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Creating lift versus building the base: Current trends in marketing dynamics

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ABSTRACT

Markets are dynamic by nature, and marketing efforts can be directed to stimulate, reduce, or to utilize these dynamics. The field of marketing dynamics aims at modeling the effects of marketing actions and policies on short-term performance ("lift") and on long-term performance ("base"). One of the core questions within this field is: "How do marketing efforts affect outcome metrics such as revenues, profits, or shareholder value over time?" Developments in statistical modeling and new data sources allow marketing scientists to provide increasingly comprehensive answers to this question. We present an outlook on developments in modeling marketing dynamics and specify research directions.

This manuscript is a conference feature paper on the 2007 Marketing Dynamics Conference which the authors organized at the University of Groningen, The Netherlands.

1. Introduction

The dynamic nature of markets dictates that marketing measures are often targeted at stimulating, reducing, or utilizing market responsiveness. Firms launch new products and introduce better packaging (stimulating response), retaliate against competitive moves (reducing response), monitor trends in consumer preferences and segment membership (utilizing response), and so on. The effects of marketing efforts do not necessarily end when, for example, an advertising campaign is over. The effect, or part of it, will remain noticeable for some time.

In recent years, the determination of the long-term effects of marketing efforts has received much attention from practitioners and academics. Senior executives are increasingly interested in the long-term impact on sales, profits, but also on relatively new metrics such as shareholder value. They want to create sustainable competitive advantages for their brands and they want to see permanent effects of their investments in marketing efforts. For example, Gerard Kleisterlee, CEO of Royal Philips Electronics, stated that 'in the long-run our values and how we honor them will determine the outcome of what we strive for'.[1] Oswald Grübel, CEO of the Credit Suisse Group, specified his aims in a somewhat different way: 'Our priorities are quite clear: we want to generate long-term added value for our shareholders by offering outstanding service to our clients and by securing a leading position in the industry'.[2] For non-traded companies, firm value instead of shareholder value is an important metric (Gupta, Lehmann, & Stuart, 2004).

Such perspectives imply that marketing resources should be allocated to maximize the long-term impact on the relevant metrics such as shareholder value. This task requires, in turn, that a valid and reliable answer is found to the paramount question:

> How do marketing efforts affect outcome metrics such as revenues, profits and shareholder value over time?

To address this question, the discipline of marketing dynamics studies the short- and long-term effects of marketing actions and policies on relevant metrics. In the past ten years, we have witnessed important improvements in modeling marketing dynamics. These developments have led to the establishment of the annual "Marketing Dynamics Conference". The first conference was held at the Tuck School of Business at Dartmouth, USA in 2004 (Pauwels et al., 2004a), while the fourth conference was hosted by the University of Groningen, the Netherlands, in August 2007.

In this feature article, we discuss the relevance and challenges of modeling marketing dynamics for marketing decision-making. A number of these challenges were summarized in the keynote speech by Dominique Hanssens at the Groningen conference, and they partly overlap with those identified by Pauwels et al. (2004a). Our review of trends is largely based on the 40 presentations at

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[1] Gerard Kleisterlee, December 04, 2007, "Innovation as driver of sustainable growth", Speech at China Central Party School.

[2] Oswald J. Grubel, April 28, 2006, Speech made at Annual General Meeting of Credit Suisse Group, Zurich.

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the Fourth Marketing Dynamics Conference. We specify criteria that dynamic models should satisfy, indicate important developments in relevant research methodologies, and formulate research directions.

2. Challenges and methodologies

To address the core question of "how marketing efforts affect outcome metrics over time," we need to build suitable dynamic marketing models. Ideally, these models and methodologies:

1. use appropriate metrics,
2. disentangle temporary (short-term) from persistent (long-term) effects,
3. account for time-varying parameters, and
4. allow for cross-sectional heterogeneity.

We discuss these requirements in the following subsections.

2.1. Marketing metrics

The core question involves differentiating between marketing efforts that lift sales temporarily (flow) and efforts that build marketing stock, i.e., lead to a permanent shift in the base level. Many sales response models relate current sales to current and past marketing expenditures (see e.g., Leeflang, Wittink, Wedel & Naert, 2000, p.85–99). The demand or revenue metric is a *flow* metric. Ideally, marketing expenditures will also create beneficial changes in *stock* metrics. Examples of stock metrics are cumulative sales, brand equity, customer equity, et cetera. Pauwels and Hanssens (2007) and Hanssens and Dekimpe (2008) extend the 'flow' response models to capture the effects of marketing investments on *stock* metrics and specify the following relations:

$$S_{it} = c_{it} + \sum_k \beta_{ki}(L)M_{kit} + \varepsilon_{it}, \tag{1}$$

$$c_{it} = \delta_i c_{i,t-1} + \sum_k \gamma_{ki}(L)M_{kit} + \eta_{it}, \tag{2}$$

where S_{it} is the outcome metric, such as the sales of brand[3] or firm i, c_{it} the baseline of unit i at time t, $ß_{ki}$ (L) represents the effectiveness of marketing efforts on baseline sales with lag L, M_{kit} the marketing efforts with marketing instrument k, and ε_{it} and η_{it} disturbance terms. Most attention in marketing has been given to the determination of optimal marketing expenditures (M), how to improve marketing effectiveness ($ß(L)$) and how this leads to a larger flow (S_{it}). Relation (2) shows the development of its baseline over time. Changes in the baseline sales are interpreted as building the base. Given that baseline sales can be seen as a measure of brand equity, $\gamma_{ki}(L)>0$ indicates that marketing investments are building the brand (equity). Hence Eqs. (1) and (2) answer the question whether or not marketing efforts create demand (β_{ki}) and/or build the baseline sales (γ_{ki}) of the brand (Table 1).

Ataman, Mela and Van Heerde (2008) use a similar specification to explain how marketing mix activity generates growth and builds market potential for new brands. Their so-called 'observation equation' separates short-term fluctuations from long-term sales:

$$\bar{S}_{it} = c_{it} + \bar{X}'_{it}\beta_i + \gamma_{it}, \tag{3}$$

where $\bar{S}_{it}$ is the (standardized) sales of brand i at time t, $\bar{X}_{it}$ includes variables that may generate *short-term* fluctuations in sales, and γ_{it} is a disturbance term. Ataman et al. (2008) standardize all variables within brands and indicate this with a superscripted bar. The baseline sales c_{it} evolves over time, following the repeat-purchase diffusion process as specified in the 'state equation':

$$c_{it} = \delta_i c_{i,t-1} + \bar{Z}'_{it}\gamma\left(\bar{Z}'_{it}\mu - c_{i,t-1}\right) + w_{it}. \tag{4}$$

$\bar{Z}'_{it}$ is a vector of standardized marketing strategy (marketing policy) variables. Standardization offers the opportunity that one can pool different brands across categories and controls for unobserved fixed effects. The parameter δ_i captures the brand-specific repeat- purchase rate and γ and μ capture growth and market potential due to marketing effort, respectively; w_{it} is a random disturbance term.

Table 1
Creating lift or building the base

	$\gamma(L)=0$	$\gamma(L)>0$
$\beta(L)=0$	Ineffective marketing	Marketing builds the brand
$\beta(L)>0$	Marketing generates sales	Marketing generates sales and builds the brand

Source: adapted from Hanssens & Dekimpe (2008).

The marketing actions that build the brand are called marketing policies. Examples are investments in corporate and brand reputation, strategic entries in new markets (Pauwels & Hanssens, 2007), the introduction of new distribution channels (Deleersnyder, Gielens, Geyskens, & Dekimpe, 2002), new products, and quality improvements (Tellis & Johnson, 2007).

Hanssens and Dekimpe (2008) use four criteria as a guide to choose appropriate metrics. Metrics should:

- have financial relevance,
- be actionable: i.e., it must be possible, at reasonable cost, to collect data on the performance metric, and to relate it analytically to marketing investments,
- exhibit stable behavior, and
- offer reliable long-term guidance.

Highly volatile metrics are less desirable because they are difficult to interpret and manage. The leading indicator aspect of a metric is reflected in the criterion that the metric should have reliable long-term guidance, i.e., movements in the metric should be indicative of improving or deteriorating health for the brand or firm.

We distinguish four core metrics that can be used to specify the dependent variable S_{it} in Eq. (1). First, *sales* is a commonly used metric, for instance, to understand how marketing drives prescription drug sales (Fischer & Albers, 2007) or where the demand for a new product comes from (Albuquerque & Bronnenberg, 2007; Van Heerde, Srinivasan, & Dekimpe, 2008).

Second, a useful long-term metric is customer lifetime value and its firm-level aggregate, *customer equity*. Gupta, Lehmann and Stuart (2004) argue that customer equity can be used to value firms, and thus, to calculate the effect of marketing actions on shareholder value. Rust, Lemon, and Zeithaml (2004) and Donkers, Verhoef, and De Jong (2007) show how customer equity is affected by alternative marketing strategies.

A third metric is *brand equity*, the incremental cash flows that can be expected from carrying branded products instead of unbranded products (Simon & Sullivan, 1993). Pauwels, Nijs, and Srinivasan (2007) look at the effects of product-line decisions on brand equity, whereas Ataman, Van Heerde, and Mela (2007) consider the impact of all relevant marketing instruments.

A fourth metric is *stock market value*, which is frequently analyzed by VAR models. For example, Pauwels, Silva-Risso, Srinivasan and Hanssens (2004b) study the effects of new products and sales promotions, and Joshi and Hanssens (2008) assess the influence of advertising and R&D on the stock return of firms in the PC manufacturing and sporting goods industries. Other methodologies include event-studies for a single marketing initiative and regression-based stock return models. Event studies have looked, for example, at

[3] Instead of sales one can also work with revenues or stock prices.

the introduction of a new channel (Geyskens, Gielens, & Dekimpe, 2002), the entrance of a major retailer such as Wal-Mart (Gielens, Van de Gucht, Steenkamp, & Dekimpe, 2008), and the effects of the evaluation of new products that are evaluated in The Wall Street Journal on abnormal returns on stock prices (Tellis & Johnson, 2007). An example of a regression-based stock return model is the brand equity analysis in Rao, Agarwal and Dahlhoff (2004). Stock-market value receives much more attention nowadays than at earlier conferences on marketing dynamics (compare Pauwels et al., 2004a). Recent developments on stock markets, however, cast doubts on the use of this metric because stock prices might be more driven by market turbulences than by firm value.

2.2. Disentangling short-term and long-term effects

The VAR-X (Vector AutoRegressive with independent variables) model disentangles short-term from long-term movements (e.g., Dekimpe & Hanssens, 1999, 2000; Horváth, Leeflang, Wieringa, & Wittink, 2005). When the model variables are connected through a long-term equilibrium relationship, a VEC (Vector Error Correction) model is needed, which has recently gained popularity in marketing (Fok, Horváth, Paap, & Franses, 2006; Van Heerde, Helsen & Dekimpe, 2007; Van Heerde, Srinivasan & Dekimpe, 2008). Montoya, Netzer and Jedidi (2007) use Markov models to disentangle short- from long-term effects in the context of direct-to-physician marketing in the pharmaceutical industry.

Short- and long-term breaks in marketing metrics are often due to discrete (marketing) events such as the entry of a new product (Albuquerque & Bronnenberg, 2007; Van Heerde et al., 2008), the use of a new channel (Verhoef, Neslin & Vroomen, 2007), the introduction of a loyalty program (Leenheer et al., 2007) or its termination (Melnyk & Bijmolt, 2007). Recently, tests have been developed to find more than one break, where the breaks are determined endogenously (Kornelis, Dekimpe & Leeflang, 2008).

To disentangle cyclical or seasonal effects from short-term and long-term trends one can use a filter such as the Hodrick-Prescott filter (Hodrick & Prescott, 1997; see, for example, Deleersnyder, Steenkamp, Dekimpe & Leeflang, forthcoming; Leeflang et al., 2008).

2.3. Time-varying parameters

Not only can the base (intercept) parameter vary over time (Eq. (2)), other response parameters (β_{ik} in Eq. (1)) can evolve as well, due to marketing activities. Time-varying response parameters imply that the lift-effects of marketing instruments M_{kit} in Eq. (1) vary over time. There are different methods to account for time-varying parameters. One may perform simple analyses such as moving window regression (Mahajan, Bretschneider & Bradford, 1980) or piecewise regression (Parsons, 1975). In more recent research, the structural parameters are modeled as a function of relevant independent variables through process functions (Mela, Gupta & Lehmann, 1997; Foekens, Leeflang & Wittink, 1999). These models are also known as Time Varying Parameter Models (TVPM). In this context, Pauwels and Hanssens (2007) and Yoo and Hanssens (2008) specify performance regimes or windows of performance decline, stability and growth in sales and customer equity, respectively.

The most comprehensive methods to account for varying parameters over time are the Kalman-filtering and Dynamic Linear Models (DLM). Examples of marketing applications that use the Kalman-filter approach are Xie, Song, Sirbu, and Wang (1997), Naik, Mantrala, and Sawyer (1998), Cain (2005), Van Everdingen, Aghina, and Fok (2005), Kolsarici and Vakratsas (2007), Osinga et al. (2008), Sriram and Kalwani (2007) and Sriram, Chintagunta, and Neelamegham (2006).

DLMs are closely related to TVPMs and VAR models because they all have their roots in state-space modeling. State space models represent a large class of models in which the dynamic relationships between the variables of interest are expressed in two equations. The first equation, the measurement (or observation) equation, specifies how the vector of endogenous variables depends on the state of the system; see Eqs. (1) and (3). In the second equation, the transition (or state) equation, the evolution of the state vector is specified; see Eqs. (2) and (4) for examples. The generality of this type of model formulation is illustrated by the fact that it is possible to formulate state-space analogs of TVPMs and VARs (Ataman, 2007). The estimation of state-space models traditionally relies on frequentist statistical techniques, such as maximum likelihood. DLMs are Bayesian extensions of state space models. Like any other state space model, DLMs are derived from the Kalman filter. Specifically, Kalman filters are equivalent to the updating equations in a DLM (Ataman, 2007; Harrison & Stevens, 1976).

DLMs have the following desirable properties. First, the specification of DLMs allows for a single-stage analysis of long-term phenomena. For example, Eqs. (1) and (2) are estimated simultaneously instead of in two stages, leading to greater statistical efficiency (Van Heerde, Mela & Manchanda, 2004). Second, a DLM copes naturally with missing data arising from, e.g., product introductions or deletions. Third, the Bayesian nature also allows for inclusion of subjective data, which also means that forecasts can be produced with little or no past data. Finally, DLMs accommodate longitudinal as well as cross-sectional heterogeneity.

(i) Capitalizing on these advantages, recent DLM applications have provided fresh insights on: how a radical innovation affects market structure (Van Heerde et al., 2004);
(ii) how the preferences for product attributes evolve over time (Neelamegham & Chintagunta 2004);
(iii) how a product-harm crisis hurts marketing effectiveness (Van Heerde et al., 2007);
(iv) how to use the marketing mix to manage brand equity (Ataman, Van Heerde, & Mela, 2007);
(v) how the decomposition of the demand for a radical innovation varies over time (Van Heerde, Srinivasan, & Dekimpe, 2008);
(vi) what strategies build new brands (Ataman, Mela, & Van Heerde, 2008). The latter study concludes that distribution breadth is the single most important marketing mix instrument in both generating growth (relative effect of 32%) and building market potential (relative effect of 54%) for a new brand;
(vii) how the effects of advertising and word of mouth for new products (such as movies) evolve over sequential (such as theatre-then-video) distribution stages (Bruce & Foutz 2007).

These advantages come at the cost of high computational requirements. Estimating a DLM may take several hours or days, depending on the dimensionality of the problem. Furthermore, at present, few software packages include a DLM module, so that coding in a matrix language (e.g., Gauss, Matlab, Ox, and R) is required. While there has already been much attention for time-varying parameters and the disentangling of short-term and long-term effects at earlier conferences on marketing dynamics (see Pauwels et al., 2004a), based on the number of recent (published) papers we conclude that the interest in these topics has further increased.

2.4. Cross-sectional heterogeneity

Eqs. (1) and (2) allow for heterogeneous response parameters β_{ki} and γ_{ki}, i.e., they are specific to each unit (e.g., brand, store, or firm) i. Andrews, Currim, Leeflang and Lim (2008) investigate whether store-level heterogeneity in marketing mix effects improve the model accuracy (estimates, fit, prediction) of the widely applied SCAN*PRO model of store sales. Models with continuous and discrete representations of heterogeneity are empirically compared to the original, homogenous model. Contrary to expectations, accommodating store-level heterogeneity does not improve model accuracy. Horváth and Wieringa (2008) compare several VAR modeling approaches that accommodate different levels of heterogeneity. They conclude that random coefficient modeling is an overall appropriate technique when the VAR model is used for forecasting only.

3. Developments, trends and research needs

We now discuss trends, developments and research needs in modeling marketing dynamics. We use the papers of the conference as illustrations of these trends, and we present a summary table of these papers and related publications. In the final subsection, we specify our future outlook.

3.1. Marketing, revenues and firm value

There is increasing evidence that longer-term firm value is affected by marketing expenditures (Yoo & Pauwels, 2007). On the other hand, many corporate executives are concerned about shorter-term performance metrics. How to reconcile these seemingly contradictory behaviors is an interesting research avenue (Srinivasan & Hanssens, 2009). Osinga et al. (2008) investigated this issue in the pharmaceutical market. They developed a methodology that assesses the effect of direct-to-consumer-advertising (DTCA) on three components of shareholder value: stock return, systematic risk and idiosyncratic risk.

3.2. Normative studies

In general, most studies in marketing dynamics either focus on describing how marketing works (i.e., the exact effect of sales promotions), or what drives brand performance. However, there is an acute shortage of normative studies developing navigation systems that allow managers to optimize marketing efforts, or at least investigate what-if scenarios. Notable exceptions are Naik and Raman (2003) (the impact of synergy in multimedia communications) and Naik, Raman and Winer (2005). In the latter study, the optimal advertising and promotion budgets are determined. They observe that while some brands over-promote whereas others under-promote, all brands in their study under-advertise. Montoya, Netzer and Jedidi (2007) look at how long-term profitability can be managed through marketing-mix allocation. Normative studies are susceptible to the Lucas critique (see also Pauwels et al., 2004a; Van Heerde, Dekimpe & Putsis, 2005). The inclusion of varying parameters and a sharper distinction between short-term and long-term dynamics in structural models are some approaches used to deal with the Lucas critique.

3.3. Global models

Within the new-product-diffusion literature there has been ample attention devoted to understanding the drivers of adoption, new-product take-off and new product-growth across nations (e.g., Gielens & Steenkamp, 2007; Tellis, Stremersch & Yin, 2003; Stremersch & Tellis, 2004; Stremersch & Lemmens, 2009). However, in a globalizing economy we need to extend our knowledge on the short- and long-term effects of marketing efforts beyond western economies, especially with respect to the emerging economic giants China and India (Burgess & Steenkamp, 2006).

3.4. Inclusion of attitudinal (soft) data

Many models within the field of marketing dynamics are based on hard behavioral data. However, in the customer management and service marketing literature, models have been developed that link attitudinal data to both individual customer behavior (i.e., churn, customer share) and firm performance (Gupta & Zeithaml, 2006; Van Doorn & Verhoef, 2008). The inclusion of attitudinal data in dynamic models may be a fruitful new research direction given the increased availability of longitudinal attitudinal data due to continuous survey-research and CRM-systems (see also Dekimpe & Hanssens, 2000). For example, Knox and Van Oest (2007) model how complaints by consumers precede churn, while Venkatesan, Reinartz and Ravishanker (2008) show that detailing is more effective among physicians with positive attitudes towards the firm. Srinivasan, Vanhuele and Pauwels (2008) combine “soft” customer mindset metrics (awareness, affect and purchase consideration) with “hard” data (sales and marketing mix) in a joint VAR model.

3.5. Model development

Models within marketing dynamics have strongly evolved over time. Econometric regression-based models were most common until the mid-90s. Since the end of the 90s, time-series models (in particular VAR models) have become very influential, and recently, new Bayesian models and DLMs have entered the field and are gaining momentum. A particularly interesting development has been Bayesian state space models for non-metric dependent variables (e.g., Lachaab, Ansari, Jedidi, & Trabelsi, 2006). These models allow for the study of short- and long-term marketing effects on choices and other limited-dependent variables at the individual customer level, which is valuable for firms, yet has not been captured by traditional methods. Other model sophistications will emerge in the more distant future. However, we have some cautionary notes. First, the focus on model development should not be at the cost of a focus on the core issue of marketing dynamics: understanding and predicting the persistent impact of marketing efforts. Second, over-sophistication may hamper the diffusion of marketing models and knowledge into practice because the complexity may be higher than the perceived benefits (Roberts, Kayande & Stremersch, 2007). Thus, new methods should balance technical and insight contributions.

3.6. New applications

Pauwels et al. (2004a) review many examples of applications of dynamic models. The number of applications has increased over the last few years. The rise of the internet and the increasing availability of customer data due to CRM-systems have proven to be very fruitful research areas (e.g., Batislam, Deniziel & Filizetekin, 2007; Reimer, Rutz & Bucklin, 2007; Deleersnyder et al., 2002). The increasing use of new technologies where firms can observe product choice (i.e., MP3 music systems) provide great new data sources. For example, Chung, Rust and Wedel (2007) develop a model to optimize the music assortment for each individual customer.

Rapid changes in communications technology are creating communities of customers and prospects rather than a multitude of isolated customers. Consequently, “the Connected Customer” is MSI's overarching research theme for 2006–2008 (Marketing Science Institute, 2007). Within this theme, Van der Lans, Van Bruggen, Eliashberg, & Wierenga (2007) study the “hot topic” of viral marketing. A particularly promising approach to studying network effects is agent-based modeling (Jager, 2007). These models represent decision rules of agents in a virtual market. Next, by means of simulations, the consequences of alternative scenarios and marketing strategies can be assessed. For example, Delre, Jager, Bijmolt and Janssen (2007) use the agent-based approach to study alternative communication strategies for new product introductions. Goldenberg, Libai, Modovan, & Muller (2007) use agent-based models to assess the net present value of bad news in conjunction with a new-product introduction.

As marketing budgets gradually move to online media, there is a need for studies that assess the effects of these marketing efforts. The adoption of digital recorders (e.g., TIVO), where customers can watch television without exposure to commercials, will for instance change the allocation of advertising budgets over the media

Table 2
Overview of papers, Marketing Dynamics Conference

Marketing Dynamic Modeling Methodology	Examples of related published papers	Conference papers	Substantive insights from Conference paper
Regression models	Narayanan, Desiraju, and Chintagunta (2004)	Fischer and Albers (2007)	Physician-oriented marketing efforts are effective in increasing primary demand. Patient-oriented marketing efforts are not: they are effective in market stealing
	Tellis, Stremersch and Yin (2003)	Stremersch and Lemmens (2009)	Effects of regulation, national culture and economic wealth on international growth of new pharmaceuticals
	Foekens, Leeflang and Wittink (1994)	Andrews, Currim, Leeflang and Lim (2008)	Accommodating store-level heterogeneity in the SCAN*PRO model does not improve the accuracy of marketing-mix elasticities relative to the homogenous model
		Reimer, Rutz and Bucklin (2007)	Different marketing instruments (TV, Radio, print and Internet advertising) affect customer spending on music downloads differently
Time-series	Lamey, Deleersnyder, Dekimpe and Steenkamp (2007)	Deleersnyder, Steenkamp, Dekimpe and Leeflang (forthcoming)	This study investigates the cyclical nature of advertising expenditures for different countries
		Albuquerque and Bronnenberg (2007)	Combines time series with information on the distribution of consumer behavior variables to examine the effect of a new entrant on brand switching
VARX-models	Dekimpe and Hanssens (1999)	Horváth and Wieringa (2008)	Accuracy of impulse response functions and forecasting of various pooling approaches at different levels of heterogeneity
	Pauwels, Srinivasan and Franses (2007)	Yoo and Pauwels (2007)	There is stronger long-term response to price increases than to decreases
State-space-models: DLM	Villanueva, Yoo and Hanssens (2008)	Bruce and Foutz (2007)	Assessment of dynamic effects of WOM and advertising at different stages of sequentially distributed products
	Van Heerde, Mela and Manchanda (2004)	Van Heerde, Srinivasan and Dekimpe (2008)	Time-varying decomposition of the demand for a pioneering innovation into brand switching, category switching, and primary demand effects
		Ataman, Mela and Van Heerde (2008)	Diffusion model assessing the effects of different marketing launch strategies; distribution has largest impact on new brand success
Kalman filters		Osinga, Leeflang, Srinivasan and Wieringa (2008)	Direct-to-consumer advertising reduces systematic risk and increases idiosyncratic risk of stocks of pharmaceutical companies
Choice models	Gupta (1988); Van Heerde, Gupta and Wittink (2003)	Ebling and Klapper (2007)	The effect of past price promotions on current price sensitivities on purchase incidence, brand choice and quantity
	Bolton and Lemon (1999)	Prins, Verhoef and Franses (2007)	Early adopters tend to increase their post-adoption usage, while for late adopters the adoption usage decreases
	Bell and Lattin (1998); Leenheer et al. (2007)	Breugelmans and Zhang (2007)	Using data from an internet retailer, the authors study the effect of a category loyalty program on store visits, number of purchased items and total spending
		Bonfrer, Knox, Eliashberg and Chiang (2007)	Using a Brownian motion model, the authors show that the change in usage over time and variability in usage are important predictors of churn
		Van Diepen, Donkers and Franses (2007)	Direct mailing has short- and long-term impact on revenues, which also depend on competitor mailings
		Szymanowski and Gijsbrechts (2007)	Consumption of a private label brand leads consumers to update their beliefs about the quality of other private label brands
Spatial models		Hunneman, Bijmolt and Elhorst (2007)	Spatial model predicting store performance at the zip code level
Markov models	Paas, Vermunt and Bijmolt (2007)	Montoya, Netzer, and Jedidi (2007)	Hidden Markov model for dynamics in customer behavior and the long-term impact of marketing mix
		Van der Lans et al. (2007)	Markov process model predicting the number of participants in a viral marketing campaign
Agent-based models	Delre et al. (2007); Goldenberg et al. (2007)	Garcia (2007)	Studying market dynamics through a simulation model for manufacturer actions and consumer-level decision making

landscape. In sum, these new technologies will provide more time-series data, and may also reveal that certain traditional marketing efforts are losing their impact. At the same time, new marketing tactics will rise in application (online-advertising), which in turn calls for input from the marketing dynamics community to assess their impact.

3.7. Overview of conference papers

Table 2 gives a schematic overview of most papers presented at the 2007 Marketing Dynamics Conference and their substantive insights. We classify papers using different research methodologies/models. We also provide examples of related papers that have been published recently.

It is also interesting to note that several approaches and topics are absent or underrepresented in Table 2. Hazard models, purchase timing models, and structural models did not receive much explicit attention at the Groningen Marketing Dynamics Conference. This also holds for topics that drew more attention at earlier conferences and that deal with recent data richness: aggregation, level of parameterization and data pruning (Pauwels et al., 2004a).

3.8. Future outlook

In this section we abstract from the specific papers presented at the 2007 Marketing Dynamics conference by providing a helicopter view on where we believe the field of marketing dynamics is heading. A useful way to structure the discussion is to contrast four major approaches on a number of criteria. We include the three methods that have received ample attention in this article (VAR models, VEC models, State Space models), but also Dynamic Structural Models. These models are rooted in micro-economics and show how agents, on the demand side as well as the supply side, behave optimally in a context that involves dynamic relationships between variables. Chintagunta et al. (2006) and Sun (2006) provide an excellent overview of the type of marketing problems that can be studied with Dynamic Structural Models. We foresee that Dynamic Structural Models may grow in importance in the marketing literature in the future.[4]

[4] To capitalize on this expected trend, there will be a tutorial on Dynamic Structural Models taught by Jean-Pierre Dubé at the next Marketing Dynamics Conference (University of Waikato, New Zealand, 4–6 January 2009).

Table 3
Ratings of four core dynamic approaches on six criteria

Criterion Method	Disentangle temporary (short-term) from persistent (long-term) effects;	Time-varying parameters	Cross-sectional heterogeneity	Equilibrium modeling	Systems approach with many endogenous variables	Limited-dependent endogenous variables
Vector Autoregressive Model	+: based on impulse response functions	+/−: moving window approach possible, but requires proper window choice	−: leads to explosion in number of parameters	+/−: no explicit equilibrium but it can be added	+: key purpose	−: endogenous variables are continuous
Vector Error Correction Model	+: has separate parameters for short-term and long-term effects	+/−: moving window approach possible , but requires proper window choice	+: with Bayesian estimation	+: includes an equilibrium component	+/−: frequentist estimation faster than Bayesian estimation	−: endogenous variables are continuous
State Space Models (Kalman filters and DLMs)	+: observation equation for short-term effects and state equation for long-term effects	+: state equation is time varying	+/−: possible yet time-consuming with Bayesian estimation	−: does not include an equilibrium component	−: state space quickly becomes very large	+: use a nonlinear transformation in observation equation
Dynamic Structural Model	+: simulation for short- and long-term responses to policy changes	−: complicates deriving optimality conditions	+: micro-economic model at the firm or consumer level	+: the economic optimum is often an equilibrium	−: complicates deriving optimality conditions	+/−: deriving optimality is easier for continuous variables

It goes without saying that each of these four methods should capture appropriate metrics (the first criterion discussed in Section 2.1). To contrast the approaches, we select six criteria, three of which have been discussed previously (1–3) and three new ones (4–6) that are linked to model aspects we expect to be increasingly relevant in future studies in marketing dynamics:

1. disentangle temporary (short-term) from persistent (long-term) effects;
2. account for time-varying parameters;
3. allow for cross-sectional heterogeneity;
4. equilibrium modeling (i.e., including equilibrium as a model component, or deriving the full model as an equilibrium outcome);
5. systems approach (i.e., modeling relationships between many endogenous variables), and
6. limited-dependent (i.e., non-metric or non-continuous) endogenous variables. Examples include a binomial variable for purchase incidence, a multinomial variable for brand choice, a discrete variable for purchase quantity, a duration variable for interpurchase time, and other endogenous variables that are often (but not always) the result of modeling at the individual level.

Table 3 summarizes our (arguably personal) view on how well each method (in the rows) scores on the criteria (in the columns). We adopt a consumer-report style scale, with a "+" means it copes well, "−" means it copes poorly, and a "+/−" means it copes neither well nor poorly. Of course, these ratings are somewhat generalistic. They do not reflect the fact that, within some methods, there are already some developments that will eventually lead to better ratings on the criteria — after all, science evolves[5].

Table 3 shows that none of the methods dominates all others on all criteria. Choosing a suitable method thus depends on the purpose of each research study. All methods are suited for disentangling short- from long-term effects, but their philosophies are vastly different (see the second column of Table 3). If parameter variation over time is essential, State Space models are the most natural choice. However, these models are less suited to handle many endogenous variables, in which case a systems approach (VEC or especially VAR) becomes more desirable. On the other hand, allowing for cross-sectional heterogeneity in VAR models implies a separate model for each cross-sectional unit, which leads to an explosion in the number of parameters. The other approaches, especially when captured in a hierarchical Bayesian specification, seem more suited for handling cross-sectional heterogeneity.

When the research project involves an equilibrium around which the endogenous variables are evolving, and the researcher wants to make micro-economic assumptions on how this equilibrium is obtained, Dynamic Structural Models are the best option. If a researcher has fewer prior insights on the nature/existence of an equilibrium relationship between non-stationary variables, cointegration testing and (in case cointegration is present) VEC models can be used (Dekimpe & Hanssens, 1999, 2004). However, VEC models are not only appropriate in case of cointegrated, non-stationary variables. They can also be used to make the equilibrium underlying a set of stationary variables more explicit. We refer to Hendry (1995, Section 6.5) for an in-depth discussion, and to Fok et al. (2006), Van Heerde, Helsen and Dekimpe (2007) and Van Heerde, Srinivasan and Dekimpe (2008) for recent marketing applications using Bayesian estimation.

When the model involves limited-dependent endogenous variables (e.g., it is specified at the individual level), we recommend either a State Space Approach (without micro-economic assumptions) or a Dynamic Structural model (with micro-economic assumptions). We anticipate that, going forward, the relative importance of the criteria in Table 3 will determine how frequently the four different methods will be applied in studying dynamic marketing problems.

4. Conclusion

The fascinating field of marketing dynamics is developing rapidly. The issues that are tackled are typically highly relevant for senior management, the (modeling) challenges are intellectually stimulating, and the scope of new research opportunities is endless. The field attracts studies from all paradigms. For example, the 2007 Marketing Dynamics Conference featured not only aggregate time-series models, but also individual-level structural models (e.g., Kopalle, Neslin, Sun, Sun, & Swaminathan, 2007), consumer learning models (e.g., Szymanowski & Gijsbrechts, 2007; Lourenço, Gijsbrechts & Paap, 2007), and a latent Markov model for dynamic segmentation (Paas, Vermunt & Bijmolt, 2007). We anticipate that the study of marketing dynamics (as reflected in the 2007 Conference) will lead to several milestone papers in the marketing literature. We are confident that the exciting debate about modeling marketing dynamics will continue, not only in the academic journals, but in particular at future (Marketing Dynamics) conferences.

[5] For example, the VAR model may be extended to a Qual-VAR model that allows for binary endogenous variables and is estimated by MCMC methods (Joshi, 2007).

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