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Time-series models in marketing: Past, present and future

Marnik G. Dekimpe [a,*], Dominique M. Hanssens [b,1]

[a] Catholic University of Leuven, Naamsestraat 69, 3000 Leuven, Belgium

[b] The Anderson Graduate School of Management, University of California, Los Angeles, CA 90095-1481, USA

Abstract

Time-series methods have been available to explain and forecast the behavior of longitudinal variables for several decades. We first discuss why, at first, these methods received relatively little attention from marketing model builders and users. We then show how a number of obstacles to their more widespread use have recently been attenuated. Finally, we identify four developments that may significantly affect the future use of time-series techniques in marketing: the ever-increasing size of marketing data sets, the rate of change in the market environment, a growing interest in exploring the finance–marketing interface, and the emergence of Internet data sources.

Keywords: Market response models; Time-series analysis; Long-term marketing effects

1. Introduction

Leeflang and Wittink (2000) identify three past stages in marketing model building and implementation, review the current status, and provide some intriguing thoughts on how the model-building process may evolve in response to ongoing and anticipated developments in the marketing environment. It is interesting to note that *time-series* (*TS*) *techniques* are not mentioned in their review of the past, received considerable attention in their assessment of the current situation (mainly in the context of the insights these techniques can provide on marketing's long-run effectiveness), and are again absent in their speculations about the future. In this paper, we first discuss why, in the past, TS techniques received little attention from marketing model builders and users. Second, we show how each of the identified obstacles has recently been attenuated, and review recent TS contributions in marketing science. Finally, we elaborate on some expected future developments in marketing research, and discuss opportunities and continued challenges to applied TS modelers.

2. Past

A variety of TS techniques has been applied to marketing problems, mainly (a) for forecasting purposes, (b) to determine the temporal ordering among

* Corresponding author. Tel.: +32-16-326-957; fax: +32-16-326-732.

E-mail addresses: marnik.dekimpe@econ.kuleuven.ac.be (M.G. Dekimpe), dominique.hanssens@anderson.ucla.edu (D.M. Hanssens).

[1] Tel.: +1-310-525-4497; fax: +1-310-206-7422.

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some variables through Granger-causality tests, or (c) to determine the over-time impact of marketing variables (through transfer-function analysis) or of specific discrete events (through intervention analysis). A common characteristic of these studies is the *data-driven* approach to model specification: historically observed, often univariate, patterns are extrapolated to derive one- or multi-step forecasts, these same patterns are filtered out before cross-correlating the lagged values of the variables among which one wants to establish the causal (temporal) relationship, and no a priori functional form is imposed on the over-time impact of marketing control variables (as, e.g., the geometrically decaying pattern in the Koyck model). This form is identified instead on the basis of sample-based summary statistics as the auto-, cross- and cross-correlation function (see, e.g., Franses, 1998). An overview of TS studies which appeared over a 20-year time span (1975–1994) in the *International Journal of Research in Marketing*, *Journal of Marketing*, *Journal of Marketing Research*, *Management Science* and Marketing Science is given in Table 1.

In spite of these studies, it seems fair to say that TS analysis has yet to experience widespread acceptance in the marketing research community. Indeed, as early as 1976, more Koyck applications had already been identified in a meta-analysis of advertising effect duration (Clarke, 1976) than the 23 studies reported in Table 1.

We attribute the limited diffusion of TS concepts to several factors: (1) marketing scientists' lack of training in TS methods and access to user-friendly TS software, (2) a resistance to data-driven ap-

Table 1
Traditional time-series techniques in marketing

Study	Application area
Aaker et al. (1982)	Quantification of the sales-advertising dynamics when feedback relationships are present.
Bass and Pilon (1980)	Are market shares in a long-run equilibrium that is temporarily disturbed by marketing activities?
Carpenter et al. (1988)	Inclusion of dynamically-weighted attraction variables in market-share models.
Didow and Franke (1984)	Reliability and validity assessment in a time-series context.
Doyle and Saunders (1985)	The use of lead effects to capture the anticipations of consumers and other economic agents.
Doyle and Saunders (1990)	Transfer-function analysis to infer the dynamic impact of advertising campaigns.
Franses (1991)	Adding exogenous variables to the Autoregressive Moving-Average specification of a dependent performance variable.
Geurts and Ibrahim (1975)	Comparison of the univariate forecasting performance of Box–Jenkins and exponential smoothing.
Hanssens (1980)	Granger causality testing to identify competitive reaction patterns.
Helmer and Johansson (1977)	Transfer-function analysis to model the dynamic impact of advertising on sales.
Jacobson and Nicosia (1981)	Evaluation of the causal relationship between macro-advertising and aggregate consumption.
Kapoor et al. (1981)	Both deterministic and stochastic components are needed to model sales with pronounced, non-homogeneous seasonal patterns.
Krishnamurthi et al. (1986)	Using intervention analysis to assess the build-up effect of advertising in a field-experimental setting.
Leeflang and Wittink (1992)	The use of Granger-causality tests to reduce the information set in scanner environments.
Leone (1983)	Transfer-function analysis to quantify the over-time impact of own and competitive advertising on sales performance.
Moriarty (1985)	Decomposition of forecasting bias and development of a composite forecasting model from individual forecasts.
Moriarty (1990)	The use of boundary value models to combine forecasts.
Moriarty and Adams (1979)	Tests for a common structure in time-series models fitted to multiple brands, territories, ...
Moriarty and Adams (1984)	Combining management judgement forecasts with econometric and time-series forecasts.
Moriarty and Salamon (1980)	The use of seemingly unrelated time-series models to improve on the performance of univariate forecasting models.
Roy et al. (1994)	Granger-causality testing to identify leader–follower behavior in price setting.
Umashankar and Ledolter (1983)	How to improve the forecasting performance of univariate models by accounting for the contemporaneous correlations across the series.
Wichern and Jones (1977)	Intervention analysis to quantify the over-time impact on market shares of a discrete event.

proaches in model specification, (3) a lack of adequate data sources, and (4) the absence of a substantive marketing area where TS modeling was adopted as primary research tool.

First, while most marketing scientists are well trained in standard econometric and experimental-design techniques, only few have received a formal training in TS analysis. For example, of the 43 applicants for a tenure-track marketing position at UCLA in Fall 1996, only six (14%) had taken a graduate course in TS analysis, while 24 (56%) had received training in traditional econometrics and 28 (65%) in experimental-design methods. Furthermore, dedicated TS software was slow to develop, making the TS analytical tools less accessible to empirical researchers than other statistical procedures.

Second, TS techniques are data driven, and therefore said to “lack foundations in marketing theory” (Leeflang et al., 2000, p. 458). Many marketing researchers prefer to impose an a priori (supposedly theory-based) structure on the data, which could explain the frequent use of the Koyck model to capture lagged advertising effects.

Third, the application of TS techniques in marketing settings has been hampered by data limitations. Indeed, it is often easier for marketing researchers to obtain cross-sectional rather than longitudinal data sets. A major reason for the historical scarcity of longitudinal marketing data relates to the firms’ incentive and data collection systems. Managers typically have little incentive to build databases of historical performance and marketing effort for their products and services. Only current and future performance is rewarded, and many managers argue that as the market place is constantly changing, historical data are less relevant. In addition, assembling a data set of historical spending, pricing and performance used to require the retrieval of old accounting records. These were often highly aggregated, necessitating subjective allocations across time periods.

Fourth, unlike structural-equation modeling (LISREL) in the satisfaction and channel-relationships literature, or discrete-choice (logit/probit) models in the promotions literature, there was no single substantive marketing area where TS modeling was adopted as a logical, superior research tool. While several of the early applications considered the over-time effectiveness of marketing instruments (and specifically of advertising), econometric distributed-lag approaches remained far more popular.

3. Present

In recent years, these inhibiting factors have begun to disappear and marketing scientists now pay increasing attention to TS techniques. For example, the 2nd editions of two marketing-modeling textbooks (Hanssens et al., 2000, Chapters 5 and 6; Leeflang et al., 2000, Section 17.3) devote considerable more attention to TS techniques than their first editions. Similarly, the year 2000 marketing faculty applicant pool at UCLA that was trained in TS analysis rose to 21%. On the software side, several user-friendly PC-based packages such as EViews, Forecast Pro and SCA were brought to market that significantly facilitate the implementation of TS techniques.

As for the a-theoretical character of the approach, two recent developments offer more of a confirmatory potential: cointegration analysis (cf. infra) allows to test for the existence of theoretically-based equilibrium relationships between stochastically-trending variables, while structural VARX models (see, e.g., Pesaran and Smith, 1998) are specifically designed to supplement sample-based information with managerial judgement and/or marketing theory. These two developments are expected to give TS techniques more credibility, even though all current applications of cointegration analysis are still exploratory, rather than confirmatory, in nature (i.e., one tests for the existence of a long-run equilibrium relationship rather than for the presence of a *specific*, theory-derived, relationship). We are not yet aware of marketing applications of theory-driven structural VARX models. Apart from these two advances, we note a growing openness in the marketing community towards empirical generalizations (EGs) derived through the repeated application of data-driven techniques to multiple data sets (see, e.g., the 1995 special issue of *Marketing Science*).

Third, the advent of new data sources based on the automatic, real-time recording of purchase or consumption transactions, as opposed to the retrieval of old accounting records, significantly affects the potential of TS techniques in marketing. The cross-

Table 2
Application of long-run time series concepts in marketing

Study	Sample length (years)	Temporal aggregation	Entity aggregation	Contribution
Baghestani (1991)	54	annual	Sales	Advertising has a long-run impact on sales if both variables are (a) evolving and (b) in long-run equilibrium (cointegrated).
Bronnenberg et al. (2000)	5	weekly	Market share	Distribution coverage drives long-run market shares, especially the coverage evolution early in the life cycle.
Chowdhury (1994)	32	annual	Macro-variable	No long run equilibrium (cointegration) relationship is found between UK aggregate advertising spending and a variety of macro-economic variables.
Dekimpe and Hanssens (1995a)	6.3	monthly	Industry Sales (Chain Level); Sales	Persistence measures quantify marketing's long-run effectiveness. Image-oriented and price-oriented advertising messages have a differential short- and long-run effect.
Dekimpe and Hanssens (1995b)	–	–	–	Sales series are mostly evolving, while a majority of market-share series is stationary.
Dekimpe and Hanssens (1999)	5; 4.4	monthly	Sales	Different strategic scenarios (business as usual, escalation, hysteresis and evolving business practice) have different long-run profitability implications.
Dekimpe et al. (1999)	2.2	weekly	Industry Sales; Sales	Little evidence of long-run promotional effects is found in FPCG markets.
Dekimpe et al. (1997)	1 or 2	monthly and bimonthly	Estimated Brand Loyalty (Sales)	New product introductions may cause structural breaks in otherwise stationary loyalty patterns.
Franses (1994)	29	annual	Industry Sales	Gompertz growth models with nonconstant market potential can be written in error–correction format.
Franses et al. (1999)	2.2	weekly	Market Share	Outlier-robust unit-root and cointegration tests are called for in promotion-intensive scanner environments.
Franses et al. (2000)	2	weekly	Market Share	Unit root and cointegration tests which account for the logical consistency of market shares.
Hanssens (1998)	3.7	monthly	Sales	Factory orders and sales are in a long-run equilibrium, but shocks to either have different long-run consequences.
Hanssens and Ouyang (2000)	5	monthly	Sales	Derivation of advertising allocation rules (in terms of triggering versus maintenance spending) under hysteresis conditions.
Johnson et al. (1992)	28	annual	Industry Sales	The long-run consumption of alcoholic beverages is not price sensitive.
Jung and Seldon (1995)	42	annual	Macro-variable	Aggregate US advertising spending is in long-run equilibrium with aggregate personal consumption expenditures.
McCullough and Waldon (1998)	34	annual	Macro-variable	Network and national spot advertising are substitutes.
Nijs et al. (2000)	4	weekly	Industry Sales	Limited long-run category expansion effects of price promotions. The impact differs in terms of the marketing intensity, competitive structure, and competitive conduct in the industry.
Pauwels et al. (2000)	2.2	weekly	Sales; Industry Sales	The decomposition of the promotional sales spike in category-incidence, brand-switching and purchase-quantity effects differs depending on the time frame considered (short versus long run).
Srinivasan and Bass (2000)	2	weekly	Market Share; Sales; Industry Sales	Stable market shares are consistent with evolving sales if brand and category sales are cointegrated.
Srinivasan et al. (2000)	7	weekly	Market Share	Temporary, gradual and structural price changes have a different impact on market shares.
Zanias (1994)	27	annual	Sales	Feedback effects occur between sales and advertising. The importance of cointegration analysis is demonstrated with respect to Granger-causality testing and multi-step forecasting.

sectional heterogeneity of these databases has led to many effectiveness and segmentation studies, at the level of brand choice, purchase quantity and purchase timing (see Section 3.2 of Leeflang and Wittink, 2000 for a review). Over time, these databases started to cover longer time spans, which made it possible to also study their longitudinal dimension using TS techniques.[2]

Fourth, we have seen the development of techniques specifically designed to disentangle short- from long-run movements: unit-root tests, cointegration and error–correction modeling, and persistence estimation.[3] This provided a natural match between TS analysis and one of marketing's long-lasting interest fields: quantifying the *long-run* impact of marketing's tactical and strategic decisions. In Table 2, we review marketing applications of these long-run techniques, focusing on relevant data dimensions (cf. infra) and the substantive findings of each study.

The main contribution of the earlier studies was to demonstrate how these TS concepts could quantify marketing's long-run impact (e.g., Baghestani, 1991, on cointegration analysis and Dekimpe and Hanssens, 1995a, on persistence modeling). These studies were descriptive in nature, considered a single data set, and applied TS tests that were drawn from other disciplines such as econometrics and statistics. More recent work has matured along three dimensions: (1) EGs are derived from multiple product categories, and the observed variability in short- and long-run effectiveness estimates is related to theory-based descriptors (see, e.g., Nijs et al., 2000; Pauwels et al., 2000; Srinivasan et al., 2000), (2) marketing theory is developed (e.g., Bronnenberg et al., 2000) and normative guidelines for marketing spending in evolving environments are derived (e.g., Hanssens and Ouyang, 2000), and (3) statistical tests are designed to deal with some unique characteristics of marketing data sets, such as the logical consistency requirement in market-share models (Franses et al., 2000) and the presence of multiple outliers in promotion-intensive scanner environments (Franses et al., 1999).

4. Future

We have described four developments that contributed to the recent surge in interest for TS techniques in marketing. We now identify several expected future developments, and discuss the potential opportunities and/or threats they offer to the continued use of TS techniques in applied marketing research. In turn, we consider (1) the expanding size of data sets, (2) the accelerating rate of change in the market environment, (3) the opportunity to study the marketing–finance relationship, and (4) the emergence of internet data sources.

4.1. Larger data sets

The shift from a period of scarce and highly aggregated data to more abundant, disaggregated data was identified as one of the main drivers for the growing popularity of TS techniques in marketing. The question emerges, however, whether a continued evolution towards ever-growing data sets will remain a blessing. To focus our discussion, we consider four dimensions along which marketing data sets tend to grow: more variables, for which information is available over longer time spans, at a smaller level of both temporal and entity aggregation.

4.1.1. Number of variables

Traditionally, TS modelers were able to analyze the over-time impact of one or two marketing-mix variables (often advertising and/or price), and competitive information was, at best, available for a limited set of players or for the combined competition. In scanner data sets, price, feature, display, ... information is available for all players in the market, even at the SKU level, resulting in a vastly increased information set. Given that the causal ordering among all these variables tends to be unknown, we expect a growing use of Granger-causality tests to empirically determine exclusion restrictions (see, e.g., Leeflang and Wittink, 1992). Most Granger-causality tests in marketing are of a bivariate nature, however, which

[2] See, e.g., Bronnenberg et al. (2000), Dekimpe et al. (1999), Franses et al. (1999), Nijs et al. (2000), Pauwels et al. (2000), Srinivasan and Bass (2000) for recent time-series applications on scanner data.,

[3] Because of space limitations, no technical details on these techniques are provided. We refer the reader to Franses (1998) for a recent review, or to Bronnenberg et al. (2000) and Dekimpe and Hanssens (1999) for expositions in a marketing context.

may lead to the erroneous neglect of some key influencing variables. It may, therefore, be advisable to test for Granger causality in higher-dimension models, but a trade-off has to be made between parsimony considerations and potential misspecification biases.

In addition, Granger-causality tests are well suited to test for temporal precedence between different variables, but cannot identify the direction of instantaneous relationships. Yet, these are the relevant restrictions needed to identify structural VARX models (Pesaran and Smith, 1998). A popular identification procedure in marketing has been the a priori imposition of a causal ordering on the variables, thereby making the system recursive (see, e.g., Bronnenberg et al., 2000; Dekimpe and Hanssens, 1995a). However, a unique recursive system is harder to defend when the information set becomes larger. In that case, the multivariate normality property of the VAR residuals can be used to derive the expected instantaneous values for the other variables once the focal variable is shocked (Dekimpe and Hanssens, 1999).

The large set of potentially relevant variables may not only pose problems in the specification of the instantaneous and short-run dynamics, they may also make the application and direct interpretation of cointegration, and hence long-run, estimates more difficult.[4] Indeed, up to $N-1$ cointegrating relationships (some of which can have opposite signs) may be found if the information set contains N unit-root series. An often-used pragmatic solution is to pick the cointegrating vector corresponding to the largest eigenvalue in Johansen's FIML approach (see, e.g., Johansen and Juselius, 1990; Nijs et al., 2000),[5] or one could try to impose (test) theory-based restrictions on some of the cointegrating coefficients. In competitive settings, however, few theoretical insights are available to help in this exercise.

The information set may not only be extended along the usual dimensions, such as more detailed marketing-mix control variables for a larger and more detailed set of competitors. Another potentially interesting data development is the emergence of TS of attitudinal variables that can be matched with transactional observations. In the past, attitudinal data such as awareness and preference were collected infrequently, and it was impossible to use the power of modern TS techniques on such variables. Some industries and specific companies have now begun to build tracking databases of attitudes and preferences. For example, banks can use teller, telephone or computer transaction occasions as opportunities to gauge key customer attitudes such as satisfaction. Hanssens (1998) used a TS of inferred consumer preference from conjoint measurement to estimate the elasticity of sales with respect to customer-defined product quality. Even though the collection of prolonged, equally spaced attitudinal data may pose some additional challenges (e.g., in terms of costs, panel attrition, and error structures inherent in those kinds of data[6]), we feel these expanded behavioral/attitudinal databases will raise new and important research questions, such as: Are there long-term sales consequences of short-lived customer dissatisfaction? Are there threshold values of awareness that are associated with long-term sales growth? Is there an equilibrium between customer attitudes and sales performance?

4.1.2. Length of the time span

As marketing data capture becomes automated and virtually costless, longer TS will become available for research.[7] This offers substantial opportunities. First, as the sample properties of the parameter estimates improve, so does the reliability and precision of our insights. Second, we can make more powerful strategic inferences on certain marketing

[4] Lutkepohl and Reimers (1992), therefore, advocate the use of impulse–response functions and the associated persistence estimates to circumvent this interpretational issue.

[5] This eigenvalue corresponds to the square of the largest canonical correlation between the following two sets of variables: (a) the original, evolving variables, and (b) their stationary first differences. In cointegration analyses, one tries to determine which linear combinations between evolving variables are stationary. The linear combination that has the highest correlation with the set of stationary first differences is a prime candidate.

[6] See, e.g., Dall'Olmo Riley et al. (1997).

[7] As indicated in Table 2, some prior studies already had access to long (multiple-decade) time series, in which case the data were invariably aggregated to the annual level. In the future, we expect long time spans of temporally disaggregated data to become available (see also Section 4.1.3).

actions, as we gain a better understanding of their long-term, perhaps irreversible, impact. Third, we can better explore changes in regimes, be it in the business environment itself or in the role of marketing. The latter issue is especially important to reconcile statistical and managerial considerations when trying to make inferences about marketing's long-run effectiveness. Too short a time period may make it more difficult to distinguish spurious from true long-run fluctuations (see, e.g., Hakkio and Rush, 1991), while too long a time span may affect the managerial relevance of the findings, and make the constant-parameter assumption used in most TS models harder to defend.

Moving-window regression and VAR models, as well as time-varying parameter models, are ideally suited to exploit the advantages of longer time spans (see Bronnenberg et al., 2000, for a recent marketing application). With the estimation technology firmly in place, we are optimistic about the potential for new marketing knowledge generated from long-time-span studies. As an example, we may want to revisit product life cycle and diffusion-of-innovation theory with these powerful methods. Do the traditional definitions of "introduction", "growth", "maturity" and "decline" stages pass some rigorous TS tests on evolution vs. stability? Or do we need new stage definitions that are more in line with the changing role of word-of-mouth, marketing and competition over time?

4.1.3. Level of temporal aggregation

Growth of marketing databases will also occur through finer time grids. While previous studies often used quarterly or monthly data, we see a recent movement towards weekly observations (see Table 2). As reviewed in Leeflang and Wittink (2000), this development resulted, for instance, in a more accurate estimation of post-promotional dips and competitive reaction patterns, phenomena which are harder to detect with temporally aggregated data.

We expect even further refinements in terms of the level of temporal aggregation in the near future. One example in this respect is the recent transfer-function analysis of the hourly effects of direct-response television advertising, the first study to identify peaks and declines in advertising effects within the same day (Tellis et al., 2000). These databases offer unique opportunities for the study of fast, tactical adjustments in the marketing-mix, and can be expected to have a major impact on the practice of ad copy development and replacement and price promotion management, especially in the direct-marketing arena. At the same time, we will learn to what extent superiority in tactical execution creates long-term strategic advantages for marketers. From an estimation perspective, one can of course apply the different techniques to these micro-grid databases, but care should be exercised to ensure a "logical correspondence" between the frequency of sampling and the rate of change in the phenomenon at hand. For instance, to assess whether the diaper market is stable or evolving, sampling on an hourly basis does not increase the reliability of unit-root and cointegration tests (see the statistical-power discussion in Hakkio and Rush, 1991), nor does it offer additional managerial insights. To analyze eye-movement data, in contrast, finer sampling is called for to study the intricacies of the dynamic inter-relationships.

4.1.4. Level of entity aggregation

Data now become available at more disaggregate levels, i.e. at the individual consumer, SKU and/or store level. TS studies have traditionally worked with more aggregated variables (cf. Table 2), the appropriateness of which can be questioned given recent evidence that this may lead to biased estimates in case of heterogeneity in consumer preferences and/or marketing-mix activity across stores (cf. Leeflang and Wittink, 2000, Section 3.5). This evidence, however, has mostly focused on short-run response parameters, and more research is needed to assess the sensitivity of long-run inferences to aggregation biases.[8]

[8] The currently available evidence is mixed. Pesaran and Smith (1995) illustrate the sensitivity of cointegration tests when aggregating across heterogeneous panels. They show that, even when each micro-relationship is cointegrated, the aggregate relationship may not reflect a long-run equilibrium when there is heterogeneity in the micro-level cointegration coefficients. Nijs et al. (2000), on the other hand, apply a nonlinear (log–log) model to linearly aggregated data (aggregated across stores), and find the impulse–response functions to be highly correlated with the ones obtained from the more robust (in terms of aggregation bias) linear model. This result is encouraging, especially in light of the observation that many TS modelers work in log–log form to obtain direct elasticity estimates.

Entity disaggregation may reflect a movement towards more analyses at the individual-*store* or *SKU* level, in which case traditional "aggregate" TS techniques can still be applied, or at the individual-*consumer* (household) level, where individual-choice models seem more appropriate. Indeed, weekly data on the purchases of an individual household may predominantly contain zeros, interrupted by an occasional positive spike, making them less appealing to TS analysts. While this evolution may not seem to bode well to TS modelers, it is interesting to note that recent developments in the individual-choice literature try to integrate the dynamic flexibility of TS techniques into multinomial logit and probit models (see especially the work of Haaijer and Wedel, 1999, and Paap and Franses, 1999). Similarly, Steenkamp and Baumgartner (2000) show how the application of structural equation models to longitudinal data may involve the integration of TS concepts.

In combination, these different data developments will create great opportunities for applied TS modelers and users, and they will also create new challenges. For instance, even though attitudinal data become easier to collect on an ongoing basis, TS' requirement to have a sufficiently long sequence of equally spaced observations within and across series will pose implementation difficulties in terms of costs, panel composition and panel attrition. Also, after a period of data scarcity, TS modelers in marketing are now faced with the unfamiliar problem of selecting what information to use or to discard, in terms of what variables to incorporate in the information set and at what level of entity aggregation, and in terms of what historical time span to consider. On both dimensions, more research is needed on how to make the most appropriate trade-off between statistical-power and managerial-relevance considerations.

4.2. Rapidly changing market environment

In the past, product markets evolved relatively slowly. For example, we observe 30 to 40 years elapsed between introduction and maturity for major household appliances launched in the 1930s. Marketing-mix models were therefore built on time samples that constituted only a fraction of the evolutionary cycle, and often appeared stationary. Indeed, most of the scholarly knowledge base of market response has been developed on databases that were assumed to be stationary, i.e., the variables have constant means and variances, so that traditional estimators can be applied. As a result, we know a great deal about short-term marketing-mix elasticities and their determinants, but relatively little about how the marketing-mix functions in a nonstationary (trending) environment.

The new reality of marketing decisions operates much more in rapidly changing and turbulent environments, or at least such is assumed by the market participants, who are typically accountable for *growth* in performance. Even relatively short time windows, say 1 to 2 years of weekly data, are now sufficient to capture most of the relevant evolution of a product, and the assumption of stationarity in the data will increasingly become untenable. An empirically-tested knowledge base can and should develop that accounts for marketing's role over the entire life of a product.

One area of study that will be affected significantly is competitive reaction. A recent meta-analysis on 560 product categories established that the predominant form of competitive reaction to price promotions is *no reaction* (Nijs et al., 2000). Can such a finding, based on data from the 20th Century, be expected to hold in the high-information context of the 21st Century? Our casual observation of the competition between book e-tailers Amazon and Barnes and Noble suggests otherwise. For example, when Amazon recently announced a substantial discount on its best-seller books, Barnes and Noble matched the discount within hours. Similar fast reactions are now routinely observed in the airline industry. While game theory has developed the principles of optimal strategic behavior with competition, its empirical knowledge base is small, and we conjecture that much will be learned by empirically examining game-theoretic principles in the context of fast-changing markets.

4.3. Exploring the marketing–finance relationship

The goals of marketing have traditionally been formulated from a customer perspective. However, there is a growing interest in expanding this view to include the investor or shareholder perspective, in such a way that the separated disciplines of marketing and finance may serve a common purpose (see, e.g. Doyle, 2000). The finance discipline, with its inherent focus on growth and the valuation of assets over time, has long embraced TS analytic techniques. However, the finance literature has only rarely examined how marketing actions affect the valuation of the firm, the exception being some work on the effects of new-product announcements and brand equity on stock prices. Recent work has established that marketing investments in advertising, promotions and product improvement can have a long-term impact on sales, and therefore cash flows and profits. On the other hand, such marketing investments are costly and may have a negative impact on short-term profit streams. Thus, the important question arises to what extent the investor community either rewards or punishes firms for engaging in these marketing activities. Given that firm valuation data are widely available over long TS, that question may be addressed by expanding the scope of TS models with a firm valuation measure.

4.4. The emergence of Internet data sources

Last, but not least, we address the potential offered by Internet databases, and its impact for TS research in marketing. These databases are likely to make the developments in previous sections even more prominent. Indeed, they allow to easily integrate transactional and attitudinal data (cf. Section 4.1.1), and to quickly create high-frequency data (Section 4.1.3) at the individual-consumer level (Section 4.1.4). As such, Internet data will easily and rapidly build up to long TS (Section 4.1.2) with substantial cross-sectional detail. In much the same vein as we can currently track weekly sales performance, we will be able to track weekly, or even daily, changes in consumer interest (e.g., number of Web site visits), shopping intensity (derived from visitation patterns), and first-time and repeat purchases, not only at the aggregate level, but also at the individual-consumer level. These data can be supplemented with frequent Web enabled market research studies on customer satisfaction, usage rates and future purchase intentions. The resulting databases set up a rich laboratory for experimentation. For example, TS models can be used to infer the long-term effect of an awareness or preference increase on the revenue and profitability of a brand (Section 4.3). Internet data will also enable a more detailed understanding of the dynamics of consumer choice, as they will quickly generate sufficient degrees of freedom to integrate TS techniques with existing logit/probit specifications (cf. Section 4.1.4).

The Internet will not only create vaster and more detailed data sets, it is also expected to cause a faster diffusion of new ideas and more turbulent competitive environments (Section 4.2). Moreover, as Leeflang and Wittink (2000) correctly point out, to many firms and industries, it will create a radical break in the way business is conducted, both in terms of the channel relationships with suppliers and intermediaries, and in terms of interactions with customers. From a TS perspective, these abrupt and radical changes pose both challenges (e.g., how to merge pre- and post-Internet performance and control series) and opportunities, especially in light of the recent developments on structural-break unit-root and cointegration tests (see Maddala and Kim, 1998, for a review). Indeed, the constant-parameter assumption in many persistence-based models may no longer be appropriate to test the long-run implications of Internet-related decisions. Instead, structural-break analyses will likely be needed to determine whether, for instance, the introduction of a dual, Internet-based, distribution channel elevated stationary category sales to a new and higher level, cannibalized existing revenue streams and/or affected prevailing competitive reaction patterns.

5. Conclusions

In the past, TS models have had limited use in marketing science because adequate data sources, doctoral-level training and user-friendly software were scarce, because researchers were reluctant to embrace a data-driven approach to model specification, and because a unique marketing problem that demands a TS approach was lacking. Recent developments have attenuated these obstacles. Most notably, scanner data covering longer time spans have become available, and much progress has been made on the important yet difficult problem of assessing long-term marketing effectiveness.

As a scientific method for inferring and forecasting longitudinal behavior, TS analysis is well suited for a discipline where a large number of repeated, equal-interval data are available. The most productive use of TS models in marketing science is therefore expected to lie ahead, given the recent growth of marketing databases in various directions. This outlook is expected to be accelerated by the emergence of internet databases. Furthermore, as product life cycles shorten and market environments change more rapidly, models of evolution become critical to shape our understanding of the drivers of market performance, and how it in turn influences the valuation of the firm. Finally, while TS analysis has already demonstrated, and will continue to do so, its value on aggregated data, we expect to see more TS concepts used at the micro-level, such as in individual-choice and structural-equation models. We are therefore confident that, for TS modelers in marketing science, the best is yet to come.

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References

Aaker, D.A., Carman, J.M., Jacobson, R., 1982. Modeling advertising–sales relationships involving feedback: A time-series analysis of six cereal brands. Journal of Marketing Research 19, 116–125.

Baghestani, H., 1991. Cointegration analysis of the advertising–sales relationship. Journal of Industrial Economics 34, 671–681.

Bass, F.M., Pilon, T.L., 1980. A stochastic brand choice framework for econometric modeling of time series market share behavior. Journal of Marketing Research 17, 486–497.

Bronnenberg, B.J., Mahajan, V., Vanhonacker, W.R., 2000. The emergence of market structure in new repeat-purchase categories: The interplay of market share and retailer distribution. Journal of Marketing Research 37, 16–31.

Carpenter, G.S., Cooper, L.G., Hanssens, D.M., Midgley, D.F., 1988. Modeling asymmetric competition. Marketing Science 7, 393–412.

Chowdhury, A.R., 1994. Advertising expenditures and the macro-economy: Some new evidence. International Journal of Advertising 13, 1–14.

Clarke, D.G., 1976. Econometric measurement of the duration of advertising effect on sales. Journal of Marketing Research 13, 345–357.

Dall'Olmo Riley, F., Ehrenberg, A.S.C., Castleberry, S.B., Barwise, T.P., Barnard, N.R., 1997. The variability of attitudinal repeat rates. International Jounal of Research in Marketing 14, 437–450.

Dekimpe, M.G., Hanssens, D.M., 1995a. The persistence of marketing effects on sales. Marketing Science 14, 1–21.

Dekimpe, M.G., Hanssens, D.M., 1995b. Empirical generalizations about market evolution and stationarity. Marketing Science 14, G109–G121.

Dekimpe, M.G., Hanssens, D.M., 1999. Sustained spending and persistent response: A new look at long-term marketing profitability. Journal of Marketing Research 36, 397–412.

Dekimpe, M.G., Steenkamp, J.-B.E.M., Mellens, M., Vanden Abeele, P., 1997. Decline and variability in brand loyalty. International Journal of Research in Marketing 14, 405–420.

Dekimpe, M.G., Hanssens, D.M., Silva-Risso, J.M., 1999. Long-run effects of price promotions in scanner markets. Journal of Econometrics 89, 269–291.

Didow, M.N., Franke, G.R., 1984. Measurement issues in time-series research: Reliability and validity assessment in modeling the macroeconomic effects of advertising. Journal of Marketing Research 21, 12–19.

Doyle, P., 2000. Value-Based Marketing. Wiley, New York, in press.

Doyle, P., Saunders, J., 1985. The lead effect of marketing decisions. Journal of Marketing Research 22, 54–65.

Doyle, P., Saunders, J., 1990. Multiproduct advertising budgeting. Marketing Science 9, 97–113.

Franses, P.H., 1991. Primary demand for beer in the Netherlands: An application of ARMAX model specification. Journal of Marketing Research 28, 240–245.

Franses, P.H., 1994. Modeling new product sales; an application of cointegration analysis. International Journal of Research in Marketing 11, 491–502.

Franses, P.H., 1998. Time Series Models for Business and Economic Forecasting. Cambridge University Press, Cambridge, UK.

Franses, P.H., Kloek, T., Lucas, A., 1999. Outlier robust analysis of long-run marketing effects for weekly scanner data. Journal of Econometrics 89, 293–315.

Franses, P.H., Srinivasan, S., Boswijk, P., 2000. Testing for unit roots in market shares. Working Paper, Erasmus University Rotterdam, Rotterdam, Netherlands.

Geurts, M.D., Ibrahim, I.B., 1975. Comparing the Box–Jenkins approach with the exponentially smoothed forecasting model: Application to Hawaii tourists. Journal of Marketing Research 12, 182–188.

Haaijer, R., Wedel, M., 1999. Habit persistence in time series models of discrete choice. Working Paper, University of Groningen, Netherlands.

Hakkio, C.S., Rush, M., 1991. Cointegration: How short is the long run. Journal of Econometrics 10, 571–581.

Hanssens, D.M., 1980. Market response, competitive behavior and time series analysis. Journal of Marketing Research 17, 470–485.

Hanssens, D.M., 1998. Order forecasts, retail sales, and the marketing mix for consumer durables. Journal of Forecasting 17, 327–346.

Hanssens, D.M., Ouyang, M., 2000. Modeling marketing hysteresis. Working Paper, University of California, Los Angeles, CA.

Hanssens, D.M., Parsons, L.J., Schultz, R.L., 2000. Market Response Models. 2nd edn. Kluwer Academic Publishers, Boston, MA.

Helmer, R.M., Johansson, J.K., 1977. An exposition of the Box–Jenkins transfer function analysis with an application to the advertising–sales relationship. Journal of Marketing Research 14, 227–239.

Jacobson, R., Nicosia, F.M., 1981. Advertising and public policy: The macroeconomic effects of advertising. Journal of Marketing Research 18, 29–38.

Johansen, S., Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration with applications to the demand for money. Oxford Bulletin of Economics and Statistics 52, 169–210.

Johnson, J.A., Oksanen, E.H., Veal, M.R., Frets, D., 1992. Short-run and long-run elasticities for Canadian consumption of alcoholic beverages: An error-correction mechanism/cointegration approach. The Review of Economics and Statistics 74, 64–74.

Jung, C., Seldon, B.J., 1995. The macroeconomic relationship between advertising and consumption. Southern Economic Journal 61, 577–588.

Kapoor, S.G., Madhok, P., Wu, A.M., 1981. Modeling and forecasting sales data by time series analysis. Journal of Marketing Research 18, 94–100.

Krishnamurthi, L., Narayan, J., Ray, S.P., 1986. Intervention analysis of a field experiment to assess the buildup effects of advertising. Journal of Marketing Research 23, 337–345.

Leeflang, P.S.H., Wittink, D.R., 1992. Diagnosing competitive reactions using aggregated scanner data. International Journal of Research in Marketing 9, 39–57.

Leeflang, P.S.H., Wittink, D.R., 2000. Building models for marketing decisions: Past, present and future. International Journal of Research in Marketing 17, 105–126 (this issue).

Leeflang, P.S.H., Wittink, D.R., Wedel, M., Naert, P., 2000. Building Models for Marketing Decisions. Kluwer Academic Publishers, Dordrecht, Netherlands.

Leone, R.P., 1983. Modeling sales–advertising relationships: An integrated time-series econometric approach. Journal of Marketing Research 20, 291–295.

Lutkepohl, H., Reimers, H.E., 1992. Impulse response analysis of cointegrated systems. Journal of Economic Dynamics and Control 16, 53–78.

Maddala, G.S., Kim, I.-M., 1998. Unit Roots, Cointegration, and Structural Change. Cambridge University Press, Cambridge, UK.

McCullough, B.D., Waldon, T., 1998. The substitutability of network and national spot television advertising. Quarterly Journal of Business and Economics 37, 3–15.

Moriarty, M.M., 1985. Design features of forecasting systems involving management judgments. Journal of Marketing Research 22, 353–364.

Moriarty, M.M., 1990. Boundary value models for the combination of forecasts. Journal of Marketing Research 27, 402–417.

Moriarty, M.M., Adams, A.J., 1979. Issues in sales territory modeling and forecasting using Box–Jenkins analysis. Journal of Marketing Research 16, 221–232.

Moriarty, M.M., Salamon, G., 1980. Estimation and forecasting performance of a multivariate time series model of sales. Journal of Marketing Research 21, 239–250.

Moriarty, M.M., Adams, A.J., 1984. Management judgment forecasts, composite forecasting models, and conditional efficiency. Journal of Marketing Research 21, 239–250.

Nijs, V.R., Dekimpe, M.G., Steenkamp, J.-B.E.M., Hanssens, D.M., 2000. The category demand effects of price promotions. Working Paper, Catholic University Leuven, Belgium.

Paap, R., Franses, P.H., 1999. Estimating dynamic effects of promotions on brand choice. Working Paper, Erasmus University Rotterdam, Netherlands.

Pauwels, K., Hanssens D.M., Siddarth, S. 2000. The long-term effect of price promotions on category incidence, brand choice and purchase quality. Working Paper, University of California, Los Angeles, CA.

Pesaran, M.H., Smith, R.P., 1995. Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics 68, 79–113.

Pesaran, M.H., Smith, R.P., 1998. Structural analysis of cointegrating VARs. Journal of Economic Surveys 12, 471–505.

Roy, A., Hanssens, D.M., Raju, J.S., 1994. Competitive pricing by a price leader. Management Science 40, 809–823.

Srinivasan, S., Bass, F.M., 2000. Cointegration analysis of brand sales and category sales: stationarity and long-run equilibrium in market shares. Applied Stochastic Models and Data Analysis, forthcoming.

Srinivasan, S., Popkowski Leszczyc, P.T.L., Bass, F.M., 2000. Market share equilibrium and competitive interaction: The impact of temporary, permanent and structural changes in prices. Working Paper, University of California, Riverside, CA.

Steenkamp, J.-B.E.M., Baumgartner, H., 2000. On the use of structural equation models for marketing modeling. International Journal of Research in Marketing 17, 195–202 (this issue).

Tellis, G.J., Chandy, R.K., Thaivanich, P., 2000. Which ad works, when, where, and how often? Modeling the effects of direct television advertising. Journal of Marketing Research 37, 32–46.

Umashankar, S., Ledolter, J., 1983. Forecasting with diagonal multiple time series models: An extension of univariate models. Journal of Marketing Research 20, 58–63.

Wichern, D.W., Jones, R.H., 1977. Assessing the impact of market disturbances using intervention analysis. Management Science 24, 329–337.

Zanias, G.P., 1994. The long run, causality, and forecasting in the advertising–sales relationship. Journal of Forecasting 13, 601–610.