible ones offered. This interest is further fuelled by opportunities offered by the Internet or modern customer loyalty programs using smart card technologies, making it easier as well as cheaper for companies to implement micromarketing strategies.

These recent developments have lead to a shift in the managerial requirements of direct marketers: they want to find out which specific products or categories need to be featured in promotional activities customized for specific (groups of) customers. In this study, we present a decisionsupport tool that assists direct marketers in selecting subsets of promising categories from the large assortment they typically offer for inclusion in targeted promotions. The proposed analytical approach combines conventional wisdom of market basket analysis in a novel two-stage procedure (Boztug and Reutterer, 2008). In a first (exploratory) step, jointly purchased product categories across the entire assortment are identified by looking at pronounced cross-category interrelationships in the observed frequency patterns. Customers are next assigned to the identified shopping basket prototypes and we allow them to be members of multiple prototypes. This data-compression step is followed by a second (explanatory) step where the cross-category effects in response to marketing actions are modeled across the pre-selected categories. Our procedure takes both interdependencies in purchase behaviour across categories and customer heterogeneity with respect to cross-category effects in response to marketing actions into account.

For calibrating the model we obtained purchase transaction data of a major online grocery retailer for almost 4 year, resulting in a customer base of 17,312 households (purchased at least 3 times in the observation period). For the same retailer and time period, we also have detailed information on price and other important marketing-mix variables. A total number of 302,632 retail transactions with pick-any choices among an assortment of 121 categories are first subject to the data compression step. This first stage revealed 13 interesting and distinct prototypes which were subject to estimation of segmentspecific multivariate MNL models. Currently, we are about to empirically test the resulting recommendations derived from the above suggested two-stage approach vis-à-vis alternative approaches in a controlled field experiment conducted in cooperation with a major online grocery retailer. The experimental setup is projected to consist of a control group (no recommendations) and different experimental groups of which one group will receive recommendations derived by our suggested twostage approach and other groups will receive recommendations coming from other recommender systems that differ in their degree of intelligence. During the conference, we will present the underlying mechanism of our decision-support tool as well as show some preliminary results of its performance.

Keywords

recommending, decision, promising, support, categories, targeted, tool, promotions

Disciplines

Business | Social and Behavioral Sciences

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Conference program

Monday, January 5th

(The primary presenter's name is in italics. The last presenter of each session acts as a session chair.)

7:45-8:15	<i>Registration</i> (breakout area Novotel)	
8:15-9:15	Keynote speaker: <i>Russ Winer</i> , William Joyce Professor of Marketing, Stern School of Business, New York University and Executive Director of the Marketing Science Institute (Fairfield/Pukete/Whitiora room)	
9:15-9:30	<i>coffee break</i> (breakout area)	
9:30-11:00	Session 1a: Customer Relationship Management (Fairfield/Pukete room)	
	Modeling the Evolution of Customers' Service Portfolios	<i>David Schweidel</i> , Eric Bradlow, Peter Fader
	Measuring Customer Lifetime Value with Competitive Information: A Theoretical Framework Using A Dynamic Programming Approach	V. Kumar, <i>Jia Fan</i>
	Modeling Churn and Usage Behavior in Contractual Settings	<i>Eva Ascarza</i> , Bruce Hardie
	Session 1b: Response to Competitive Entry (Whitiora room)	
	Behemoths at the Gate: Incumbent Responses to Acquisitive Entry	Prokriti Mukherji, Alina Sorescu, Jaideep Prabhu, <i>Rajesh Chandu</i>
	When Wal-Mart Enters: How Incumbent Retailers React and How This Affects Their Sales Outcomes	Kusum Ailawadi, <i>Jie Zhang</i> , Aradhna Krishna, Michael Kruger
	Competing with Big-Box Retailers	<i>Vincent Nijs</i> , Qingyi Huang
11:00-11:30	<i>coffee break</i> (breakout area)	
11:30-13:00	Session 2a: Dynamic Learning Models (Fairfield/Pukete room)	
	Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics in the Wake of a Product Harm Crisis	Yi Zhao, Ying Zhao, <i>Kristiaan Helsen</i>
	Investigating Salespeople's Learning by Doing in a Bayesian Learning Structural Framework	<i>Qiang (Steven) Lu</i> , Ranjit Voola
	A Behavioral Perspective on Preference Evolution in Choice-Based Conjoint Experiments	Berk Ataman, <i>Robert Roederkerk</i>
	Session 2b: New Product Introduction (Whitiora room)	
	Modeling Product Entry and Pricing Decisions	<i>Federico Rossi</i>
	Skimming or Penetration? Strategic Dynamic Pricing for New Products	Martin Spann, <i>Marc Fischer</i> , Gerard Tellis
	Drivers of Adoption for Successive Generation of High-Tech Products	<i>Maria Kaya</i> , Paul Steffens

Monday, January 5th, continued

13:00-14:00	<i>Lunch</i> (restaurant)	
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	CEO Succession and the Impact on Competitive Behavior	<i>André Bonfrer</i> , Jagmohan Raju
	A Theory of Double Couponing	<i>Chi-Cheng Wu</i> , Shan-Yu Chou, Chyi-Mei Chen
14:00-15:30	Session 3b : Advertising Effectiveness (Whitiora room)	
	Asymmetric Advertising Response	<i>Ganaël Bascoul</i> , Julien Schmitt
	A Dynamic Goodwill Model for Drugs Coming Off Patent	<i>Ernst Osinga</i> , Peter Leeflang, Prasad Naik, Jaap Wierenga
	Determining Dynamically Optimal Budget Across Geographical Regions	<i>Ashwin Aravindakshan</i> , Kay Peters, Prasad Naik
15:30-16:00	<i>coffee break</i> (breakout area)	
16:00-17:30	Session 4a: Private Labels (Fairfield/Pukete room)	
	Dynamic Market Effects of the Introduction of Store Brands' Imitations of National Brands' Feature Extensions	<i>Vijay Hariharan</i> , Debu Talukdar, Sri Devi Duvvuri
	New products, the Antidote to Private Label Growth? Who is Fighting Whom?	<i>Katrijn Gielens</i>
	Proliferating Private Label Portfolios: How Introducing Economy and Premium Private Labels Influence Brand Choice	Inge Geyskens, Katijn Gielens, <i>Els Gijbrecchts</i>
	Session 4b: Online Consumer Search (Whitiora room)	
	Consumer Search and Online Demand for Online Products	Jun Kim, Bart Bronnenberg, <i>Paulo Albuquerque</i>
18:00	Busses leave from the Novotel to the dinner venue: Hamilton Gardens	
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19:00	<i>Conference Dinner in Hamilton Gardens</i>	
± 22:00	End of the Conference Dinner, bus transfer back to Novotel and IBIS hotel	

Tuesday, January 6th

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	Is All Publicity Good Publicity? The Impact of Mass Media, Firm Public Relations Activities and Advertising on Corporate Reputation	<i>Seema Pai</i> , Natalie Mizik, S. Siddarth
	Consumer Attitude Dynamics and Marketing Spending Rules	<i>Dominique Hanssens</i> , Koen Pauwels, Shuba Srinivasan, Marc Vanhuele
	Session 5b: Price Promotion (Whitiora room)	
	The Long-Term Impact of Price Promotions on Consumer Purchase Behavior: Investigating the Role of Consistency in Deal Calendars	<i>Christine Ebling</i> , Daniel Klapper
	Price-Promotion Effectiveness during A Price War	<i>Francesca Sotgiu</i> , Katrijn Gielens, Marnik Dekimpe, Berend Wierenga
10:00-10:30	<i>coffee break</i> (breakout area)	
10:30-12:00	Session 6a: Drivers of Firm Performance (Fairfield/Pukete room)	
	Do Mindset Metrics Explain Brand Sales?	<i>Shuba Srinivasan</i> , Marc Vanhuele, Koen Pauwels
	The Role of Marketing Investments in Successful R&D Commercialization over Time	<i>Henning Kreis</i> , Lutz Hildebrandt
	Utilizing Survey Data to Augment Revenue Forecast Accuracy in Volatile Middleware Market	<i>Mina Kung</i> , Charlie Geringer
	Session 6b: Research Methodology (Whitiora room)	
	A Framework for Investigating Endogeneity in Marketing Models	Peter Ebbes, <i>Michel Wedel</i> , Peter Lenk
	Modeling Endogeneity in Logit-Based Demand Models: Inappropriate and Dynamic Instruments	Rick Andrews, <i>Peter Ebbes</i>
	Identifying the Most Informative Consumer Segments for Sales Prediction	<i>Sarah Gelper</i> , Christophe Croux
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Tuesday, January 6th, continued

13:00-14:30	Session 7a: Timing of Advertising and Promotion (Fairfield/Pukete room)	
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	Understanding the Timing and Magnitude of Advertising Spending Patterns	<i>Maarten Gijsenberg</i> , Harald van Heerde, Marnik Dekimpe, Jan-Benedict Steenkamp, Vincent Nijs
	Timing of Sales Promotion of Durable Goods: An Example of Taiwan Automobile Market	<i>Ching-I Chen</i> , Ting-Ling Lin
	Session 7b: Marketing Decision Models (Whitiora room)	
	A Decision-Support Tool for Recommending Promising Categories for Targeted Promotions	<i>Els Breugelmans</i> , Yasemin Boztug, Thomas Reutterer
	Choosing Response Models for Budget Allocation in Heterogeneous and Dynamic Markets: Why Simple Sometimes Does Better	Dennis Proppe, <i>Sönke Albers</i>
	The Dynamics of Marketing Decision Models	<i>Berend Wierenga</i>
14:30-15:00	<i>coffee break</i> (breakout area)	
15:00-16:30	Session 8a: The Networked Consumer (Fairfield/Pukete room)	
	An Empirical Analysis of Recommender Systems and Market Diversity	Daniel Fleder, <i>Kartik Hosanagar</i>
	Modeling the Effects of Normative and Informative Word-of-Mouth on Product Adoption using Social Simulation Techniques	<i>Peter van Eck</i> , Wander Jager, Peter Leeftang
	Session 8b: Consumer Response (Whitiora room)	
	Responses of Unprofitable Customers to Demarketing Actions	<i>Eva Blömeke</i> , Michel Clement, Tammo Bijmolt
	Unplanned Category Purchase Incidence: Shopper Traits and Shopping States	David Bell, Daniel Corsten, <i>George Knox</i>
	Pay What You Want - Successful In The Long Run? Conceptualization of a Measurement Model for a Dynamic Experimental Study	<i>Mario Rese</i> , Wiebke Rasmussen, Laura Marie Schons, Daniel Weber, Wolf Strotmann
16:30-17:30	Discussion, next year's MDC	
	<i>Dinner on your own</i>	

Modeling the Evolution of Customers' Service Portfolios

David Schweidel, Eric Bradlow, Peter Fader

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Understanding how customers' service portfolios evolve over the course of their relationship can provide multi-service firms, such as telecommunication and financial service providers, with useful guidance for managerial issues such as customer valuation and targeting. Complicating matters, however, is the fact that ownership of individual services may be related to each other. Additionally, customers may be highly heterogeneous in terms of the portfolios they choose and the sequence of adoption/retention decisions they make over time. In this research, we propose a joint timing and multivariate choice model that nests extant singleproduct models to capture co-purchasing behavior and underlying choice dynamics.

We employ a hidden Markov model to identify latent relationship states through which households may pass during their tenure as customers of the firm. These states enable us to understand how subscription patterns evolve over a customer's relationship, including changes in their preferences for the available services and the duration of time for which they will maintain their chosen portfolio. The proposed model also provides a framework within which multiservice providers can assess the value of their customers, as well as evaluate the impact of promotional activities.

We apply our modeling framework to data from a major telecommunications provider, for which we empirically identify three relationships states. The behavior of customers is found to vary across these states in three ways. First, the portfolios to which customers in each state are likely to subscribe differ. In addition, the duration for which customers are likely to maintain their chosen portfolio varies not only across the states, but within the state for different portfolios. Lastly, customers in each of the states exhibit different tendencies to move between the states and to discontinue their relationship with the service provider.

Taking these three aspects together, we find that the value that customers represent to the service provider varies significantly across the states. It is not enough to just consider the number of services and their prices when evaluating a customer's lifetime value. When we account for the duration for which customers maintain their portfolios and the propensity to end the relationship with the service provider, we find that those customers who initially subscribe to many services are worth the most to the service provider, despite not

having the longest expected tenure. In addition, while those customers who start with a minimal number of services may not spend as much each month, they are expected to maintain service the longest and are of more value to the service provider than customers who begin with service portfolios of an intermediate size.

We also introduce and explore the notion of the "terminal customers" – the propensity for current customers to discard all services on their next action, an important economic consequence to the firm. Companies can extract the remaining value from these customers by continuing to provide service. The firm should, however, think twice before investing substantially in them, as their next decision may be to terminate the relationship.

Measuring Customer Lifetime Value with Competitive Information: A Theoretical Framework Using A Dynamic Programming Approach

V. Kumar, Jia Fan

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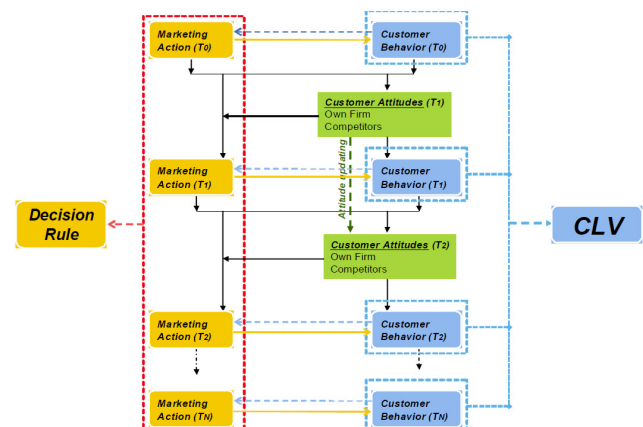
This paper develops a theoretical framework to measure Customer Lifetime Value (CLV) with competitive information using a dynamic programming (DP) approach. Measuring CLV accurately is the key to the success of customer relationship management. The previous CLV calculation has suffered criticisms due to lack of incorporating individual competitive information at the individual level. The competitor actions change the customers' preference towards the firms and their buying behaviors. The customers' preference could be captured by the customers' attitude towards the own firm over the competitors, and the survey data make this information available. This is the first research to incorporate the competitive information obtained through customer attitude in the CLV calculation using a DP approach. In addition, we see more and more customers' strategic behaviors in the market now, and this model incorporates the customer's strategic behaviors, which have not been modeled in the traditional CLV approach. Today, due to the fast growth of E-business, it becomes easier for both the firm and the customers to obtain additional market information on the market condition. The firms can conduct customer survey more frequently at a much lower cost. Customers can get more information on price and promotion of the products/services by searching on the Internet, which makes them exhibit strategic behavior. This framework accommodates this new situation in the market and makes use of the information from both sides (firm and customer) to improve the efficiency of the CLV calculation, and thereby leading to an optimum contact and promotion strategies for the firm.

We develop a game-theoretical framework for measuring CLV by incorporating consumers' strategic behavior and the effects of the competition through customers' attitudinal measurements. This framework features forward-looking customers, who make decision on whether or not to purchase, and how much to purchase at the beginning of every period to maximize their present value of current and future utilities. The firm makes the decisions on marketing contact and promotion accounting for customer's best decisions. It is essentially a sequential game with a

finite variable space and on a finite horizon (depending on the horizon of CLV calculation). This conceptual framework is in the Appendix. The development of the customers' state variable is based on the exchange characteristics, customer heterogeneity and marketing actions. A customer's state variables include his or her purchase count, purchase recency, average quantity and attitude. Purchase recency is defined as the number of time periods elapsed since the last purchase; purchase count is defined as the total number of purchases the customer made with the firm; average quantity is defined as the average number of items per purchase the customer bought across all purchases until the beginning of period t ; and attitude is defined as the customer's relative preference to the focal firm over the competitors. The transition probabilities can be easily obtained for all the state variables except for attitude, where we don't know how attitude at time t update to the new attitude at $t+1$. This is a challenge to this framework and we use Generalized Maximum Entropy (GME) to estimate these transition probabilities of attitude. The customers' utility function depends on three components: (1) Purchase recency, purchase count, average quantity and attitude; (2). Firm's marketing decisions, and (3) the interaction of firm's marketing decisions with attitude. The firm's expected utility from a customer depends on his or her probability of purchasing specific amount, which is a function of the customer's utilities. As a result, CLV can be expressed as a Bellman equation for the firm's with the firms' contact and promotion decision as control variables.

We develop an algorithm based on successive approximation to estimate this model. The main idea is to estimate the transition matrix of attitude by GME first, and then calculate the firm's and the customer's next period's value functions based on the new state variables updated by transition matrices and iterate until the value functions for both the firm and the customer are converged. We prove that this algorithm will lead to the Markov Perfect Equilibrium. In this equilibrium, firm optimizes its contact and promotion strategies and the forward-looking customers maximize their utilities.

Appendix: Conceptual Framework



Modeling Churn and Usage Behavior in Contractual Settings

Eva Ascarza, Bruce G. S. Hardie

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The ability to retain existing customers is a major concern for many businesses, especially in mature industries where customer acquisition is very costly and the competitive environment is rather severe (Blattberg et al. 2001, Rust et al. 2001). One way to increase retention is to identify which customers are most likely to churn, and then carry out targeted strategies to persuade them to stay. Hence not surprisingly, the marketing literature has focused its efforts on providing models explaining and predicting churn (e.g., Blattberg et al. 2008, Neslin et al. 2006).

Nevertheless, retention is not the only dimension of interest in the customer relationship. Customer revenue is another key factor influencing customer profitability. In most contractual situations the revenue generated per customer is uncertain (e.g., credit cards, wireless services, insurance contracts, leisure centers). In these settings, customer revenue is determined by how much each individual consumes the provided service. Therefore, modeling usage and retention is needed in order to make predictions about customer profitability. The literature about modeling usage in contractual settings is rather scarce. Some work has modeled usage looking at attitudinal constructs that affect consumption. However, the purpose of modeling usage in these articles is understanding the effect, if any, of the satisfaction/loyalty characteristics rather than a tool for predicting, as is the purpose of our study.

Even though the usage dimension has been barely investigated in contractual settings (from a predictive modeling perspective), its relationship with lifetime duration (i.e., retention behavior) has received much attention in the literature. Lemon et al. (2002) show how expected future usage influences the churn decision. Reichhel and Teal (1996) state that in most business settings usage tends to increase with relationship duration. Hence, does longevity increase usage or is it consumption what drives retention? We do not think there is such a direct cause-effect relationship between these two behaviors. Rather, we contend that this is an spurious correlation that vanishes if we take into account what is driving both processes. The literature has shown that usage and attrition are both driven by some unobserved characteristic, something that drives both phenomena and can be inferred from them.

Some researchers talk about satisfaction (Bolton et al. 2000, Bolton and Lemon 1999), some others talk about commitment (Gruen et al. 2000, Verhoef 2003). The attempt of this paper is not to theoretically define this underlying construct, but to model these phenomena in a less ad-hoc way. Recognizing the existence of an unobserved construct would allow us to approach these two processes in a more appropriate manner and thus make accurate predictions of people's behavior.

We propose a dynamic latent trait model, able to predict usage and renewal simultaneously. The model is built on the assumption that both behaviors are driven by the same (individual-level) underlying process that evolves over time. As this latent trait (e.g., commitment, satisfaction) drops, the customer decreases her usage levels and eventually churn. We capture the dynamics on the underlying commitment using a hidden Markov model, and then incorporate unobserved heterogeneity in the usage process. The model is estimated using hierarchical Bayesian methods, hence predictions are easily computed at the individual level. We validate the model using the renewal and transaction history of the members of an arts organization.

First we show how the proposed model outperforms those existing in the literature to model either usage or retention. Then we illustrate how the model can be easily implemented to forecast customers' behavior in contractual settings. In contrast to most churn models, this dynamic approach is able to identify changes in behaviour before the contract is close to expiring, thus predicting churn well in advance. Moreover, the model also gives interesting managerial insights about the customer base. For example, this method provides a dynamic segmentation tool not only based on transaction propensity but also taking into account the risk of default. Also, as new periods are observed, this information is easily incorporated in the model making possible to identify those customers whose underlying commitment is decreasing.

Behemoths at the Gate: Incumbent Responses to Acquisitive Entry

Prokriti Mukherji, Alina B. Sorescu, Jaideep C. Prabhu, Rajesh K. Chandy

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Open a random page from a business newspaper these days, and the odds are high that it will feature at least one corporate acquisition. Frequently, the news is about yet another acquisition by a corporate behemoth seeking to enter a new market. Corporate acquisitions number in the tens of thousands each year, and the total price tag of these acquisitions is in the trillions of dollars. Many large firms see acquisitions as a means to enter new markets, and leverage economies of scale. But as the volume of acquisitions grows ever larger, so do concerns about their effect on competitors and consumers. There is much fear that acquisitive entry by large firms could reduce competition in the markets they enter and lead to underserved consumer segments.

The fear that large entrants may hurt incumbents, especially small ones, is driven in part by the fact that large entrants often have the advantages of lower costs, access to greater resources, and the ability to leverage resources from other markets. Large entrants can raise entry barriers for new firms and potentially hamper startup activity in the market. Moreover, large firms have a tendency to favor mass markets over niches, and emphasize efficiency over relationships in their customer transactions. As such, some argue that acquisitive entry by large firms will leave small sized customer segments underserved.

These arguments have wide implications. For incumbent firms, their very survival may be at stake. For consumers, there exists the real possibility that some segments may be left out in the cold. For policy makers, these arguments imply that the proverbial Main Street may be in danger.

However, these arguments are not without their skeptics. For example, the Economist provides a more sanguine view of acquisitive entry: "The recent mergers among former Baby Bells are to be cheered precisely because they are due to competition and herald yet more rivalry to come". Increased competitive pressure may increase firms' propensity to seek out and serve hitherto ignored

customer segments. Additionally, not all incumbents need be hurt by the entry of large firms; some may even thrive as a result of such entry.

What is the actual impact of acquisitive entry by large firms on the performance of incumbents in a market? Why do some incumbents do poorly, while others do well? This paper presents a dynamic view of the impact of acquisitive entry on the responses and performance of incumbent firms. We propose a new theoretical framework that seeks to explain how systematic differences across firms on a fundamental marketing decision – customer targeting – drive performance outcomes among incumbents after acquisitive entry. This theoretical framework brings together insights from corporate strategy and social psychology to explain the marketplace impact of acquisitive entry. We then test the predictions from this framework by applying recently developed dynamic panel models on a unique panel dataset.

A stumbling-block for research on the marketplace impact of acquisitive entry has been the limited availability of market-wide, objective data. Since few mom-and-pop stores make financial information publicly available, researchers face many obstacles in assessing, in a comprehensive and bias-free way, the impact of acquisitive entry by large firms on existing firms in a market. Consequently, research and policy analysis so far has been based on analytical models, simulations, and case studies of individual firms. Existing multi-firm studies tend to focus on stock prices or market shares. A focus on the stock prices of public firms may lead to inaccurate inferences about the effects of acquisitive entry on small firms, many of which are private. A focus on market share may also be similarly inadequate. As the Federal Trade Commission (2003) notes, "market share and concentration data provide only the starting point in analyzing the competitive impact of a merger". Perhaps most importantly, these limited analyses often yield widely varying conclusions. Few papers have examined the impact of acquisitive entry across a large number of markets, and across all the competitors in these markets. This research seeks to go beyond this starting point, by examining the impact of acquisitive entry across a large number of firms and markets over time.

We propose a new explanation for why some incumbents do better than others after acquisitive entry by large firms. Our theoretical framework – which we refer to as a theory of strategic aspirations – argues that performance differences among incumbents can be explained by the customer targeting decisions they make in response to acquisitive entry. In doing so, we highlight the critical but unexplored role of firms' market choices in driving performance.

We set our empirical analysis in an industry that involves over \$1 trillion in annual transactions:

the US commercial and industrial banking industry. This industry is an important exception to the data difficulties that hobble much of the research on the impact of acquisitions. In this industry, information on a wide variety of strategic variables is required by law to be reported regularly. As such, we are able to obtain information on variables of relevance to our research questions for all firms – small and large, public and private. Our data includes 5,260 incumbent banks in 784 US metro areas during 1995-2003. The banking industry has also been the arena of a spate of mergers and acquisitions involving assets in the trillions of dollars in total since the early 1990s. We use detailed information on banking acquisitions at the firm and metropolitan statistical area levels to study customer targeting in a more refined way than previous research has done.

We apply a recently developed dynamic model, specifically, a distributed-lag panel data model estimated using Generalized Method of Moments (GMM) (Arellano and Bover 1995; Blundell and Bond 1998). Dynamic models with lagged dependent variables cannot be estimated using OLS, given the correlation between the lagged dependent variable and the error (Wawro 2002), but rather are typically estimated using GMM after first differencing and using levels as instruments. Usually, for such estimators the predetermined and endogenous variables in first differences are instrumented with suitable lags of their own levels, but often the lagged levels of the variables are poor instruments. Further the absence of information about the parameters of interest in the levels of the variables may result in the loss of a substantial part of the total variation in the data. To overcome this problem Arellano and Bover (1995) and Blundell and Bond (1998) propose a system GMM estimator which includes both the differences in, and the levels of the variables as instruments. Additional instruments for this estimator are the lags of the first difference of the predetermined and endogenous variables. The use of these additional instruments renders the system GMM estimator more efficient than the first difference estimator. Further, the use of the GMM technique in the estimation of a system which contains equations in both first differences and levels alleviates concerns about endogeneity. We therefore use the system GMM approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998), and apply the Windmeijer (2005) finite sample correction to estimate the coefficients and standard errors for our model.

Results from the analysis indicate find that the impact of acquisitive entry by large firms is neither straightforward nor equally distributed across incumbents. Some incumbent firms are hurt by such entry, while others actually thrive as a result of it. Moreover, we show how these performance differences are driven by the customer targeting

decisions made by firms in response to acquisitive entry.

When Wal-Mart Enters: How Incumbent Retailers React and How This Affects Their Sales Outcomes

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Despite extensive press coverage and anecdotal stories about the so-called “Wal-Mart Effect”, academic research that empirically examines the impact of Wal-Mart entries has been limited. Researchers have studied impact on consumer purchase behavior and consumer welfare, and the accounting profit and stock price impact on affected retailers. But, little is known about how incumbent retailers have adapted their marketing activities in reaction to Wal-Mart’s entries. Analyzing retailers’ reactions is important not only in its own right, but also because it provides insight into why some retailers, categories, and brands are affected immensely by a Wal-Mart entry, while others are more immune to it.

In this study, we conduct a systematic examination on how incumbent retailers react to Wal-Mart’s entries into their local markets, and the consequences of these reactions for sales outcomes. We measure the impact of Wal-Mart entries on the sales of incumbent retailers and their reactions to Wal-Mart entries in terms of various marketing mix activities. Building upon these analyses, we explore the differences in incumbent retailers’ reactions across retail formats, stores and categories, and then examine how these reactions affect the sales impact by the Wal-Mart entries on the incumbent retailers. The specific objectives of this study are:

- 1) To estimate how incumbent retailers changed their pricing, promotion, and product assortment in reaction to Wal-Mart entries, and how their sales are affected;
- 2) To explore how these reactions vary across retail formats, stores, and product categories;
- 3) To study how sales changes experienced by the incumbent retailers were affected by the way they reacted to Wal-Mart entries.

Our analyses are carried out using detailed store movement data for over forty product categories from close to 100 supermarket, drug, and mass merchandiser stores. The dataset includes

seven first-time Wal-Mart entries during the 2000-2002 period. We identify experimental stores of incumbent retail chains in the vicinity of each entry that either had no prior Wal-Mart exposure or did not experience any Wal-Mart entries within five years, as well as their corresponding control stores of the same chain in similar areas. This allows us to employ a before-and-after-with-control-group approach and obtain clean assessment of the changes in incumbent retailers’ sales and marketing mix reactions due to each Wal-Mart entry. In carrying out the analyses for objectives (2) and (3), we use a combination of instrumental variable and simulated maximum likelihood estimation to account for uncertainty in parameter estimates as well as possible endogeneity in retailers’ marketing mix reactions.

Our study shows that Wal-Mart entries had strong negative effects on the incumbent retailers’ sales in general, and that there was substantial variation across categories and retail formats both in retailer reactions and in sales outcomes. Importantly, we find that a retailer’s sales were indeed affected by its reactions to a Wal-Mart entry, and that the relationship between reactions and outcomes varied across retailer formats. Results from our analyses provide many valuable insights for how retailers in different formats can adjust their marketing mix activities to minimize the negative impact of Wal-Mart entry.

Competing with Big-box Retailers

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Big-box retailers such as Wal-Mart and Target have made significant inroads into the food retailing industry in recent years by selling groceries and general merchandise in their super-center store format. The rapid growth of these retail formats has fundamentally changed the competitive structure of the grocery industry. Traditional retailers are reportedly facing squeezed margins, diminished traffic and a reduced market share of grocery purchases. Retailers like Dominick's, Von's, and Fred Meyer have merged with others and several have declared bankruptcy.

Big-box retailers (hereafter BBRs) often use their grocery business as a loss-leader to generate store traffic. For example, Wal-Mart's most formidable competitive advantage lies in its unbeatable Every Day Low Prices, which are 14% lower than its competitors, according to a study by the investment bank UBS Warburg (Currie and Jain, 2002). This advantage has propelled Wal-Mart to become the nation's largest grocer (Singh et al. 2006).

Currently little is known about how exactly traditional grocery stores are affected by, and react to, market entry by BBRs. Singh et al. (2006) investigate the impact of a Wal-Mart entry on one supermarket and found that it lost 17% sales volume. While it has been argued in a number of anecdotal reports that stores can compete against BBRs by leveraging their local advantages, little empirical work has been done on this issue mainly due to lack of data. Most BBRs do not provide data to third parties, such as IRI and ACNielsen.

In this paper, we use a unique dataset for one packaged goods category offered by a major manufacturer in the industry. This dataset has several advantages for our analysis. First, it spans thousands of retail stores located in all US states, which allows us to evaluate the overall impact of BBR entry and investigate how local market differences influence the impact. Second, the data are available for a period of 5 years giving us a sufficiently long-time window to study local stores' merchandising tactics before and after Wal-Mart entry. Finally, the dataset is unique in that it records all weekly shipment information from wholesalers to retail stores, including BBRs. In each shipment record, we have detailed order information including brand, package form, total quantity, selling price, ordering date, etc. For approximately 1000 retail stores that experienced a local BBR entry we also have information on sales

and prices charged by the retailer to the consumer for each upc in the product category.

Our data allow us to test several predictions from theories of imperfect competition. For example, most models of imperfect competition predict that entry into a market by a low-cost competitor will reduce output prices (Basker 2005). Little empirical work has been done, however, to test these theories and quantify their effects in either the short or the long-run. In addition we are able to investigate the underlying mechanisms that may be driving this effect. On the one hand prices may be depressed through the interaction of BBRs with manufacturers, using their clout to reduce wholesale prices. These lower costs may spill over to other outlets in the immediate vicinity, thus leading to lower consumer prices. On the other hand consumer prices may be lowered by the increase in competitive pressure faced by local retailers after BBR entry. The following quote supports this view: "Wal-Mart's mania for selling goods at rock-bottom prices has trained consumers to expect deep discounts everywhere they shop, forcing competing retailers to follow suit or fall behind." (Washington Post 2003). Our data on wholesale and consumer prices will allow us to disentangle these two mechanisms.

Various other predictions exist in the literature on factors that may influence the market impact of BBR entry. For example, competition is usually assumed to be more severe if stores locate close to their competitor since consumers can easily compare product prices and search costs are limited (Gabszwick and Thisse 1986). For such stores it is very likely that sales and prices will drop substantially after nearby Wal-Mart entry. However, there is no empirical evidence showing how far the impact can spread and how the magnitude of impact varies with distance.

By quantifying how entry of BBRs affects an incumbent store on dimensions such as sales volume, price, price elasticity, and assortment we also provide insights of value to managers. Retail managers should understand the impact on performance of BBR entry to formulate an effective response. The effectiveness of changing prices and product assortment to mitigate the impact of entry also needs to be established. Our research may point to ways in which retailers can shield themselves from the harshest effects of BBR entry.

Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics in the Wake of Product-Harm Crisis

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Product-harm crises can be defined as discrete, well-publicized incidents wherein products are found to be defective or even dangerous for consumption. The purpose of this paper is to empirically study consumer-choice behavior in the wake of a product-harm crisis using scanner data. A market in which a product-harm crisis arises usually creates uncertainty about product quality. Under uncertainty, past experience with the crisis-affected brand(s) as well as marketing mix elements and other brand-related information will affect a consumer's information set and ultimately his brand choice. In our model, consumers are assumed to have uncertainty about quality levels and priors about quality. They learn about quality levels over time through usage experience, advertising exposure, and the exposure to events such as a product-harm crisis. Processing the information contained in such signals, consumers update their quality perceptions using Bayesian rules. As an outcome of our model, we are able to understand how different information sources (e.g., use experience, product-harm crisis) affect consumers' perception of product quality and their ultimate brand choices; whether and how consumers' sensitivities to product quality, price, and risk evolve (before, during, and after the crisis), and to explain why a product-harm crisis may affect the focal brands and their competitors differently.

The contributions of our paper are twofold. On the methodological front, our model enriches the existing marketing literature on consumer learning under uncertainty by providing a new model that allows consumers to update their perceptions of both the mean product quality levels and the precisions of the signals carried in the information sources. The latter capability is especially necessary in better capturing consumers' decision making process in the wake of sudden shocks such as the event of a product-harm crisis in the product category. We find that the extended model substantially outperforms the standard consumer learning model.

Our model also offers substantive insights derived from a dataset that spans a product-harm crisis that hit the peanut butter division of Kraft

Food Australia in mid-1996. Three key substantive findings are presented. First, our parameter estimates indicate that consumers are risk averse with regard to variations in product quality. In particular, we find that consumer learning and perceived risk play a role – at least partially – in explaining why a product-harm crisis may have different ramifications for the focal brands (i.e., those that were recalled following the crisis) as well as for the non-focal competing brands. Second, a product-harm crisis can also have a major influence on consumers' sensitivities to product quality, price, and risk. More specifically, consumers care more about the consistency of product quality delivered over time than the mean level of quality compared to the pre-crisis period. Further, consumers' price sensitivities decline during the product-harm crisis. Finally, our results suggest that usage experience provides more precise information about product quality than the advertising and product-harm crisis signals.

Investigating Salespeople's Learning by Doing in a Bayesian Learning Structural Framework

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Identifying the characteristics that differentiate an effective salesperson from an ineffective salesperson has had a long history in both academic and practitioner arenas (e.g. Sujan, Sujan and Bettman 1988; Leong, Busch and John 1989; Franke and Park 2006), as this distinction has clear implications for sales force management and firm performance. Sales force management is the most expensive aspect of marketing (Godes 2003). As contemporary firms conduct business in a dynamic environment (Turley and Geiger 2006), the strategic renewal of sales organizations is imperative, requiring questioning the assumptions of doing tasks in order to learn new methods and techniques and exploiting current knowledge (March 1991). Therefore, examining how salespeople learn is a critical aspect in understanding salespeople's effectiveness.

Although various sales force issues have been examined in the marketing literature, salespeople learning, a critical area in the sales force management arena, has had limited investigation (e.g. Sujan, Weitz, and Kumar 1994; Kohli, Shervani and Challagalla 1998; Wang and Netemeyer 2002). Studies that have examined learning are primarily survey-based. To this end, based on Erdem and Keane's (1996) Bayesian learning model, we develop a salespeople learning model to estimate salespeople's learning by doing. Specifically, in order to identify individual salesperson level parameters, we build a Hierarchical Bayesian Model and use Markov Chain Monte Carlo methods. To our knowledge, this is the first study to use a structural Bayesian Learning model to investigate salespeople's learning through experience. Data from a large multinational software company was used to illustrate our approach.

Our structural model contributes to the sales force management literature in several ways. First, we provide a mechanism for monitoring salespeople's learning through experience from their historical records. This would reduce the costs of obtaining further information to estimate salesperson learning. Second, we estimate the individual salesperson level parameters. This provides managers with detailed information that can be used for better managing the sales force than aggregate level parameters. For instance, we can

identify a salesperson's potential skill, which represents his/her match with the job. Third, we investigate the impact of demographics. This provides managers with useful information in relation to the recruitment of salespeople. Finally, we run policy experiments, which provide valuable information without risk of failure. For example, our policy experiments show that it is critical to encourage salespeople to learn through experience, to retain effective sales people, and to allocate tasks according to a salesperson's strengths.

The results from the large software company data suggest that: 1) learning by doing plays an important role in a salesperson's performance; 2) on average, salespeople learn more from failure than success; 3) heterogeneity in salespeople learning exists; 4) salespeople's salary, age, gender, marriage status and education can influence salespeople learning and performance in different ways. These findings have clear implications for sales force management in terms of job allocation and in providing an environment where learning is encouraged.

Besides the contributions we make, there are some limitations. First, we do not have detailed and accurate information on salespeople's salary across time. With more information on this dimension, the impact of compensation on salespeople's learning and performance can be further investigated.

Second, we do not consider the hierarchical structure of the organization which may have some impact on the salespeople's performance (Misra 2007), in our model. Lastly, although we have briefly discussed the impact of salespeople learning and performance on turnover, it has not been emphasized. These issues are beyond the scope of our paper; however, they provide fruitful avenues for future research in sales force management.

A Behavioral Perspective on Preference Evolution in Choice-Based Conjoint Experiments

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Recent studies provide compelling evidence that consumer preferences evolve over the course of a conjoint exercise (e.g., DeSarbo et al. 2005). Yet, very little is known about the process underlying preference evolution in conjoint studies. In this paper we seek to explain the drivers of preference dynamics in choice-based conjoint (CBC) experiments by relating the evolution of choice model parameters to covariates that account for the influence of behavioral phenomena.

In a CBC exercise respondents make repeated choices from sets of varying alternatives. Consequently, subjects are exposed to changes in attribute ranges and frequencies of attribute-level occurrences. In line with range-frequency theory (Parducci 1965) we argue that consumers adapt their preferences based on the changing attribute ranges and frequency distributions. The range effect implies that the difference between two choice options on an attribute decreases when the attribute range increases; the frequency effect states that the difference between two choice options increases when the frequency (number of choice options between the focal pair on that attribute) increases (Pan and Lehmann 1993). A second source for potential preference adaptation stems from the nature of the exercise, i.e., subjects are asked to make choices. The option chosen from the previous set may serve as a reference point in the focal choice set. This could manifest itself in two ways. First, it could alter a subject's interpretation of the no-choice option, i.e., (s)he takes the no-choice option as the previously chosen option. Secondly, it may change the respondent's preference structure because (s)he now prefers options that are relatively better than the status-quo, i.e., (s)he includes gains (losses) from preferring an option over the status quo in the utility function. These would both be manifestations of the status quo bias, which is the disproportional tendency not to change anything or to stick to the status quo (Samuelson and Zeckhauser 1988). All aforementioned mechanisms can be interpreted as a dynamic anchoring and adjustment heuristic used to construct preferences for attribute levels (Einhorn and Hogarth 1985).

As our goal is to obtain insights into how behavioral mechanisms guide the preference dynamics, we specify a Bayesian Dynamic Heterogeneous Choice Model (e.g., Lachaab et al. 2006). In this specification preferences for attribute-levels are allowed to vary across choice sets following a transfer function. The model implies that preferences for attribute-levels serve as anchors that are adjusted based on new information that becomes available on attribute ranges and frequencies, and based on the characteristics of the status quo option. We calibrate this model on CBC data using MCMC techniques.

Choice-based conjoint experiments perform a central role in academia and practice in measuring consumer preferences. It is frequently applied to important questions such as product line pricing and new product design. This study sheds more light on the process underlying consumer preference evolution during the course of data collection. Our increased understanding of the dynamics of consumer preferences should facilitate the design of products that better meet consumer needs. In addition, our study has implications for the design of choice-based conjoint experiments. Besides attribute-levels, design algorithms for choice-based conjoint studies could also focus on attribute range and – frequency dimensions.

Modeling Product Entry and Pricing Decisions

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Every year multi-product firms launch in the market thousands of new products. Each product introduction is the result of the investment choice of a firm, which decides to pour dollars into R&D and marketing activities in order to reach more profitable demand in the future. The investments needed to develop and launch new products are substantial. Moreover, they are sunk, i.e. they can no longer be recovered once the product is introduced. On the other hand, the stakes are huge: on average, one third of U.S. firms' revenues are made on products that did not exist five years ago (Cooper, 2001). Despite the evidence suggesting the strategic relevance of new product introduction, the supply models proposed so far in marketing and economics for differentiated product markets do not include new product introduction in their equilibrium analyses, and instead treat product attributes as exogenous (Berry, Levinsohn, Pakes, 1995). As a result, these models produce unrealistic counterfactual analyses, where firms hold the same product portfolio for different market scenarios. Consider, for example, how the valuation of a merger could change after accounting for new product introduction; the introduction of new products could in fact compensate for the loss in welfare due to the price increase predicted by standard analyses (Nevo, 2000).

In this paper we investigate the new product introduction strategy of oligopolistic firms. By endogenizing both pricing and new product introduction decisions, we can separate the contribution to profitability of demand, marginal costs, fixed cost of introduction, and fixed cost of assortment. Using this model, we can quantify the effects of demand and competition on new product launch and product assortment. The model also shows that the reduction in the number of firms does not always decrease welfare, suggesting market conditions under which mergers increase consumers' welfare.

We estimate a dynamic game of pricing and new product introduction decisions using the framework of Ericson and Pakes (1993). Modeling multi-product entry and exit using the standard approach, however, would be impossible due to the size of state space of this problem; instead, we follow an approach recently proposed by Nevo and Rossi (2008) for dynamic games with multi-product firms, which significantly reduces the number of state variables needed for each firm.

Also, instead of numerically solving the Bellman equations using the fixed-nested point algorithm, to reduce the computational burden of the problem we estimate the value functions with the approach suggested by Aguirregabiria and Mira (2007) for dynamic discrete games.

We estimate the model using data on ready-to-eat cereal sales from IRI scanner panel. We focus on the three key players of the industry: Kellogg's, General Mills, and Post. Preliminary results on the static part of the game show that, on average, Kellogg's receives less benefit from introducing new products than general Mills. This is due to the higher share of Kellogg's incumbent products, which results in higher cannibalization of new products on existing sales. Moreover, Kellogg's faces higher assortment costs, as it scraps from the market products with higher profitability compared to the other firms. Starting from the profitability of new product implied by the results of the static model, the dynamic estimation computes for each firm the value of launching and scrapping products and compares it with the observed decisions, in order to recover the entry and assortment (or scrapping) costs.

This study represents the first attempt to model new product introduction and pricing decisions in differentiated-product markets. The inclusion of product launch decisions in models of price competition allows researchers to produce more realistic counterfactual analyses and account for the strategic role played by new products in oligopolistic markets.

Skimming or Penetration? Strategic Dynamic Pricing for New Products

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The current market environment, especially for high-tech categories, is characterized with rapid introductions of new products. The literature suggests two basic dynamic pricing strategies for new products, skimming and penetration strategy (e.g., Kotler and Armstrong 2005; Monroe 2003; Nagle and Hogan 2006). A skimming strategy is to charge a high price initially that is subsequently lowered (Dean 1976). A penetration strategy involves charging a low price to rapidly penetrate the market (Dean 1976; Nagle and Hogan 2006). The choice of the pricing strategy is particularly important for high-tech products such as digital cameras where new products are frequently introduced and life cycles are short. Differentiation by features leads to a proliferation of brands in each price tier. Text books recommend a skimming strategy for differentiated products where companies have some source of competitive protection (e.g., Kotler and Armstrong 2005; Nagle and Hogan 2006). But text books also recommend a penetration strategy for price-sensitive markets where new products usually face strong competition soon after introduction (e.g., Kotler and Armstrong 2005; Monroe 2003), which is the case for digital cameras. Hence, while the normative literature on dynamic pricing strategy provides plausible explanations under what conditions to choose which strategy, it fails short of offering guidance in markets where conditions favor both strategies. Unfortunately, many if not most markets for modern consumer durables (e.g., computers, mobile phones, TV sets and digital cameras) present the same dilemma: extensive feature differentiation supporting a skimming strategy concomitant with strong competition supporting a penetration strategy. No empirical study has examined the pattern of pricing in such markets and its impact on market share and profits.

This study addresses the question of whether a skimming or penetration strategy is more profitable in a differentiated competitive market by an in-depth empirical analysis of one product market. Specifically, we analyze three price segments of the market for digital cameras in a large West-European country in its early growth phase. The data cover 663 camera models introduced

under 79 brand names over a period of four years. We adopt a structural approach to model demand and competition in this market and therefore account for the endogeneity of price decisions. The structural model enables us to obtain a classification of dynamic pricing strategies that were pursued by the firms in this market. In addition, it provides us directly with period-specific estimates of price-cost margins, which we use to compute the net present value (NPV) of each camera model. Based on these NPV estimates, we compare the profitability of the various identified pricing strategies. To the best of our knowledge, this is the first study to measure the actual profit implications of dynamic new product pricing strategies.

Our approach identifies three classic strategies: premium (high introductory price which stays high), skimming (high introductory price which is subsequently lowered) and penetration (low introductory price which stays low or is subsequently lowered), as well as two non-monotonic strategies: Inverted U-shape (price starts low, increases and then drops over time) and U-shape (price starts high, drops and then increases over time). Further, we identify three price-quality segments in the market.

In the low-price and medium-price segment, we find that most cameras follow a penetration strategy rather than a skimming strategy. However, in the high-price segment, more cameras follow a skimming than a penetration strategy. Almost 27% of cameras follow a non-monotonic strategy. Most importantly, we find strong evidence that the skimming strategy is more profitable than the penetration strategy even accommodating for experience effects.

Drivers of Adoption for Successive Generation of High-Tech Products

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To understand the diffusion of high technology products such as PCs, digital cameras and DVD players it is necessary to consider the dynamics of successive generations of technology. From the consumer's perspective, these technology changes may manifest themselves as either a new generation product substituting for the old (for instance digital cameras) or as multiple generations of a single product (for example PCs). To date, research has been confined to aggregate-level sales models. These models consider the demand relationship between one generation of a product and a successor generation. However, they do not give insights into the disaggregate-level decisions by individual households – whether to adopt the newer generation, and if so, when. This paper makes two contributions. It is the first large-scale empirical study to collect household data for successive generations of technologies in an effort to understand the drivers of adoption. Second, in contrast to traditional analysis in diffusion research that conceptualizes technology substitution as an “adoption of innovation” type process, we propose that from a consumer's perspective, technology substitution combines elements of both adoption (adopting the new generation technology) and replacement (replacing generation I product with generation II).

Key Propositions

In some cases, successive generations are clear “substitutes” for the earlier generation (e.g. PCs Pentium I to II to III). More commonly the new generation II technology is a “partial substitute” for existing generation I technology (e.g. DVD players and VCRs). Some consumers will purchase generation II products as substitutes for their generation I product, while other consumers will purchase generation II products as additional products to be used as well as their generation I product.

We propose that substitute generation II purchases combine elements of both adoption and replacement, but additional generation II purchases are solely adoption-driven process. Moreover, drawing on adoption theory consumer innovativeness is the most important consumer characteristic for adoption timing of new products.

Hence, we hypothesize consumer innovativeness to influence the timing of both additional and substitute generation II purchases but to have a stronger impact on additional generation II purchases. We further propose that substitute generation II purchases act partially as a replacement purchase for the generation I product. Thus, we hypothesize that households with older generation I products will make substitute generation II purchases earlier.

Methods

We employ Cox hazard modeling to study factors influencing the timing of a household's adoption of generation II products. A separate hazard model is conducted for additional and substitute purchases. The age of the generation I product is calculated based on the most recent household purchase of that product. Control variables include size and income of household, age and education of decision-maker.

Results and Implications

Our preliminary results confirm both our hypotheses. Consumer innovativeness has a strong influence on both additional purchases and substitute purchases. Also consistent with our hypotheses, the age of the generation I product has a dramatic influence for substitute purchases of VCR/DVD players and a strong influence for PCs/notebooks. Yet, also as hypothesized, there was no influence on additional purchases. This implies that there is a clear distinction between additional and substitute purchases of generation II products, each with different drivers. For substitute purchases, product age is a key driver. Therefore marketers of high technology products can utilize data on generation I product age (e.g. from warranty or loyalty programs) to target customers who are more likely to make a purchase.

Dynamic Learning in Behavioral Games: A Hidden Markov Model Approach

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In competitive settings, firms often exhibit dynamic behavior. The rich literature dealing with learning in behavioral games suggests that such dynamics may arise from the firm's learning from its own or its competitors' actions and outcomes. However, over time, an additional source of dynamics may arise from a shift in the firm's learning strategy; for example shifting from learning from its own actions to learning from the outcomes of the game. In this research we focus on the later source of dynamics in the context of repeated games.

Over the course of a repeated game, players often exhibit some degree of learning in electing their best response. Research in economics and marketing has identified several types of learning strategies. Examples of such learning strategies include belief, reinforcement, and imitation learning. In belief learning, players form their beliefs based on the opponents' prior decisions. In reinforcement learning, strategies that paid off in the past get reinforced. Imitation learning implies that players may learn through imitation of other players' actions. Previous research has demonstrated that accounting for such learning may help understanding and predicting games' outcomes (Camerer and Ho 1999). Specifically, it has been shown that players use either one of the above learning strategies or a combination of them as in the Experience-Weighted Attraction (EWA) learning model.

In this research, we explore not only the combination of learning strategies used by the players, but also the dynamics in the employment of these strategies over time. We demonstrate that over the course of a repeated game, players not only learn from their own and their opponents' strategies and outcomes, but also change their learning strategies over time. For example, a player may shift from exploration to exploitation behavior based on the intrinsic strategy she may be employing to maximize the expected outcome. We investigate the degree of state dependence in learning and uncover the latent learning strategy and learning paths used by the players.

We build a hidden Markov model (HMM) in which over the course of the repeated game, players could move between different states of

learning strategies. Given each one of the states, players make a decision that is probabilistically consistent with their learning strategy. Thus, we extend previous studies that have examined the existence of multiple types of learning, by allowing players to switch over time between the alternative latent learning strategies. The proposed model allows us to better uncover the strategies utilized by the players and predict their future decision.

We empirically validate our model using data from several repeated games including the R&D patent race games (Rapoport and Amaldoss, 2000); a median-action order statistic coordination game with several players (Van Huyck, Battalio and Beil, 1990); and a coordination game about entry to two markets of different sizes (Amaldoss and Ho, 2001). We demonstrate that by accounting for the dynamics in the learning strategies, one can improve the ability to uncover the learning strategies used over the course of the game and predict future decisions.

CEO Succession and the Impact on Competitive Behavior

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Previous research has noted the impact of CEO changes on corporate earnings performance (e.g., Godfrey, Mathers and Ramsay 2003). The effect of CEO changes on firm value has also been examined in a number of studies (Lubatkin, Chung, Rogers and Owens 1989, Beatty and Zajac 1987, Reinganum 1985). One key argument in these studies is that CEOs affect employee/organizational performance which in turn results in different financial outcomes. Miller (1993) examines organizational consequences of CEO Succession and finds significant and important changes in the way the organization evolves. In particular, changes were found in intra-organizational power dispersion, information processing and competitive aggressiveness. Miller's work also suggests that CEO changes can "break organizational momentum." Lubatkin, Chung, Rogers and Owens (1989) highlight the controversies on how organization performance is affected by CEO changes. Some (e.g. Hannan and Freeman 1977) believe that leadership does not matter for firm performance, and that the replacement of a leader has no significant impact on large organizations because of considerable operational inertia that allows them to continue to perform the way they have in recent history. Others believe that a change in leadership is disruptive to the organization but the positive effect of replacing the leader may be enough to cancel this negative effect (Pfeffer and Davis-Blake, 1986).

Our paper takes a marketing perspective on this problem and, instead of looking inside an organization, our study focuses on the outside and examines whether and how a CEO change can affect competitive interactions. In other words, do competitors react differently once one of the competing firms acquires a new leader with a different management style?

Our focal industry in this study is the paper products industry. In April of 1994, Al Dunlap took over the role of Chief Executive Officer at Scott Paper Products, with the result that both its competitors (Kimberly-Clark and Procter & Gamble) faced a competitor with a significantly different management style. Our research examines whether this event changed how competitors reacted to Scott Paper Products in the marketplace

after controlling for changes in demand behavior. More specifically, our research attempts to address the following questions:

1. What is the impact on the demand (elasticities and cross-elasticities) after a change in top management? A change in top management could also have a direct impact on the demand behavior for brands under Scott Paper Products, and on the substitution rates among competing brands in the category. This could be due to changes in pricing strategy, distribution, promotions, advertising, brand assortment and quality changes.
2. What is the impact on competitive behavior of a change in top management?
3. Was there any measurable change in the way each of the three brands interacted with its channel members?

Our approach uses the NEIO paradigm (e.g., Bresnahan 1989). For the demand side, we use the Almost Ideal Demand System (Deaton and Muellbauer 1980a,b), used extensively in marketing (Cotterill, Putsis and Dhar 2000, Cotterill and Putsis 2001). A major benefit of this approach is its solid grounding in consumer demand theory. While parsimony is sacrificed in markets with a large number of competing brands, a major advantage of the AIDS approach lies its simplicity of estimation. Our econometric model is calibrated using IRI data available for the facial tissues category. Our data are available at the brand-city level, for 46 major US cities.

We make several contributions in our paper. First, we provide some substantive results on how competitive behavior changes when a new CEO with a different management style comes in. Our initial findings suggest that CEO changes can have a significant impact on how competing brands interact with one another. An important finding from our study is that the demand side (elasticities and cross-elasticities) does not tell the complete story about changes in competition. Second, marketing theorists recommend that a firm should fully understand its competitive environment. In order to do this well, empirically grounded results about competitive conduct, and how competitive conduct may be affected by key industry events, must be understood. Finally, we demonstrate the power of an NEIO based methodological framework in its ability to help managers assess competitive behavior despite having access to only limited data. The framework used in this study can be applied to readily available scanner data, with no information required on competitors' costs or retailers' behavior. From a strategic perspective, the framework can help managers understand macro patterns of competitive behavior due to changes in either observed substitution patterns or exogenous changes.

A Theory of Double Couponing

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Most literature on couponing has analyzed the function of coupons issued by the manufacturer and therefore has focused on the brand management level (e.g. Gerstner, Hess, and Holthausen 1992; Gerstner and Holthausen 1986; Levedahl 1986; Narasimhan 1984; Vilcassim and Wittink 1987). However, in the past two decades, the phenomenon of double couponing has emerged, in which a retailer reimburses those consumers who use a manufacturer's coupon not the face value of the coupon but double that amount; some retailers even use triple couponing (e.g., music-space.com). Double couponing is widely prevalent. For example, Advertising Age (1989) reports that approximately 30% of retailers in the U.S. market use double couponing, Hess and Gerstner (1993) notes that the usage rate is much higher than 30% in many markets.

Despite its concentration on the prevalence of double couponing, the literature largely has failed to analyze the effects of it on manufacturer's decisions and on the competition intensity among retailers. This lack of analysis may be due to the fact that researchers have considered double couponing a competition tool between retailers (e.g., Bolton and Shankar 2003; Kumar and Karande 2000; Walters and Mackenzie 1988), in which case they simply use the reasoning behind promotion competition among manufacturers to infer the impact of double couponing. In this sense, the adoption of double couponing often is believed to be the outcome of a prisoners' dilemma (Bhasin and Dickinson 1987; Varadarajan 1986), which implies that retailers do not benefit from the use of double couponing.¹ However, Walters and Mackenzie (1988) in their empirical study show that double couponing increases retailers' profit. Therefore, the outcome of prisoners' dilemma does not provide a satisfactory explanation of why retailers adopt double couponing.

In contrast with previous research, we attempt to provide a theory of double couponing from the perspective of the strategic interaction between the manufacturer and retailers instead of just

promotion competition among retailers. By taking both competition among retailers and the strategic interaction between the manufacturer and retailers (including the wholesale price and coupon face value) into account, we attempt to answer the following two questions: Is double couponing a profitable practice to retailers? How does a double-couponing policy affect the competitive status of various retailers? To answer these two questions, we build a dynamic model and use the concept of subgame perfect equilibrium (SPNE) to analyze how a manufacturer's coupon policy and wholesale price are affected when a retailer announces it will double a manufacturer's coupon, as well as how the adoption of double couponing influences the competition status between duopoly retailers.

Our results show that when a manufacturer uses coupons to enhance channel price coordination (Gerstner and Hess 1991, 1995), the retailer obtains two benefits from adopting a double couponing policy. First, in terms of vertical competition, double couponing mitigates the effect of the manufacturer's coupon on improving the cooperation from retailers and returns bargaining power to the retailer over the wholesale price. Second, in terms of horizontal competition between duopoly retailers, when one retailer adopts a double couponing policy and another does not, under some conditions, the double couponing retailer commits to setting a higher price and thereby softens the competition between the retailers. In turn, both retailers benefit from the adoption of double couponing policy. In some cases, the softened retail competition also forces the manufacturer to lower its wholesale price, which again benefits both retailers.

Finally, our results also extend the finding of Gerstner and Hess (1991). We show that the manufacturer's and the retailer's equilibrium pull expenditures satisfy a crowding-out relationship. When the retailer reimburses coupon users by adopting a double-couponing policy, the manufacturer would make less pull expenditures, thus benefiting the retailer.

¹ That is, if retailers could coordinate, they would not adopt double couponing policies.

Asymmetric Advertising Response

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There has been considerable research on the measurement of advertising impact on brand performance. Most of the time, however, it is assumed that advertising effects are symmetric. In other words, the numerical sales impact of a marketing spending increase or decrease is the same in absolute value. While some authors have proposed more general, asymmetric response patterns (e.g., Little 1979), they are rarely used in practice, especially on time-series data. For example, the discontinuation of advertising may have slower erosion in sales which is different from the typically faster sales impact of a new advertising campaign. Modern time-series methods such as VAR models have not investigated such important asymmetries. Pauwels et al. 2004 identify as a key challenge the incorporation of asymmetric response effects in modeling marketing dynamics. Our paper addresses this gap by developing a new methodology based on the multivariate time-series analysis to capture the dynamic relationship between advertising spending and sales.

Our first research question is therefore to what extent is there asymmetric sales response to advertising? Second, are the impacts of positive versus negative shocks to advertising on sales different in magnitude? Finally, are there significant differences in the wear-in and wear-out durations in response to positive versus shocks to advertising? We answer our research questions by applying Vector Autoregressive (VAR)/Vector-Error Correction (VEC) models with multiple years of data on sales, prices, promotions and advertising expenditure for numerous brands from four product categories, namely, two car categories in the US and two consumer packaged goods categories in France. Our results show that there is evidence of asymmetric advertising response and point to the need for using models that allow for such asymmetric effects. Further, we find significant differences in the magnitude of the impact of positive and negative shocks to advertising as well as differences in wear-in and wear-out times for such shocks to advertising. We conclude with the managerial implications for marketing managers as well as academic researchers.

A Dynamic Goodwill Model for Drugs Coming Off Patent

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In recent years a growing number of studies looked into the effects of pharmaceutical marketing. Whereas the level of analysis in these studies ranges from aggregate sales (e.g. Narayanan, Desiraju, Chintagunta 2004; Osinga, Leeftang, Wieringa 2008) to individual physician's prescription behavior (e.g. Manchanda and Chintagunta 2004) and patients' behavior (e.g. Wosinska 2005) the focus typically is on prescription drugs that are covered by patent or exclusivity rights. An understudied area is that of drugs that are about to lose their patent or exclusivity rights. In this study we aim to fill this gap. We study how the pharmaceutical brand's goodwill stock changes after patent expiration and what role marketing efforts play during this period. We spend specific attention to the role of price in this respect.

Pharmaceutical brands facing patent expiration show different marketing expenditure patterns. Some brands decrease their expenditures right after patent expiration, other brands give a strong expenditures pulse just before or during patent expiration. Yet other brands keep on spending after patent expiration. This raises the question as to what the optimal spending pattern is. To answer this question we develop a dynamic goodwill model and apply it to data from several drugs coming off patent.

In our model we link marketing expenditures to a goodwill stock, which, in turn, influences sales (before and after patent expiration). We accommodate the effect of patent expiration on sales by means of a shock to the goodwill stock as well as by a changing goodwill carryover parameter. Since the model cannot be written in linear state space form, we rely on importance sampling based Kalman filtering. We first construct a linear (Gaussian) approximating model and use this model to obtain sampled states. We use these samples to obtain the likelihood of the model. We estimate the parameters by means of maximum likelihood (Durbin and Koopman 2001).

We have monthly data on several pharmaceutical brands coming off patent. For each of the brands we observe sales, expenditures on detailing, physician meetings, medical journal advertising, direct-to-consumer advertising, the moment the generic enters the market, and sales and marketing expenditures for this generic product. Our data pertains to the U.S. market and covers the period of 1993-2000.

The outcomes of this study will be of interest to managers from pharmaceutical companies as well as to marketing scholars in the field of pharmaceuticals. In addition, the model may be used by scholars studying the effects of patent expiration in different industries.

Determining Dynamically Optimal Budget Across Geographical Regions

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Companies strive to grow brand sales over time and across regions. The brand manager, who manages the sales growth and decides the allocation of marketing budget, faces the dilemma whether to invest marketing effort across all regions uniformly, or focus in strong regions or develop the weaker regions. In the context of new product launch, Libai, Muller and Peres (2005) show that dispersing marketing efforts spatially via support-the-weak strategy or uniform spending strategy are generally superior to the support-the-strong strategy. Does this recommendation hold for mature brands?

In mature product categories, brand shares and category sales are stable over time (Lal and Padmanabhan 1995). Additionally, Bronnenberg, Dhar and Dubé (2007a and 2007b) observe that geographic differences in market shares are persistent. That is, sales and advertising are both spatially and temporally stationary. How, then, should firms estimate the spatio-temporal effects of advertising? How should firms determine dynamically optimal advertising budget and its allocation across regions?

To address the above questions, we formulate a stationary spatio-temporal model of a mature brand's regional sales, which are impacted not only by the advertising effort in its own region, but also by advertising efforts from all other regions. For example, advertising efforts in regions contiguous to the focal region might spillover, thereby affecting the brand's sales in the focal region. Two main challenges we potentially encounter are high dimensionality and multi-collinearity. In general, first, the number of geographical regions can be many (e.g., 50 major cities in a country). Consequently, the inclusion of "advertising efforts from all other regions" as covariates increases dimensionality of the regression model and, in the extreme case, it can even exceed the number of available observations (e.g., 12 monthly observations and 50 plus regressors). Second, due to stable geographical differences, advertising spending levels across regions are highly

correlated. To resolve both the dimensionality and collinearity, we apply the principal components analysis to extract the principal eigenvector, which furnishes the relative influence of geographical regions. While principal components analysis is well known, the statistical significance of the estimated eigenvector is not known (see, e.g., Johnson and Wichern 2007, Ch.8). Hence, we derive a new closed-form formula that enables statistical inference by providing standard errors and t-values of the regional influence weights.

We next determine the temporal effects of advertising by controlling endogeneity of advertising decisions and incorporating diminishing returns. To this end, we apply instrumental variables method to obtain the generated regressors (see Greene 2008) and then transform them by taking their square-root. Specifically, we generate the new regressors by projecting the observed advertising over time on the instrumental variable served by lagged advertising.

Finally, we apply this procedure to spatio-temporal dataset from the largest cosmetics company in Germany. The data includes information on brand sales and advertising spends over seven Nielsen regions and 126 weeks. Table 1 presents the descriptive statistics, and Tables 2 and 3 display the empirical results. Table 2 indicates that the regional advertising variable, which is a weighted average across the focal and other regions, is significant across every region. Hence, we document evidence that advertising from other regions affect sales in the focal region, highlighting the role for spatio-temporal modeling. Furthermore, the second column in Table 3 presents the estimated principal eigenvector (rescaled to sum to unity), which reveals the relative influence weight of each region. The outer-product of the regional influence weights and the estimated advertising effects yield the regional impact scores (see Table 3), which captures both the inter- and intra-region effects on the brand's regional sales.

Based on the estimated regional impact scores, we plan to determine the optimal budget and its allocation that maximizes the total brand profit. The next steps involve formulating and solving the optimal allocation problem, whose solution not only offers a new methodology to managers for (re-)allocating budgets, but yields new insights to researchers into the appropriateness of strategies (uniform, support-the-weak, support-the-strong) for mature brands.

Dynamic Market Effects of the Introduction of Store Brands' Imitations of National Brands' Feature Extensions

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Supermarket store brands have market shares as high as 20.8% and dollar sales as high as \$40.9 billion (The Food Institute Report 2006). Studying the performance of store brands is crucial for retailers, manufacturers and consumers. Not surprisingly, a steady stream of academic research has been dedicated to store brands (e.g. Raju, Sethuraman and Dhar 1995, Pauwels and Srinivasan 2004, Ailawadi and Harlam 2004). Studies in this field have focused either on the pricing and positioning decisions of store brands (e.g. Meza and Sudhir 2005) or on the effect of store brand introduction on national brands (e.g. Raju, Sethuraman and Dhar 1995).

After store brand's entry into a category, its performance is measured by the performance of its individual SKUs within the category. Store brands introduce new SKUs when it is either introducing different sizes of existing products or when imitating national brands' new product introductions. For example, Ralcorp, a store brand, copied General Mills' Frosted Cheerios just three months after the introduction of Cheerios (Fusaro 1996). After a novel product is successful on introduction, competitive brands imitate these extensions to reduce the cost of innovation and to be on par with the feature pioneers in regard to the options rendered to the customers. Such imitations reduce the innovator's profits while generating broader gains in economic welfare as prices and costs fall. It is important to understand the factors that affect success of such imitations and how such introductions affect the feature pioneers.

In this study, we address the following research questions, with respect to store brand imitations ("me-too"s):

- (i) Do retailers price their imitations in line with existing store brand products within the category or against national brand feature pioneers?;
- (ii) How are the profit margins for store brand, national brand and category affected by the introduction of store brand imitation?;

(iii) How does the introduction of an imitation affect the feature pioneer and other followers of the feature pioneer; and what are the category variables that moderate such effects?; and

(iv) What are the category variables that moderate the short-term and long-term price-sensitivities before and after the introduction of store brand imitations?

Our methodological approach consists of the following steps. First, we investigate whether the entry of me-too creates a structural change to the national brands' sales and price using structural break unit-root tests. Next, we analyze how performance and marketing variables of national brand features interact in a vector autoregressive model with exogenous variables (VARX) and how these interactions changed with the entry of a store brand me-too. Finally, we observe the short-term and long-term price sensitivities in the pre- and post-entry periods by estimating and comparing impulse response functions. Earlier dynamic models have analyzed these effects either at the SKU level (e.g., Macé and Neslin 2004) or at the brand level (e.g. Pauwels and Srinivasan 2004). Since consumers choose among same feature of various brands, we estimate the dynamic effects at the product feature level. The model is also estimated for groups of stores having the same pricing format to eliminate store aggregation bias.

Our analysis uses a comprehensive consumer transaction dataset from 70 retail stores and covers about 25 store brand imitations over a 275 week time period. Three types of me-toos considered in our analysis are: fast followers, first me-too and later me-toos. Our initial results indicate that there is no structural break in the sales of the national brand feature pioneers. However, we find evidence for structural break of the price of national brand feature pioneers. We also estimated a high short-term cross price sensitivities between national brand feature pioneers and store brand imitations, whereas there is no significant long-run effect of cross price sensitivity.

New products, the Antidote to Private Label Growth? Who is Fighting Whom?

Katrijn Gielens

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Over the past years, private label brands have entered and won share in more and more grocery categories, advancing from fresh foods to packaged goods and beverages to household products to personal care (Boston Consulting Group 2007). Moreover, most business analysts believe that private labels are set for further, and even accelerated, growth, with a majority of the world's leading grocers increasing their own label penetration (Planet Retail 2007). This continuing growth of private labels has served as a catalyst for consumer packaged good companies to re-evaluate how and where to compete. Throughout the business literature, real product innovation is credited as one of the strongest competitive weapons against private labels in the manufacturer's arsenal (Kumar and Steenkamp 2007). A good innovative product leaves private labels in a category in the position of imitating yesterday's favorites (Steiner 2004).

However, at the same time, improved private label quality is believed to be a major reason for the growing acceptance of private labels (e.g. Hoch and Banerji 1993). Moreover, retailers emerge ever more as customer oriented, versatile innovators with relevant customer information at their disposal, ready and able to develop and quickly market new products. As retailers' private labels strategies evolve from functional price-based products to ones that embrace broader brand credentials, national brand manufacturers increasingly feel they have fewer moves left to fight private labels. They could never compete with stores on price. Now many of them feel they can not compete on quality either. The question therefore emerges to what extent brand manufacturers can truly fight private labels through expensive, rapidly imitated, new product innovations. Or, do these new product introductions, in contrast, –as argued by some– actually benefit private label growth? Moreover, is the impact of national brand innovation on competing private labels still different from its impact on competing leading national brands? Is it likely to assume that national brand innovations steal more market share from private labels than from competing national brands in the category? Next, how should the new product be positioned within the category on quality, features, and price? Are only truly innovating new products effective or can relatively minor feature oriented new products work as well? To what extent is it more important

to offer a continuous stream of relatively minor innovations rather than to hit the market with one breakthrough innovations on fewer occasions? To address these questions, a study is carried out to evaluate the effect of new products on three metrics that are of paramount interest to the brand manufacturer, the retailer, or both: (i) own brand market share, (ii) competing national brands' market share, and (iii) private label market share, using data on over 150 new CPG launches between January 2003 and May 2006 in the U.K. In a first step, new product introductions are treated as separate events allowing the effectiveness of new product introductions to differ between events. A multi-break model that quantifies the impact of these individual new-product events on both the level and growth of the focal brand and competing private and national brands in the category is developed. In a next step, we explore what type of innovations and introduction strategies are truly able to impact these metrics.

First results suggests that, overall, it is really hard to impact competitors' long-term market position as only in approximately 12% of all cases a negative impact can be achieved. Moreover, NB new product introductions seem to be more effective in fighting traditional national brand competitors than premium and standard private labels. What is more, standard private labels even seem to benefit more from NB new product introductions than that they are hurt by them.

Proliferating Private Label Portfolios: How Introducing Economy and Premium Private Labels Influence Brand Choice

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Three-tiered private label portfolio strategies (low-quality tier: economy private labels; mid-quality tier: standard private labels; top-quality tier: premium private labels) are gaining interest around the world. Having been developed in the U.K, we are beginning to see major U.S. retailers adopting similar strategies (IRI 2007). In this research, we build upon the literature on context effects to postulate how the introduction of economy and premium private labels may affect the choice of premium-quality and secondary-quality national brands, and of the retailer's existing private label offering. To the best of our knowledge, this is the first study that distinguishes between standard, more upscale (premium), and more downscale (economy) private labels to provide a deeper understanding of the effects of private label entry on the choice share of market incumbents.

We use the natural experiment offered by the introduction by Asda (a subsidiary of Wal-Mart) of economy and premium private label tiers in the breakfast cereals category in the U.K. to test our framework. Additional evidence from a second retailer and product category corroborates our findings. Using brand choice models that accommodate context (compromise, similarity, and attraction) effects, we find that incumbent private labels disproportionately suffer from the introduction of economy and premium private labels. More specifically, economy private labels are found to cannibalize standard private labels. Likewise, premium private labels cannibalize incumbent private labels (economy but especially standard private labels). In both cases, this is at least partly due to the brand-type similarity effect. While these findings are consistent with the "divided loyalty" argument, they also support the notion of "brand strength dilution through quality variation": as quality variation increases through either downscale or upscale private label line extensions, consumers feel less able to place confidence in the private label brand as a signal of a given quality level.

In comparison, we find that economy and premium private label introductions are not necessarily detrimental, and in some cases even

beneficial, for incumbent national brands. Premium private label introductions mainly benefit premium-quality national brands because of the attraction effect, while economy private label introductions mainly benefit secondary-quality national brands, as these become a compromise or middle option in the retailer's assortment on the quality-tier dimension.

These findings are important to both the retailer and the national brand manufacturer. For retailers, they refute the common management belief that covering a full range of private label quality tiers, rather than triggering cannibalization, primarily makes private labels stronger competitors to manufacturer brands. If retailers wish to reduce the cannibalising effects of private label introductions, they should counter the brand-type similarity effect, for instance, by creating stand-alone brands instead of sub-brands under the retailer brand name to delink their different private label tiers. For national brand manufacturers, we find that the fear that private label proliferation will cause national brand sales to flag even further has been overstated. Our results for the underlying context effects suggest different strategies for national brand manufacturers to ensure beneficial or reduce harmful effects of private label introductions.

Consumer Search and Online Demand for Online Products

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Using aggregate, product search data from Amazon.com, we jointly estimate consumer information search and online demand for durable goods. To estimate the demand and search primitives, we introduce an optimal sequential search process into a model of choice and treat the observed product search data as aggregations of individual-level optimal sequential search sequences. The model enhances the dynamic programming framework of Weitzman (1979) and combines it with a choice model. The model can accommodate highly complex demand patterns at the market level, and at the individual level it has a number of attractive properties in estimation, including closed-form expressions for the probability distribution of alternative sets of searched goods and breaking the curse of dimensionality. Using numerical experiments, we verify the model's ability to identify demand primitives of the random effects choice based demand model plus the distribution of search cost. Empirically, the model is applied to the online market for camcorders and is used to answer manufacturer questions about market structure and competition and to address policy maker issues about the effect of recommendations on consumer surplus outcomes. We find that consumer online search for camcorders at Amazon.com is typically limited to 3 to 10 choice options. This implies a less price elastic market than predicted by full search. We also find that lowering search cost through product recommendations or links to popular product pages may cause worse choice outcomes or higher total search cost for households with atypical preferences.

Dynamics of Online Consumer Generated Word-of-Mouth on the Financial Performance of the Firm

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Consumers not only use the information in the numerous online media such as blogs and product reviews, but also generate content in these media to share their experience with other consumers. This data is valuable in getting feedback from the consumers and it could be used to evaluate the firm performance and design marketing strategy. Prior research on the dynamics of the Word-of-Mouth (WoM) concludes that dispersion has significant impact on the TV ratings (Godes and Mayzlin 2004), and that the volume of the reviews matter more than the valence (Liu 200). Also, some of the recent research focusing on the impact of the negative word of mouth concludes that the negative consumer voice could influence the firm's idiosyncratic returns, cash flows, stock returns, and stock volatilities (Luo 2007; Luo 2008). Some studies have looked at expert third party reviews and its direct impact on the stock returns of the firm (Tellis and Johnson 2007). In spite of these studies, there is no conclusive evidence for the influence of the online word-of-mouth on the stock market performance of the firm. This study seeks answers to the following questions using multiple time series analysis:

- Is there a relation between the online word-of-mouth and the stock market performance of the firm? If there does exist a stock market response to word-of-mouth, what is the direction of causality?
- What is the lag period for the stock market to reflect the information in the consumer generated online reviews of the product?
- What underlying factors drive the dynamic relation between the online word-of-mouth and the stock market returns of the firm?
- Finally, how does stock market respond to the different measures of online word-of-mouth such as the valence, volume, and word-of-mouth share of the firm? Which of these metrics best explain the stock market indicators of a firm?

To answer these questions, we first build a conceptual model for the influence of the online word-of-mouth on the stock returns. We argue that the stock returns are influenced through directly by the online word-of-mouth and indirectly through the sales of the firm. The underlying drivers of the word-of-mouth and sales could be factors such as customer satisfaction and product quality. In order to test this model, we use a multistage approach. In the first stage, we use the Fama-French three factor model with momentum (e.g. Sood and Tellis 2008) to test the impact of the online word-of-mouth variables in the stock returns. In the second stage, we use Vector Auto Regressive (VAR) models to estimate the short and long term impact of the online word-of-mouth on the stock returns. We use consumer review data across a five year period for seven product markets and fifteen brands collected from multiple websites. Preliminary analysis of the limited data collected to date reveals the following results. Online word-of-mouth is strongly correlated to stock prices and stock returns. The models showed the presence of cointegration between the metrics of WoM and the stock returns, suggesting that the metrics evolved to equilibrium. Among all the different metrics of word-of-mouth, volume and WoM Index (which is an interaction between volume and valence) provides the best explanation to stock market returns. The Granger-causality tests suggests that the online word-of-mouth explain a substantial fraction of the variance in stock returns; the reverse does not hold significant.

To the marketing literature, this study has strategic managerial contributions as well as methodological contributions. Firstly, this study could help in understanding the role of the online word-of-mouth in firms' financial performance, both in short and long run, and also in establishing the causal relation between word-of-mouth and the stock market performance of the firm. This would enhance our understanding about the impact of the structural variables of the online word-of-mouth (such as the volume, valence, and the various dimensions of perceived quality) on the stock market returns of a firm. Also the study demonstrates methods to integrate the techniques from disciplines such as computational linguistics and econometrics to uncover the dynamic relation between the online word-of-mouth and stock returns of the firm, which could also be used to predict the returns of a firm using the online word-of-mouth measures.

Is All Publicity Good Publicity? The Impact of Mass Media, Firm Public Relations Activities and Advertising on Corporate Reputation

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Firms use various elements of the communications including advertising, promotion, personal selling, and public relations to drive various performance metrics that are critical to the success of the firm, such as, profits, sales, and brand image. While a majority of the marketing literature focuses on the first three of these elements, there has been little to no research on the impact of a firm's public relations activities.

A firm's public relations activities are focused on creating and maintaining positive public perceptions about the firm and typically reach consumers through the mass media that they are exposed to. Therefore, to develop a better understanding of the role of public relations efforts requires us to also understand how the mass media in general shapes the public's perceptions of a firm. Agenda Setting Theory provides a useful framework to study these effects and a body of empirical work in the communications literature, mainly in socio-political contexts, has established that the media plays an important role in shaping public perception about issues and people.

Past research in marketing has established the link between corporate reputation and firm financial performance. The sources of and the factors influencing corporate reputation perceptions, however, have not been systematically studied. We examine the relation among and the dynamic impact of the three key drivers of corporate reputation perceptions: independent mass media, firm-sponsored advertising, and public relations effort. The present research seeks to make two specific contributions to the marketing literature. First, we introduce and test agenda setting theory in a business context, by studying how corporate reputation of a firm is impacted by media coverage about the firm. Second, by identifying stories that are directly linked to the press releases that a firm distributes, we quantify the impact of this type of public relation activity on an important firm-performance metric. Recognizing that public relations, mass media coverage, and advertising may all influence each other over time, we study the dynamic relationship between the three with the objective of measuring the relative impact of the firm's own

communication mix (i.e., PR and advertising) versus independent mass media on corporate reputation perceptions.

We use several unique data sources to compile our dataset. Our Corporate Esteem metric comes from the Young & Rubicam's Brand Asset Valuator model. The Brand Asset Valuator initiative undertakes large scale surveys of consumers regarding perceptions of brands on a host of different brand metrics. The annual esteem values for a panel of 175 mono-brand firms between 2001 and 2005 forms the dependent variable in our model. Data on advertising spending comes from the TNS Media AdSpender database. Data on mass media coverage and PR comes from www.nexis.com and www.factiva.com, which combines over 1,000 news sources in the United States comprising of newspaper, magazine and radio stories. We explicitly identify articles that cite newswires and press releases as their source in order to measure the firm's public relations efforts. A combination of human raters and a computerized text-analysis methodology are used to develop measures of the volume, valence and prominence of over 200,000 news stories for the empirical analysis.

We first undertake Granger causality tests and formulate a Structural Vector Autoregression model to examine the relative influence of mass media (coverage, prominence, and valence), advertising, and public relations on Corporate Reputation over time. The model provides insights into the impact of public relations on the amount and type of mass media coverage that the firm receives over time and provides estimates of both the short- and long-term impact of public relations activities on corporate reputation.

Model estimation yields several interesting findings. First, both the valence and the prominence of the content of media articles are found to be important determinants of reputation, with negative coverage having a greater and longer-lasting impact than positive media coverage. Second, public-relations activity is found to have a significant impact on corporate reputation and its elasticity is greater than that of advertising and of independent media-reports. Finally, we find evidence that advertising and public relations tend to be used as complementary communication tools. Advertising drives future mass media coverage and media coverage also drives future advertising.

Consumer Attitude Dynamics and Marketing Spending Rules

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Brand managers are urged to compete for the 'hearts and minds' of consumers and often collect metrics to this end. But how actionable is it to know that e.g. awareness stands at 80% while brand preference stands at 60%? Conventional wisdom suggests investing in the 'weakest link', i.e. the metric with the most remaining potential. However, brand preference may have hit its glass ceiling, while momentum in awareness is still possible. Moreover, awareness could be much more responsive to marketing actions than preference for the brand is. Finally, any gains in brand preference may be short-lived due to fickle consumers or tough competitors, while gains in awareness are sticky. So how exactly can brand managers use consumer attitude information to guide their marketing actions?

To date, this important question of marketing strategy effectiveness has not received thorough quantitative answers, mainly because the data sources have been lacking. While we can – in most cases – readily observe sales, price and distribution movements, we only rarely witness the accompanying readings in customer mindset metrics such as awareness and consideration. As a result, ex-post marketing effectiveness is typically assessed as the observable transaction level, with measures such as "advertising elasticity" and "return on sales." That practice may satisfy the bottom-line oriented CFO, but leaves the deeper reasons for marketing success or failure unexplored.

This paper incorporates the evolution of key mind-set metrics for understanding and predicting marketing impact, using newly available data sources that match consumer attitudes and purchasing behavior. We conjecture that such data allow us to explain the reasons why we observe differences in marketing effectiveness, for example declining advertising elasticities over the product life cycle. Understanding these reasons, in turn, permit the formulation of strategies that are more likely to succeed, i.e. making predictions of marketing impact.

We begin by exploring some important principles for productive marketing. Recent marketing science literature has drawn the important distinction between short-term (temporary, i.e. immediate and dust-settling) and long-term (permanent) marketing impact. On the whole, most marketing efforts have only

temporary impact, and thus repeated marketing spending is needed to achieve long-term results, which is costly. However, when intermediate mind-set metrics are available, we can take advantage of differences in evolution state to derive conditions under which long-term marketing impact is achievable. For this to happen, we must of course establish first that the mind-set metric in and of itself has a long-term association with sales performance. Under such a scenario, which is empirically testable, we propose that the conditions that relate mind-set metrics to long-term marketing impact are potential, stickiness and responsiveness. First, potential as a driver of marketing impact has long been appreciated and used, especially in the context of market potential. The central premise is that of diminishing returns, i.e. the higher the remaining distance to the maximum potential, the more impactful the effort. Second, stickiness or inertia refers to the staying power of the performance metric, in the absence of further marketing effort. Overall, if a marketing effort increases a brand's score on a sticky mindset metric, then all else equal, that effort is more likely to have a long-run impact on business performance. Third, responsiveness refers to marketing's ability to "move the needle" on the performance metric. In this context, different marketing actions are known to have different responsiveness.

For these three principles to be guiding, they must be empirically verifiable, and they must have predictive capability. Our empirical verification starts with testing some mindset metrics for long-term relevance. Among the metrics that pass the test, we then formulate measures for potential, stickiness and responsiveness. We test these principles empirically on a rich dataset with comprehensive information on performance metrics, marketing mix metrics and mindset metrics for over 60 brands in four fast-moving consumer goods categories over a period of 7 years. The data are drawn from a consumer household panel, a store panel, and a consumer survey panel that each three are representative for France and that are combined in a dashboard-like brand-performance tracker, known as "Prométhée". We then establish predictive capability in a series of comparative tests that 1) diagnose two brands on the key mindset metrics at time t , 2) observe the differences in their marketing spending between time t and time $(t+k)$, 3) make a prediction on which brand will enjoy the highest return to these marketing efforts and 4) assess marketing impact at time $(t+k)$ and compare the results to the predictions. We conclude the paper with the managerial implications of our findings.

The Long-Term Impact of Price Promotions on Consumer Purchase Behavior: Investigating the Role of Consistency in Deal Calendars

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Price promotions constitute the major part of marketing expenditures in consumer goods markets (Srinivasan, Pauwels, Hanssens & Dekimpe 2004). As Ailawadi, Harlam, César and Trounce (2006) point out: Promotional spending by U.S. packaged goods manufacturers peaked in the late 1990s at more than 50% of the marketing budget, and it continues to ride high. In the German consumer goods market, more than 50% of the products are at least once a quarter on price promotion and 15% of total profit of every fifth SKU is due to price promotions. Despite their widespread use and the incontestable positive immediate impact of price promotions, there is also growing concern about possible wear-out and negative long-term effects of the frequent use of price promotions. Unfavorable long-term effects of promotions hereby have been attributed to several factors, including e.g., increased price sensitivities, changes in reference prices or increased stockpiling behavior, which results in stealing away purchases from the future that would have been occurred later at full margin. All these effects are due to the fact that consumer choice is inherently a dynamic process, where choices made in present implicitly reflect what has been learned from the past and, often, expectations about the future (Meyer, Erdem, Feinberg, Gilboa, Hutchinson, Krishna, Lippman, Mela, Pazgal, Prelec & Steckel 1997).

Yet, past research focussing on the long-term impact of price promotions has ignored important aspects of deal calendars: Most of the studies only examined the effects of discount frequency, discount depth as well as of the recency of past promotions while neglecting other, likewise important factors¹. Particularly the consistency of deal calendars, i.e., the predictability of the timing and the variability of the depth of past promotions, has drawn little attention. However, both of these two dimensions may have a dynamic impact on consumer choice behavior, and may moderate the long-term effects of frequency, depth and recency of past promotions: If the timing of promotions of a particular brand is perfectly

predictable, loyal consumers should engage in a lie-in-wait strategy, with purchases only made when the brand is on promotion and quantities chosen such that they can exactly bridge the time until the next deal (see Krishna 1994, for a normative model of optimal purchasing policy under price uncertainty). Further, prospect theory and the rational expectations view suggest, that a lack of predictability as well as a high variability in deal depth should lead to overbuying at promotions (Kalwani & Yim 1992). Finally, consistent with the constructive nature of preferences (Alba, Mela, Shimp & Urbany 1999), an increased stimulus complexity can moderate the effect (E.g., Erdem, Imai and Keane (2003), Shirai (2005), and Papatla and Krishnamurthi (1996) present models that account for the long-term impact of frequency, depth and recency on consumers' price expectations, reference prices and price sensitivities, respectively. of the stimulus: It is less likely that consumers form expectations regarding future prices, when deal patterns were unpredictable in the past as opposed to the case when they were perfectly predictable.

Summarizing, not only deal frequency, depth, and recency are important drivers of the long-term effects of promotions, but also the predictability of the timing of deals as well as the variability of their depth. The aim of this research is therefore to analyze the long-term impact of all of these dimensions of deal calendars on consumer behavior. We use data from the ground coffee market, which is particularly well suited for our analyses due to several factors, among which are that coffee can be easily stored, prices are high enough to suggest that consumers memorize them, and that the timing of deals varies across brands and over time. Based on psychological theories as well as on marketing research, we hereby first derive hypotheses on the effects of these dimensions. Thereafter, we test these hypotheses within a joint model of purchase incidence, brand choice and choice quantity. We account for consumer heterogeneity by estimating parameters at the individual level within a bayesian framework. By adding a second layer to the hierarchical model setup, we specify the individual level parameter estimates as functions of the dimensions discussed above. Thus, for each individual customer we use his past shopping experience with the different brands' deal-calendars, which results in time-varying price and promotion sensitivities at the individual level.

Our results show, that frequency, depth, and recency of past promotions are not the sole influencing variables with respect to the long-term impact of deal calendars. In fact, the predictability of the timing of promotions as well as the variability in the depth of past promotions, also have a non-negligible long-term influence on consumers' price and promotion sensitivities. Though our use of a time-varying parameters hereby might only be able to picture changes in consumer behavior due to changes in marketing mix variables (see van Heerde, Dekimpe & Putsis Jr. 2005, for a discussion on the abilities and limitations of models using time-varying parameters that depend on past marketing mix variables), our results provide important insights for the development of structural models of forward-looking behavior.

¹ E.g., Erdem, Imai and Keane (2003), Shirai (2005), and Papatla and Krishnamurthi (1996) present models that account for the long-term impact of frequency, depth and recency on consumers' price expectations, reference prices and price sensitivities, respectively.

Price-Promotion Effectiveness during A Price War

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Most prior research investigated promotional effectiveness in fairly stable business conditions, and ignores how the effectiveness of price promotions may change in more turbulent times such as price wars. When retailers start competing against each other with overall, long-lasting price decreases, which are also heavily advertised to the public, does it then still pay, as a manufacturer, to offer temporal price cuts? To what extent will the effectiveness of price-promotion events be affected? Do manufacturers have to change the implementation of their price promotions to still generate a positive effect? In this paper, we will relax the assumption of a "business-as-usual" scenario, and consider how a major price disruption in the retailing landscape may affect the effectiveness of price promotions.

We use data that capture the Dutch price war that started in the fall of 2003 (and which has been described in Van Heerde et al. 2008). We have detailed information on over 800 promotional events of a multinational CPG manufacturer, across four leading Dutch national retailers, that cover almost 80% of the retail market. Given that our dataset spans 146 weeks before the price war, and 114 weeks during the price war, we can investigate whether, and to what extent, promotional effectiveness changed following the price war. Moreover, we can evaluate to what extent promotions before and after the price war were implemented differently.

In a two-step approach, we first determine the total sales effectiveness of each individual promotion using a multiple-break analysis. With this approach, we calculate a net effect accounting for factors as deceleration, stockpiling and cross-store switching, while controlling for both synergistic advertising effects and competitive actions. In the second step, we subsequently relate the total sales effectiveness of each promotion activity, as estimated in the previous step, to various promotion implementation (e.g. timing,

framing and communication) and contextual (e.g. retailer, brand and category characteristics) characteristics, both in a "business-as-usual" and a price-war scenario.

Our preliminary results indicate that the price war reduces the effectiveness of sales promotions, even for products whose prices were not directly affected (reduced) during the price war. Moreover, we find that the effectiveness of sales promotions is driven by different promotional characteristics before the price war versus during the price war, and that these drivers differ in function of the perspective taken to assess a promotion's value, i.e. the retailer's versus the manufacturer's.

Do Mindset Metrics Explain Brand Sales?

Shuba Srinivasan, Marc Vanhuele, Koen Pauwels

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Demonstrating marketing effectiveness is key for managers answering the growing call for marketing accountability. Its study has proceeded on two parallel tracks: quantitative modelers are interested in establishing the short-term and long-term sales and profit effects of the marketing mix (e.g., Hanssens, Parsons and Schultz 2001). They treat the customer's mind and heart as a black box. In contrast, advertising and branding experts and researchers in consumer behavior focus on the influence of marketing actions on mindset metrics like awareness, affect, and purchase consideration. They typically do not examine the ultimate effect on sales and ignore the impact of competitive actions. Improvement in these buyer readiness stages should sooner or later translate into sales performance. In this study, we merge the two tracks to analyze the added explanatory value of including customer mindset metrics in a sales response model that already accounts for short and long-term effects of the marketing mix. There is, however, a recent call for an integration of metrics into models of sales response. The Marketing Science Institute included the combining of behavioral and attitudinal data to predict brand performance among its research priorities for 2006-2008 and Gupta and Zeithaml (2006) call for research that "incorporates perceptual constructs in behavioral outcome models" (p. 734).

Our main research question is whether, and to what extent, mindset metrics really help to explain brand performance when hard data on sales and marketing mix investments are already available. If both short and long-term effects of, for instance, advertising are captured in a sales response model, is there any interest in also modeling, and therefore measuring mindset effects? If we find that mindset metrics help explain sales in addition to what the marketing mix already captures, then we should also examine to what extent they are leading performance indicators. Our second and third research questions are therefore (1) how large and long mindset metric effects on sales are compared to marketing-mix effects and (2) how mindset metrics are driven by marketing actions.

To answer our research questions, we estimate Vector Autoregressive (VARX) models on a unique data set with comprehensive information on

performance metrics, marketing mix metrics and mindset metrics for over 60 brands in four fast-moving consumer goods categories over a period of 7 years. The data were drawn from a consumer household panel, a store panel, and a consumer survey panel that each three are representative for France and that are combined in a dashboard-like brand-performance tracker, known as "Prométhée". Our modeling approach using VARX models allows us to address the endogeneity problems, lagged effects and complex feedback loops that are typical with this type of data (Dekimpe and Hanssens 2007). Moreover, we quantify the size of marketing mix effects on consumer mindset metrics, and of own and competitive customer mindset metrics on brand sales and examine wear-in times of mix and mindset variables on sales.

Our results reveal that awareness, liking and purchase consideration metrics indeed impact sales above and beyond the direct effect of advertising, price, distribution and promotions. Interestingly, competitive and own mindset variables make a similar contribution to sales performance. Among the three mindset metrics, we find the strongest sales impact for changes to liking. Our analysis of wear-in times reveals that mindset metrics lead sales by several months, allowing time for managerial action before market performance itself is affected. Moreover, specific marketing actions impact specific mindset metrics, with the strongest overall impact for distribution. Our findings suggest that quantitative modelers should include mindset metrics in sales response models, while branding experts should include competition in their tracking research.

The Role of Marketing Investments in Successful R&D Commercialization over Time

Henning Kreis, Lutz Hildebrandt

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Building on the resource-based view as well as on economic theory, the paper investigates the impact of R&D and marketing investments on firm performance over time. The research contributes to marketing strategy in two different ways. We analyze the productivity of marketing investments in supporting the commercialization of R&D efforts. In this respect we follow the concern of Rust et al. (2004) about the accountability of marketing expenditures and the call of Lev and Sougiannis (1999) for an examination of performance implication of various assets, emphasizing the relevance of R&D- and marketing-related competencies with a special focus on the relationship between R&D and marketing investments. Additional valuable insights are derived not only from analyzing marketing expenditures in general, but also from its different components like sales force and advertising expenditures.

In a panel study, estimated in a structural equation modeling setting, we analyze the influence of R&D and marketing (and its relationship) on firm performance by including lagged effects and controlling explicitly for various types of intangible variables (Griliches 1974). The former are often referred to as management quality or corporate culture. Variables such as know how, however, may have an influence that dissipates over time and can be captured in a first-order autoregressive process. Stochastic effects last only one period and are modelled by the serially uncorrelated disturbance term. Although one specific benefit of the application of panel data estimation techniques is that such approaches can control for these unobservable effects most of the studies in this field of research using panel data have not used panel data methods in their analysis (Conchar et al., 2005). Following these authors' appeal for the usage of more advanced panel data estimation techniques, we apply several series of three panel models to the data.

The empirical study analyzes a time series of mainly Compustat data on 413 manufacturing firms for seven consecutive years. The results indicate that some assumptions regarding the relationships between R&D, marketing and performance have to be rediscussed. While a direct effect of R&D on performance (measured by gross margin (GM))

cannot be confirmed, a lagged indirect effect via marketing expenditures exists. Intangibles such as the quality of management or the know-how of a company are isolated and it is shown that have an impact on the relationships being studied. Especially the positive interaction effect of R&D and marketing which symbolizes complementarities of both variables, heavily relies on firm-specific circumstances. When introducing the various types of marketing expenditures more detailed results (Table 1) are generated and managerial implications can be derived.

	Modell A basic model	Modell B with individual effects			Modell C with autoregressive effects		
	G ⁽¹⁾	G ⁽¹⁾	H ⁽²⁾	L ⁽³⁾	G ⁽¹⁾	H ⁽²⁾	L ⁽³⁾
R&D→GM	-**	n.s.	+	-***	n.s.	+	n.s.
Sales Force→GM	+	+	+	+	+	+	+
Advertising→GM	+	+	+	+	+	+	+
R&D→Sales Force	+	+	+	n.s.	n.s.	+	n.s.
Intangibles	not tested	+	+	+	+	+	+
Interaction→GM	n.s.	n.s.	n.s.	+	n.s.	n.s.	+

⁽¹⁾ full sample, ⁽²⁾ high-tech companies, ⁽³⁾ low-tech companies
*** significant on 1%-Level, ** significant on 5%-Level, * significant on 10%-Level

Table 1: Results (condensed)

Table 1: Results (condensed)

While there is no direct effect of R&D investments on performance, for high-tech companies it seems to be critical to support R&D with lagged investments into the sales force division. Selling technologically rather complex products makes it obviously necessary to invest into direct communication. On the other side, for low-tech companies, the awareness of the products seems to be the critical factor of success.

The ongoing research project is extended to different industries.

Utilizing Survey Data to Augment Revenue Forecast Accuracy in Volatile Middleware Market

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Middleware is a class of business software applications that function to mediate between two or more programs to better integrate their functionalities. In the world of middleware business, rapid advancements in technology and acquisitions or mergers of firms are prevailing phenomena disruptive to forecasting. On the other hand, since middleware is typically purchased for planned, mission-critical projects, IT decision makers tend to be able to report reliable projected middleware budgets for the upcoming year. We developed two methods that utilize survey data in combination with middleware revenue time series data to forecast future quarterly revenue with great precision.

The first methodology used Holt-Winters exponential smoothing to regulate the importance of recent observations. The annual growth rate estimated with survey data was utilized to eliminate smoothing parameter combinations in the Holt-Winters updating equations that gave annual growth rates in the outfield. The final smoothing parameter combination that yielded the least aberration from quarterly revenue distributions and delivered relatively high pseudo R squared was selected. With this method, we were able to forecast revenue one year forward for straight three years with our forecasting results never deviating more than 2% from actual revenue.

The second methodology employed a Bayesian autoregressive model. This model consists of two parameters: (1) an autocorrelation coefficient for quarterly revenue associated with a lag of $t-4$, and (2) a rate of growth coefficient for weighting a non-linear function of time. The non-linear function of time was selected among several candidates as a component in the model for two reasons: (1) it fit well to the annual growth trend of the historical revenue time series data accompanied by future revenue estimated from survey, and (2) it predicted an annual growth in line with what was estimated from survey. Distributions for each forecasted point, the autocorrelation coefficient, and the rate of growth were estimated using Markov Chain Monte Carlo (MCMC) procedure. Non-informative priors were specified for the autocorrelation coefficient and rate of growth coefficient. This methodology gave forecasting results that deviated 3% from actual revenue.

Both methods produced considerably more accurate forecast than time series models without guidance of survey information. Frequentist Box-Jenkins time series models, without the aid of survey data, predicted poorly, yielding results 8%-15% different from the actual revenue. The annual growth rate estimated from the survey data served as an anchor in selecting forecast possibilities, while seasonal variation was captured by time-series analysis. Used together, they greatly improved forecast accuracy and precision.

A Framework for Investigating Endogeneity in Marketing Models

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Managers' goal of improving future company performance influences their decisions on pricing and promotions, positioning and advertising, segmentation and customization, and product development. In market-oriented companies, these and other strategic decisions are made on the basis of market research that yields information on how company strategies affect future company performance, by changing consumers' perceptions, preferences and choices of alternatives. Thus, marketing is fundamentally predicated on the idea that management's decisions are endogenous to their (expected) performance outcomes. Therefore, failure to take into account management's expectations of future performance in analyzing the effects of marketing decisions on consumer behavior often misinforms decision making. But whether or not this is the case in a specific situation is an empirical issue and depends on the extent to which relevant information is collected and/or utilized by the company.

The marketing literature has thus rightly seen an increasing focus on investigating testing endogeneity in models of consumer demand, where entry decisions, price, advertising, and detailing, have been shown to be endogenous amongst others. Problems of endogeneity may extend beyond classical demand models and may be present, for example in conjoint and survey data as well. We will add the endogenous effect of credit scores on consumer credit to that list.

The usual approach to investigate the endogeneity of marketing decision variables is based on market response models that include exogenous variables or 'Instruments' to predict the endogenous decision variable. A wide range of different models has been used for that purpose. But, the search for truly exogenous instruments in any given situation may be cumbersome, and instruments that are plausibly exogenous often prove to be weak. In these cases, inference intended to correct for endogeneity can produce results that are potentially worse than those obtained by simply ignoring the problem. Although elegant solutions for specific problems have been proposed, a general solution to this pervasive problem that can be applied in a wide range of marketing models is

not yet available. It is our aim in this paper to provide such an solution.

We propose a general framework that accommodates a variety of data encountered in marketing for dealing with endogeneity in marketing models. Our framework does not rely on specific instruments or the availability of observable instruments and it extends existing methods that use internal IVs (IIVs). These existing IIV approaches exploit characteristics of the endogenous predictors' distribution, such as skewness and heteroscedasticity to model explicitly the correlation between the endogenous predictor variables and the error terms. Therefore, in these previous IIV methods, the endogenous predictors' distribution is assumed to be non-normal (for example, skewed, heteroscedastic or discrete). However, incorrectly specifying its distribution may lead to biased estimates and the distributional assumptions are difficult to check in practice. Here we propose a general framework that approximates the distribution of the endogenous predictor nonparametrically through a mixture of Dirichlet processes. This framework also extends existing IIV methods beyond the simple linear regression model to which they were limited so far, to the class of hierarchical multivariate mixed outcome models that has broad application in marketing.

We introduce a general framework for dealing with endogeneity that does not rely on the availability of observable instrumental variables. It involves a multivariate hierarchical mixed discrete/continuous outcome representation of response variables, and a nonparametric approximation to unobserved exogenous information. The framework accommodates a variety of data encountered in marketing, such as ratings, rankings, censored data, and timing and choice data and does not rely on specific and different observable instruments in each case. It facilitates the study of endogeneity in marketing in an integrated methodological framework, rather than as a collection of seemingly independent special cases.

We provide three applications to respectively, 1) a linear demand model of price on sales, using data from the Dominick's database from the University of Chicago 2) a conjoint analysis application that involves a random coefficients hierarchical regression model of the effect of psychographics on part-worths, and 3) a model of the effect of credit scores on consumer credit behavior.

In the standard sales model, unsurprisingly strong endogeneity of prices is revealed, but importantly the IIV analysis reveals that a standard IV approach using lagged prices as instruments does not correct the estimates adequately, which has been argued previously. In the conjoint analysis setting, endogeneity is shown to exist for hierarchical effects of a psychometric variable operating on the distribution of part-worths across

individuals, and the estimates from the standard HB model were shown to be strongly biased.

Endogeneity in the population model affects the estimates of population model variables, but the individual level estimates are largely unaffected. In addition, the estimate of the heterogeneity variance was strongly underestimated for some variables (price) in the standard HB model relative to the IIV model. This confirms previous findings and may render customization more profitable. However, our results showed that negligence to account for endogeneity may also bias the estimates of the heterogeneity variances downwards, which may yield customization less profitable. Finally, the IIV framework was applied to reveal endogeneity of Credit Scores in the analysis of credit behavior, in particular with respect to mortgages. Endogeneity was revealed and it was shown that regression approaches that fail account for endogeneity may overestimate the effect of Credit Scores, which may imply that households with lower scores could receive substantially better limits and rates for their mortgages. While the models and procedures used by credit providers to determine credit limits and rates are unknown in many situations, this is clearly a topic deserving of further study.

Modeling Endogeneity in Logit-Based Demand Models: Inappropriate and Dynamic Instruments

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Endogeneity problems in demand models occur when certain factors, unobserved by the researcher, affect both demand and the values of a marketing mix variable set by managers. For example, unobserved factors such as style, prestige, or reputation might result in higher prices for a product and higher demand for that product. If not addressed properly, endogeneity can bias the elasticities of the endogenous variable and subsequent optimization of the marketing mix.

In practice, instrumental variables estimation techniques are often used to remedy an endogeneity problem. Alternatively, the dynamic and multilevel structure of the model and data may be exploited to solve for endogeneity. Though econometricians have studied the endogeneity problem for many years, these studies have focused mostly on asymptotic properties of estimators in linear regression (panel-data) models. Unlike the case of linear regression, there are no analytical results on the asymptotic properties of instrumental variables estimators for nonlinear (panel-data) models, such as logit-based demand models.

The goal of this study is to investigate the properties of instrumental variables estimators for logit-based demand models applied to finite samples, such as the scanner datasets commonly used in the literature. Specifically, given the potential difficulty of finding valid instrumental variables, we study the consequences of using inappropriate endogenous instruments (i.e., those correlated with the missing variable) and weak instruments (i.e., those having weak correlation with the endogenous price variable).

Furthermore, we investigate how the dynamic structure of the model and the data may be used to address potential endogeneity. For instance, in traditional linear panel data models, the fixed-effects estimator may be used by exploiting the within-entity dimension of the data. It can be shown that when all data (dependent variable and independent variables) are transformed in deviations from the means (here computed across stores) the unobserved demand shocks are eliminated. This fixed-effects estimator is typically less efficient than other alternatives. In linear panel data models, the fixed-effects estimator can also be seen as a special case of the IV estimator in which the endogenous regressor is instrumented by its

value in deviation from its mean. However, these data transformations that exploit the dynamic and multilevel structure of the data do not straightforwardly extend to general logit demand models. In this study we investigate whether this idea may be extended to such logit demand models.

Based on the results of a simulation study, we find that instrumental variables estimation produces mean absolute percentage elasticity errors of 10% or less when the instruments have the theoretically desired properties, but weak and endogenous instruments produce elasticities with average errors as high as 80% in some experimental conditions. In contrast, a model that ignores endogeneity produces elasticities with errors as high as 50%. We investigate improvements to estimation procedures as well as the performance of new, readily-available, dynamic instruments that exploit the panel structure of the model and the data. We find that these dynamic instruments reduce the mean absolute percentage error to 5% across all experimental conditions, including those in which the factors affecting the price setting of firms are weak and endogenous.

Identifying the Most Informative Consumer Segments for Sales Prediction

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We use a unique data set to study the predictive power of consumer confidence for future spending. More specifically, we identify informative and non-informative consumer segments based on individual characteristics as for instance gender, income and profession. The number of consumer segments is large, and only a few of them are informative. A new variable selection technique is proposed, a time series generalization of the popular least angle regression (LARS, Efron et al. (2004)), which allows to identify the most informative consumer segments for different product categories. We focus on new car registrations, retail sales of household equipment and retail sales of pharmaceutical products, yet the proposed method is very flexible and can be used for any target variable of interest.

We use detailed micro-data on Belgian consumer confidence surveys, which are part of the joint harmonized European Union programme of business and consumer surveys. These detailed data are not publicly available and were provided to us by the Belgian National Bank. As argued in Roos (2008), consumer confidence surveys can be used as a proxy for willingness to buy and an increase in consumer confidence is expected to increase spending. Several research papers study the link between consumer confidence and spending (for instance Vuchelen (2004) and Taylor and McNabb (2007)), but the out-of-sample forecast power of the confidence indicators for predicting future spending is found to be very weak. A limitation of previous studies is that only aggregated data are used. But by aggregating over all consumers in the survey, one risks to lose valuable information. Instead of combining the answers of the different consumer segments in the consumer surveys, we select the most informative segments.

Over a time range of more than 18 years (January 1990 to May 2008), we observe monthly confidence data for consumers segments according to profession, employment status, education level, gender, age and net household income. Our goal is to identify those consumer segments whose opinion, as measured by the confidence surveys, contains the most valuable information for evolutions in future spending. Studying consumer segmentation has been promising in other situations, see for instance Gielen and Steenkamp

(2007) who investigate consumer segmentation in relationship with new product introduction, and Roos (2007) who studies gender differences in macro-economic predictions.

The identification of the most informative consumer segments is achieved by using variable selection techniques in a time series context. While in the marketing literature, variable selection is most often carried out in a Bayesian setting (Smith et al. (2000), Gilbride et al. (2006), Fong and DeSablo (2007)), we work with a standard linear time series model. Denote the variable of interest by y_t and the candidate predictors by $x_{j,t}$. The time index is t and $j=1, \dots, m$ stands for the index of the predictor time series. Typically, m is a large number. A predictor $x_{j,t}$ is for example the survey outcome for the consumer segment of all employed females with a university degree. The survey outcomes of several consumer segments will not significantly help to predict y_t , and including them in the construction of an aggregate confidence indicator only increases the noise level.

The m candidate predictors $x_{j,t}$ can be used for obtaining an h -step-ahead forecast of the response. We consider the linear time series model

$$y_{t+h} = \beta_{0,0}y_t + \dots + \beta_{0,p}y_{t-p} + \beta_{1,0}x_{1,t} + \dots + \beta_{1,p}x_{1,t-p} + \dots + \beta_{m,0}x_{m,t} + \dots + \beta_{m,p}x_{m,t-p} + \varepsilon_{t+h}, \quad (1)$$

with $h \geq 1$ the forecast horizon and p the lag length. Model (1) explains y_{t+h} in terms of current and past values of the response itself and all the predictors. Not all predictors in model (1) are relevant, i.e. many of the β -parameters are zero, or almost zero. The purpose of the LARS generalization for time series (Gelper and Croux (2008)) is to identify which of these β -parameters are non-zero and to obtain accurate estimates of them. This is achieved by first ranking all m candidate predictors and then including only a few highest ranked variables in the final model. We compare the results with other dimension reduction techniques, more specifically with factor models (Stock and Watson (2002)), Bayesian variable selection, and the elastic net (Zou and Hastie (2005)). The stability of the variable selection procedure is achieved by combining it with the bootstrap method, as proposed in Khan et al. (2007), leading to more accurate results.

Moment-to-Moment Optimal Branding in TV Commercials: Preventing Avoidance by Pulsing

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This paper develops a conceptual framework for understanding the impact that branding activity and consumers' concentration of attention have on their moment-to-moment avoidance decisions during television advertising. It formalizes this in a generalized Dynamic Linear Model (gDLM) and estimates it with MCMC methods. In doing so, we incorporate temporal as well as individual and commercial-specific heterogeneity. Data on commercial avoidance through zapping along with eye tracking measures on 31 commercials for nearly 2000 participants are used to calibrate the model. We find that instances when the brand (i.e. logo, logotype, trademark) is present, its duration on screen and cardinality increase zapping likelihood, with the latter two having diminishing effect over time. Independent of this, central, as opposed to peripheral, on-screen brand positions but not brand size further raise commercial avoidance. Regarding attention levels, simple metrics of attention concentration are shown to strongly predict ad avoidance.

Based on the model estimation, the branding activity (presence, size and temporal location) under advertisers' control is optimized for all ads in our sample to reduce commercial avoidance. The result of this exercise shows that advertisers can reduce overall zapping levels from 2 to 19% using an on-off brand placement policy. This policy of "pulsing" brand presence--while keeping total brand exposure constant--decreases commercial avoidance significantly as compared to other commonly used brand placements. Implications for advertising management and theory are addressed.

Understanding the Timing and Magnitude of Advertising Spending Patterns

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Introduction

Advertising remains one of the most important and visible marketing instruments. An impressive body of prior research has looked at the effectiveness of advertising, at the brand, industry, and national level (see e.g., Tellis and Ambler 2007). Less attention has been paid to how advertising investment decisions are made, and more specifically to the timing (when) and magnitude (how much) of these investments. Still, considerable variability exists across both dimensions. We therefore investigate what factors drive the different behavior of brands.

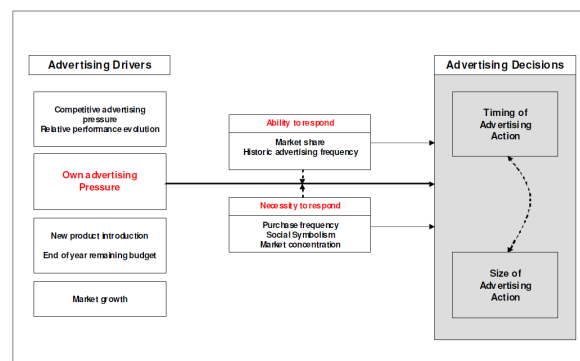
Prior Research and Relative Contribution

Prior research in this area has followed three research streams. (i) From a normative point of view, many studies have looked at the optimality of pulsing versus even spending (e.g., Sasieni 1989; Naik et al, 1998; Dubé et al, 2005). (ii) Descriptive studies have surveyed managers as to what factors they take into account when deciding whether or not to advertise (Rados 1972; Hulbert et al., 1980). (iii) Finally, other studies have used econometric and/or time-series techniques to study competitive reactions (e.g., Hanssens 1980; Steenkamp et al 2005). However, for many brands, advertising spending is infrequent and widely dispersed, causing numerous zeros in the sequence of spending levels. These are hard to handle in most time-series techniques, thus leading to a focus on large and frequently advertised brands. This was recently deplored in Slotegraaf and Pauwels (2008) as it may bias the overall inferences.

Our research contributes to the literature on advertising spending patterns in three ways. (i) We examine a much broader coverage of brands (742

brands, covering 129 product categories over a time span of four years), both large and small, both frequently and infrequently advertising. (ii) We not only consider whether or not brands react to one another, but also assess the relative impact of a wide set of drivers, including the own Adpressure, the competitive Adpressure and the own performance evolution over preceding periods. In addition, we control for a wide array of own-brand (e.g. market share) and marketplace characteristics (e.g. concentration rate and category growth). (iii) Consistent with the conceptual work of Bar-Ilan and Strange (1999), we consider the advertising investment decision as a dual process, where brands have to decide on both the timing and magnitude of their advertising actions (see Figure 1). Our model specification will allow the relative weights attached with the aforementioned drivers to vary across both dimensions.

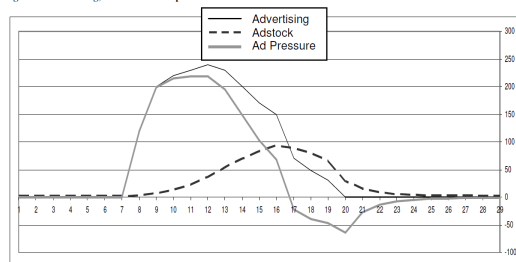
Figure 1. Conceptual framework.



Method

We face four main modeling requirements. (i) We need to model both the timing (yes/no) and spending decisions (monetary value), while allowing for different response parameters for both decisions. (ii) These response parameters are probably heterogeneous across brands. (iii) We need to accommodate the effects of the moderating variables, preferably in a simultaneous estimation step for maximal statistical efficiency. (iv) The decisions of when and how much to spend may be interrelated between brands within a category, and hence we need to specify a full error covariance structure. We therefore link the drivers to the two decision variables (i.e. timing and size) through a new multivariate hierarchical Tobit-II model, which extends the models of Fox et al. (2004) and Van Heerde et al. (2008). Central to this model is the novel concept of Adpressure (see Figure 2), which will be explained in the next paragraph. The model is subsequently estimated by means of Bayesian inference using Gibbs sampling.

Figure 2. Advertising, Adstock and Adpressure



Operationalization of the Adpressure

Adpressure is a feedback variable mimicking the brand's decision rule to start, continue and stop advertising, based on the widely accepted and applied concept of adstock (Broadbent, 1984). The latter, in turn, is defined by a Cobb-Douglas production function (e.g. Hanssens and Ouyang, 2002; Donanoglu and Klapper, 2006), implying a multiplicative adstock accumulation. Based on the advertising literature (e.g. Zufryden, 1973; Doganoglu and Klapper, 2006), we postulate that brands apply (s,S) stock replenishment systems to manage their adstock. Brands do not want the latter to depreciate below a certain minimum, but will also stop advertising when a maximum level is reached, levels which are known to the brand but unknown to the researcher. The brand feels a positive pressure to invest until the maximum is reached and the first derivative of adstock to time is zero. At that point, the manager has a clear incentive to stop advertising, although one can still find some small amounts of advertising at the end of campaigns, mainly due to so-called make-goods (Doganoglu and Klapper, 2006). Over time, however, adstock starts to decay to its minimum. Simultaneously, the Adpressure starts to increase, building up the pressure to advertise.

Results

The initial results for the main effects of the time-varying advertising drivers and for moderating effects on the effect of Own Adpressure indicate that brands are more likely to advertise (Own Adpressure = 0.270) and will also spend more on individual actions (Own Adpressure = 0.014) when Adpressure is higher. Meanwhile, they avoid getting trapped in the advertising clutter, as shown by the negative effects of Competitive Adpressure (Competitive Adpressure = -0.033 and -0.003, respectively), which confirms earlier work by Danaher et al (2008). Brands combine new product introductions with more intense advertising, as they are more likely to advertise (New Product Introduction = 1.443) and will also spend more in a single week (New Product Introduction = 0.086).

Commonly applied data pruning rules may have biased the findings of previous studies, as size and advertising frequency clearly moderate the effect of Own Adpressure on the advertising decisions. Larger brands show stronger reactions to Own Adpressure in their timing (Own Adpressure*Market Share = 1.529) and magnitude

(Own Adpressure*Market Share = 0.059) decisions than smaller brands. More frequently acting brands show a similar pattern (Own Adpressure*Historic Advertising Frequency = 0.566 and 0.030, respectively) relative to less frequent advertisers. Finally, category factors do play a role.

Timing of Sales Promotion of Durable Goods: An Example of Taiwan Automobile Market

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Sales promotion has been playing an important role in stimulating sales of a product. In contrast to advertising which intends to gradually shape consumer attitude, the objectives of sales promotion are to stimulate trial or quicker or greater purchase and to differentiate a brand from other competitors in a short time. Most of past research on sales promotion focuses its effects on retail store sales or on consumer purchase behavior, but rarely discusses the critical timing issues. Because the execution of this strategy usually at a specific time point and during a specific time period, it is important for firms to consider when to promote and how long to promote, which are designed to cope with the environment pressure and to harmony with the effects of a myriad of sales promotion tools. In this paper, we focus the sales promotion timing decision of durable goods. Durable goods have three characteristics to consumers, high expenditure, long usage life, and lots of attractive accessories. Therefore, the feasible sales promotion tools comprise preferential payment plan, postpurchase service, and accessories at a premium. Each tool means a particular advantage to consumers and probably has an optimal executing timing and time interval.

This research is based on the data coded from the reports about automotive sales and sales promotion activities issued by U-CAR, which is the most popular automotive website in Taiwan. Automobiles are subject to seasonal consumer demand induced by the timing of annual model changes. Therefore, we want to discuss in which season, such as peak season and low season, different months, and early or late execution stage in promotion period, the sales promotion tools can give rise more automotive sales. We adopt the method of Hierarchical Bayesian regression model to examine the moderator effects of seasonal variables on the relationship between the automotive sales and sales promotion tools such as price discount, preferential maintenance service, and free or lucky draw accessories. Our result shows that price discount has positive effects in the peak-season, the introduction months, and early stage of promotion period, preferential maintenance service has positive effects in year-end months and late stage of promotion period, and none of the tools have significant effects on sales in low

season. This research offers a strategic guideline for automotive firms to make timing decisions of sales promotion strategy.

A Decision-Support Tool for Recommending Promising Categories for Targeted Promotions

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When making marketing mix decisions, marketing managers of companies that offer a broad range of product categories, such as traditional offline and online retailers, mail-order companies, or financial service providers, often need to select one or a few focal categories out of all the possible ones offered. This interest is further fuelled by opportunities offered by the Internet or modern customer loyalty programs using smart card technologies, making it easier as well as cheaper for companies to implement micro-marketing strategies.

These recent developments have led to a shift in the managerial requirements of direct marketers: they want to find out which specific products or categories need to be featured in promotional activities customized for specific (groups of) customers. In this study, we present a decision-support tool that assists direct marketers in selecting subsets of promising categories from the large assortment they typically offer for inclusion in targeted promotions. The proposed analytical approach combines conventional wisdom of market basket analysis in a novel two-stage procedure (Boztuğ and Reutterer, 2008). In a first (exploratory) step, jointly purchased product categories across the entire assortment are identified by looking at pronounced cross-category interrelationships in the observed frequency patterns. Customers are next assigned to the identified shopping basket prototypes and we allow them to be members of multiple prototypes. This data-compression step is followed by a second (explanatory) step where the cross-category effects in response to marketing actions are modeled across the pre-selected categories. Our procedure takes both interdependencies in purchase behaviour across categories and customer heterogeneity with respect to cross-category effects in response to marketing actions into account.

For calibrating the model we obtained purchase transaction data of a major online grocery retailer for almost 4 year, resulting in a customer base of 17,312 households (purchased at least 3 times in the observation period). For the same retailer and time period, we also have detailed

information on price and other important marketing-mix variables. A total number of 302,632 retail transactions with pick-any choices among an assortment of 121 categories are first subject to the data compression step. This first stage revealed 13 interesting and distinct prototypes which were subject to estimation of segment-specific multivariate MNL models. Currently, we are about to empirically test the resulting recommendations derived from the above suggested two-stage approach vis-à-vis alternative approaches in a controlled field experiment conducted in cooperation with a major online grocery retailer. The experimental setup is projected to consist of a control group (no recommendations) and different experimental groups of which one group will receive recommendations derived by our suggested two-stage approach and other groups will receive recommendations coming from other recommender systems that differ in their degree of intelligence. During the conference, we will present the underlying mechanism of our decision-support tool as well as show some preliminary results of its performance.

Choosing Response Models for Budget Allocation in Heterogeneous and Dynamic Markets: Why Simple Sometimes Does Better

Dennis Proppe, Sönke Albers

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Calibrating a sales response model for budget allocation purposes is a complex task. Since sales response may differ across allocation units and usually involves dynamic relationships, a sufficient number of observations is required for estimation. However, many applications are characterized by small samples, thus raising the question of whether the available data is always rich enough for complex econometric estimation techniques. Otherwise, the researcher aiming at the most profitable budget allocation may be better off using simpler estimation techniques or allocation heuristics, even if they are theoretically inferior.

Thus, we ask ourselves which model and calibration approach leads to the most profitable allocation decision? This question cannot be answered with real data since the “true” solution is unknown to the researcher and the results cannot be evaluated against the truth. Simulation studies are well-suited and often used to deliver answers to these kinds of questions. Current simulations approaches, however, lack an appropriate measure for evaluating the estimation results as they tend to only look at parameter recovery and predictive validity.

We seek to answer our question by conducting a Monte Carlo simulation study using a large number of data conditions ranging from rich to very poor. By calculating the profit consequences of different estimates of the sales response functions, we propose a novel evaluation criterion that allows for meaningful comparisons of different model calibration methods. Our second contribution lies in the evaluation of the consequences of dynamic effects for model estimation, and subsequently, budget allocation.

Three steps must be taken to arrive at the results that build our contributions: first, we generate a large number of panel datasets with different data conditions by using simulation factors such as magnitude of the error, dynamic marketing effects, and degree of response heterogeneity. Second, based on this simulated data we estimate the parameter values with various econometric techniques, ranging from simple OLS to more complex simulation-based estimation methods like Maximum Simulated Likelihood or Hierarchical Bayes. Third, we determine the

optimal budget allocation based on the results of the estimation and calculate the profit generated by this allocation. This allows us to directly investigate the profit consequences of using various model calibration techniques.

Using profit consequences as the main measure of goodness also allows us to compare the results from econometric techniques with simple allocation heuristics. This is not possible when looking at parameter recovery because heuristics do not deliver any parameter estimates. The first heuristic used in this study is called “Equal Allocation” and simply allocating the same proportion of the marketing budget to each response unit. The second heuristic is called “Proportional to Sales Approach” and consists of allocating the budget across response unit according to their past revenue expressed as a fraction of total revenues.

The simulation results allow for at least two distinct implications, the first being that simpler can be better: when the quality of data is poor, i.e., when the error is large and there are few observations, complex estimation methods usually fail to deliver valid results. The very simple method of fixed effects is more robust to data issues and delivers better allocation results than, e.g., Hierarchical Bayes estimates in the presence of poor data. The second implication is that dynamic effects worsen the estimation results: while the econometric techniques can more or less cope with other data issues when the carry-over effects are weak, almost all techniques perform worse than the heuristics when strong dynamic effects are present. This especially holds for the Hierarchical Bayes technique. We conclude that the use of econometric methods may not always be superior to applying simple heuristics. Researchers and practitioners should carefully look at the data quality before choosing the model calibration method. Furthermore, using a simple fixed effect approach instead of complex techniques can be very effective in terms of budget allocation.

The Dynamics of Marketing Decision Models¹

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The idea that marketing decisions can be supported with analytical, mathematical models took off in the sixties of the last century. Before that time, marketing decisions were mainly based on judgment and experience. Over the last fifty years marketing decision models has developed into a core field of the marketing discipline. Marketing decision models is a dynamic field, where a rich variety of different approaches have succeeded each other over time. In this paper we will address two questions:

What patterns do we see in the development of marketing decision models over the last five decades and what can we learn from this?

What are the drivers of the developments in marketing decision models, and what can we expect for the future?

Patterns in the development of marketing decision models

The past five decades of marketing decision models can be characterized as follows:

The sixties (1960-69)	The Beginning: Approaches from micro-economics and operations research
The seventies (1970-79)	The Golden Decade: Models for marketing instruments and market response models
The eighties: (1980-89)	Towards Generalizations and Marketing Knowledge
The nineties (1990-1999)	The Marketing Information Revolution: Scanner data and consumer choice modeling
The present (2000-)	The Customer-Centric Approach: Customer relationship management (CRM) and models for online marketing

The paper discusses the different types of models that were prominent in each of these decades (together with representative examples) and analyzes their dynamics. There are evident cyclical patterns in marketing decision models. For example, marketing response functions are now in the maturity stage. Models for marketing instruments have been around for quite some time, but are continuously renewed due to new data possibilities (e.g. scanner data for sales promotion models) or new marketing instruments (e.g. online advertising). Other approaches are clearly in the growth stage (e.g. customer lifetime value models) or even in the introduction stage (e.g. financial performance effect models of marketing). Interestingly, some approaches in marketing decision models that seemed to have reached the end of their product life cycles, have come back after a certain lag period and started new “scalops”. Examples are: stochastic models, Bayesian approaches and mediaplanning models. Other approaches can be considered as “stayers”, because they seem to receive constant attention over time, for example new product diffusion models, conjoint analysis models, and marketing decision support systems. A brief review of the current (2008) highlights in marketing decision models concludes this part.

Drivers of the Development in Marketing Decision Models

The second part of the paper presents a framework that positions marketing decision models in its upstream and downstream context. Upstream are disciplines, such as economics, psychology, econometrics, operations research, information technology and artificial intelligence. Marketing decision models are driven by these upstream (supply) forces as well as (demand) forces from marketing itself. Downstream, marketing decision models find their way into the marketing science literature, and into implementations in marketing practice. We use this framework to reflect on the current state of marketing decision models and on the drivers that will shape its foreseeable future.

¹ This paper is based on the introductory chapter: “The Past, the Present, and the Future of Marketing Decision Models” of the Handbook of Marketing Decision Models (Berend Wierenga, editor), published by Springer, International Series in Operations Research and Management Science, 2008.

An Empirical Analysis of Recommender Systems and Market Diversity

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Introduction

Media has historically been a "blockbuster" industry, with sales concentrating among a small number of hits. In recent years, such concentration has begun to decrease: a large percent of sales in online markets now come from niche goods. This trend has been dubbed the "long tail," referring to sales distributions with significant mass beyond the top products. Researchers have proposed frameworks for explaining what factors contribute to the long tail. On the supply side, firms offer more products than before. Online firms stock more products because of lower inventory cost and the ability to pool demand across geography. On the demand side, consumers have new tools -- search engines and recommender systems -- for sorting through the myriad choices. However, there have been few empirical studies examining whether and how the supply and demand factors contribute. In recent work (Fleder & Hosanagar 2007), it is even questioned how much recommender systems contribute to the long tail at all. This paper investigates how recommender systems contribute to diversity in online markets. Specifically, we examine the effects of recommender systems on products and consumers:

1. At the product level, how do recommender systems affect sales diversity? A common belief is that recommenders help consumers discover niche products and increase sales diversity. Others believe that common recommender designs reinforce the popularity of already popular products.
2. At the consumer level, do recommender systems create fragmentation among users? Recommenders give consumers a new means to filter content and focus on their interests. Researchers have predicted that such filtering will undesirably fragment consumers. In contrast, others have argued that recommenders have homogenizing effects because they share information among users. The question has implications for the use of broad versus narrow targeted marketing policies and also has broader policy implications.

Data

Our data are provided by a firm that operates a recommendation service that helps users discover new music. Users install a free software plugin for the popular Apple iTunes music player. When a user listens to music in iTunes, the software recommends additional songs the user can sample and purchase. Our data are novel because they record both pre and post recommender purchase behavior. The analysis design is analogous to a two-group experiment. Group assignment is not truly randomized (more below), but the terminology of experiments simplifies the writing. Group 1 is the treated group (exposed to the recommender), and group 2 is the control (unexposed to recommender). The control accounts for factors such as time trends and maturation that might be confounded with recommender usage in a one group pre-post design. The control data are obtained from users that register for the service much later. The use of eventual users for the control affords a measure of similarity between the groups.

Initial Results

Table 1 presents initial findings based on the 2 months before and after registration.

	Before	After
<i>Summary measures</i>		
Users	1,800	2,077
Songs purchased	215,847	390,291 (+81%)
Artists (with >0 sales)	24,376	39,483 (+62%)
Entropy \hat{H} (bits)	12.10	12.37
Average overlap (density)	24%	46%
Average path length	1.78	1.54

Table 1: Summary statistics and initial findings

The summary measures show that after installing the recommender software, purchase volume and sales diversity increase. In each period, roughly 2,000 users make at least one purchase. Sales increase after registration, as shown by the total songs purchased (+81%). The increase in purchases does not occur for the control group (not shown). Diversity increases too. The number of artists with any purchases increases by 62%. The entropy of the artist market shares also increases; this measure is inversely proportional to the Gini coefficient.

To measure consumer fragmentation, we first create a consumer network in which an edge exists between two users if they purchase at least one artist in common. The average overlap is measured by the percent of users a given user is connected to, averaged over all users. The average path length is the average minimum path length between any two users. The measures show that users are becoming more similar. The network density increases and users are closer to one another.

Methodological Challenges

The research design poses several challenges. First, group assignment is not randomized. Since registration is the user's choice, the analysis cannot

account for selection on unobservables. Sensitivity analysis shows that user behavior changes sharply at the time of registration. If registration were a response to a growing demand for music, we should also observe this trend in the preceding weeks, which we do not. A second limitation is attrition: about half of the initial users in group 1 uninstall the plugin before data collection ends. Thus an analysis of only the non-attributing population may overstate the results. Finally, given that volume of purchases per user increases, we expect commonality in purchases to increase. So we need to control for volume of purchases as well. The presentation will discuss these challenges and proposed solutions.

Conclusions

The study will help reconcile the opposing conjectures in the literature on the impact of recommenders on market diversity. From a methods perspective, the study delves into interesting issues tied to network data. These questions tied to selection biases and attrition and our proposed solutions will help generate interesting discussion at the conference. Implications for marketing practice will also be discussed.

Modeling the Effects of Normative and Informative Word-of-Mouth on Product Adoption using Social Simulation Techniques

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Word-of-mouth has been an important topic for research in the past decades, especially because of its influence on attitudes and opinions of consumers, resulting in affected consumer behavior (Goldenberg, Libai and Muller, 2001). The behavioral outcomes of WOM have not been studied as much as the attitudinal outcomes. Some evidence for the relation between WOM and consumer behavior has been found by Wangenheim and Bayón (2004). WOM does not have a similar effect on all consumers, as some consumers are more influenced by WOM than others. Within the WOM process, a distinction can be made between normative influence and informational influence. Which type of influence is more important will both depend on the consumer and the product category. First, not all consumers are equally susceptible to social influence: the motivation to comply with the expectations of other people differs between individuals (Bearden, Netemeyer and Teel, 1989). With respect to the product category, there are also important differences. In some product categories social influence is hardly affecting consumer behavior, as in case of table salt. For other products, such as clothes and other fashionable items, normative influence is the dominant route in social influence. Products which are less fashionable, but complex concerning their attributes, may stimulate a lot of informational social influence, for example in the increasing number of review sites on consumer electronics. Finally, some product categories address both normative and informative social influences, such as in the case of cars, which are being discussed both in terms of their style (normative) and quality (information). Besides the factors mentioned above, there are several other important factors that might influence the effect of WOM on consumer behavior, such as *expertise* of the sender of WOM (Bansal and Voyer, 2000) and *similarity* (homophily) between consumers (Festinger, 1954). WOM is also affected by the social network in which the consumer participates: normative networks (e.g. similar people have most influence) can differ from informational networks (e.g. experts have most influence). In this study we will

answer the following question: How do similarity (normative) and expertise (informative) influence the effect of WOM on consumer behavior in a dynamic social network?

In line with Netzer, Lattin and Srinivasan (2008), we account for dynamics and heterogeneity between customers. However, in order to get more insight in the dynamics of the WOM processes we use an agent-based model to simulate a dynamic network of consumers. This type of model allows us to investigate the effect of WOM on both the individual (micro) and aggregated (macro) level at the same time (Macy and Willer, 2002). We develop a modified WOM-model which not only includes personal characteristics and social influence, but also accounts for variables which are manipulated by (marketing) managers, such as promotions and other marketing actions. This model therefore implements suggestions from Jager (2007) to include marketing variables in social simulation studies to be able to test the effect of different marketing strategies behavioral outcomes in the consumer market. The decision making process of the simulated agents is based on a logit choice model, containing variables related to social susceptibility (including normative and informative influence). The agents are placed in a dynamic network, which is also affected by the type of influence: there might be differences between normative and informative networks, which is also related to the expertise of the agents and the similarity between agents. The model will be parameterized using empirical (survey) data collected in number of product categories (e.g. online games, cell phones, restaurants and fund raising). We use this model to run several experiments to test the influence of similarity, expertise and marketing variables on how WOM affects consumer behavior in different product markets. More specifically we investigate the influence of opinion leaders, network properties, degrees of social interaction and personal characteristics on the adoption rate and adoption speed of products.

Results depend on the product category that is investigated. As an example, for online games we find that the expertise of opinion leaders increases the speed of WOM (faster adoption of information). Furthermore, the adoption speed of the online game is also positively influenced by the expertise of the opinion leader (positive effect on behavioral outcome) (WOM). Opinion leaders also account for a higher adoption percentages within social networks.

The effects of the variables of interest from this study on adoption rate and adoption speed will be tested in more detail in both the game category and other product categories. We also specify why WOM has different effects in different product categories.

Responses of Unprofitable Customers to Demarketing Actions

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Management of Unprofitable Customers

The existence of unprofitable customers is a common problem in many industries and is especially significant in the case of long-term contractual relationships. Often the affected segment contains a considerable number of customers; e.g. 30% of internet service provider clients (Ang and Taylor 2005). The predominant focus of existing customer relationship management literature is on retention, satisfaction, and a myriad of methods on how to improve the relationship with customers. Very little if any attention is paid to unprofitable segments for which traditional approaches do not seem to work (Mittal, Sarkees, and Murshed 2008).

Continuing to serve unprofitable customers clearly has a negative impact on a company's overall performance. This segment therefore requires special attention and treatment, which we would suggest falls in the area of "Demarketing" (Kotler and Levy 1979). There are different ways to demarket; ranging from a change of service level or reduction of interaction with selected customer segments to complete termination of the relationship. Once the company has decided to take specific measures for the bottom tier of the customer pyramid, advantages such as cost savings, better fulfillment of the needs of remaining customers, and perhaps even a change of the former unprofitable behaviour can be expected. But in taking action, companies also face potential risks such as negative word-of-mouth or negative media coverage.

The aim of the present study is to measure customer response (attitude, word-of-mouth, buying behaviour) towards an executed demarketing action within the context of a customer segment with high probability of imminent unprofitability.

Empirical Study

To investigate the effects of a demarketing action, we conducted a large field experiment in cooperation with a B2C direct mail company in Germany (catalogue retailer). This company had

identified a large segment of unprofitable customers and had to determine whether or not to send this group another catalogue (and therefore continue service) and/or to cease active communication with this unprofitable segment (and therefore implement a demarketing strategy).

Data collection took place in spring 2008, when we selected a random sample of 12,000 customers. Customers have been assigned randomly to either the treatment or control group. Participants in the treatment group received a package with two catalogues, a cover letter, voucher and reply postcard. The cover letter stated that customers might consider renewing (and order again) or terminating the relationship (and stop receiving catalogues). Participants were able to communicate their feedback regarding this issue with the reply postcard. Customers in the control group did not receive a package from the company.

In addition, we conducted a paper-and-pencil questionnaire. Surveys were mailed with a cover letter and postage paid return envelope. Overall response rate was 9.34% (N = 1,121 questionnaires) with almost equal distribution within the treatment and control groups. No serious non-response bias can be observed, as the sample does not significantly differ regarding the control variables of age, gender, and technical equipment. The survey covers a range of variables, which are primarily based on the existing customer relationship management literature. They can be grouped into the following areas: satisfaction, customer loyalty, buying and switching behaviour, as well as detailed measures for word-of-mouth. We also control for involvement of the customer, channel affinity, technical equipment, and other demographics.

First results show that the demarketing action has an impact on customer satisfaction – treatment group is less satisfied compared to the control group – but there is no significant influence on word-of-mouth behaviour. This distinction is important, as it indicates that the companies' goal of cost cutting or even terminating the relationship can be achieved without negative external effects (no multiplier through WOM).

In addition to the customer survey, we hold data provided by the companies' customer database regarding the past behaviour of individual customers. The data includes variables such as number of orders, returns and payments, type of products, and relationship length. In a next step the actual customer behaviour before and after the demarketing treatment will be analysed in further detail. Based on the findings and especially because of the matching of actual buying behaviour with the questionnaire data, we expect to derive interesting implications for management and research.

**Unplanned Category Purchase Incidence:
Shopper Traits and Shopping States**

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Unplanned category purchase incidence is an important source of retailer volume and profits, yet the factors that generate it are not well understood. We analyze this phenomenon in detail combining panel data on purchase incidence with in-depth interviews that capture household-specific trait and store perception data. In contrast to the extant literature, we deliberately focus on unplanned category purchase incidence as prior research on shopping lists has found that consumer purchase planning occurs at the category level, rather than at the brand or stock keeping unit (SKU) level.

A multi-level Poisson model of the number of unplanned category purchases in the shopping basket is calibrated on data from 434 households making over 18,000 purchases in 58 categories across 3,000 trips to 21 stores. We find that unplanned category purchase incidence is not proportional to the overall size of the basket purchased on the trip. Instead, the majority of the variation is across shoppers and trait-driven. Specifically, it is explained in part by demographic variables traditionally measured by marketers, but more by other “traits” that reflect long-run shopping habits such as level of planning and information gathering styles. Shopping states, i.e., trip missions and contexts are also important, yet these factors are largely outside the control of the retailer. Retailers can however stimulate state-driven unplanned category incidence by increasing exposure to in-store stimuli, and increasing the time spent in the store. We conclude with an example that illustrates the trade-off between trait-focused (i.e., attracting different shoppers) and state-focused (i.e., stimulating existing customers in-store) marketing approaches. Other implications are also discussed.

Pay What You Want - Successful In The Long Run? Conceptualization of a Measurement Model for a Dynamic Experimental Study

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As markets become more saturated and competitive, innovative and participative pricing mechanisms have developed as a means to differentiate from competitors. To assess the long-term applicability of such price mechanisms, a dynamic perspective is essential to forecast long term developments of customers' willingness-to-pay.

One of these so-called reversed pricing strategies, which has received considerable attention in marketing, is the so-called 'Pay What You Want' pricing (PWYW). With PWYW, customers instead of suppliers decide which prices to pay for goods and services, meaning that the price determination is delegated to the buyer. Although it would be individually rational to refrain from paying for goods and services, various experimental studies have shown a willingness-to-pay significantly greater than zero. Existing literature on reversed pricing primarily deals with perceived price fairness and the effect on customer satisfaction (Diller 2000, Kim/Natter/Spann 2008) and is lacking a longitudinal perspective. Hitherto, the drivers of the customers' willingness-to-pay have not been sufficiently examined. Furthermore, none of the studies conducted deal with potential dynamic aspects, e.g. a gradually decreasing willingness-to-pay. It is therefore crucial to account for these dynamic developments as they might threaten long-term profitability. Hence, we intend to answer two questions:

- i. What are the drivers of customers' willingness-to-pay especially regarding PWYW offers?
- ii. Which dynamic effects can be observed?

We develop a model measuring the factors influencing customers' willingness-to-pay based on social psychology and behavioral pricing literature. We then empirically test our model accounting for dynamic effects of changing willingness to pay in the long run.

More precisely, our model applies the theory of cognitive dissonance to explain the willingness-to-pay. This theory states that human beings intend to harmonize their own conduct with norms of behavior which are expected by society. To deviate from these norms would cause a displeasing cognitive dissonance which actors aim to avoid by conforming behavior. In our case this implies that the observed willingness-to-pay can be traced back to norms of fairness that actors would violate by free-riding.

Our basic assumption is that this anticipated cognitive dissonance (ACD) significantly drives the willingness-to-pay. We identify three factors which should have an impact on the extent of ACD, the first one being the degree of self-monitoring (Snyder 1972). In a state of strong self-focus, actors tend to show a higher degree of conformity with social norms. The theory of social identification (Tajfel/Turner 1986) provides further insight by focusing the attachment to a brand or an industry, which can be seen as a second factor influencing the ACD. The above mentioned aspects derived from social psychology can be complemented by a construct frequently referred to in behavioral pricing research, namely reference prices. According to this construct, internal as well as external reference prices are used as anchors for assessing prices (Homburg/Koschate 2005).

We conduct a dynamic laboratory experiment as well as a field experiment in cooperation with a German record company, in order to quantify the effects of the above-mentioned factors and to test for the existence of longitudinal change in these aspects resulting in a shift in willingness-to-pay. We analyze the effects of the latent variables using structural equation modeling (SEM). The longitudinal data is analyzed using the dynamic tool of Latent Growth Modeling (LGM). LGM is a longitudinal analysis technique to estimate growth over a period of time in the SEM framework. By exploring the drivers of willingness-to-pay and at the same time incorporating a dynamic perspective, valuable management implications for the long-term profitability of PWYW offers can be deduced.

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