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TIME-SERIES MODELS IN MARKETING

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ABSTRACT

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 techniques* are not mentioned in their review of the past, receive 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 complement and extend on Leeflang and Wittink's discussion in three ways. First, we discuss why, in the past, time-series 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 more extensively the recent contributions of time-series applications to marketing science. Finally, we elaborate on some expected future developments in marketing research, and discuss opportunities and challenges to applied time-series modelers.

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 techniques* are not mentioned in their review of the past, receive 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 complement and extend on Leeflang and Wittink's discussion in three ways. First, we discuss why, in the past, time-series 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 more extensively the recent contributions of time-series applications to marketing science. Finally, we elaborate on some expected future developments in marketing research, and discuss opportunities and challenges to applied time-series modelers.

2. PAST

A variety of "conventional" time-series techniques has been applied to marketing problems, ranging from univariate forecasting models such as ARIMA and exponential-smoothing models (e.g. Geurts and Ibrahim, 1975), Granger-causality testing with pre-whitening of the individual series (e.g. Hanssens, 1980a; Leeflang and Wittink, 1992), single-equation transfer-function (e.g. Aaker et al., 1982; Bass and Pilon, 1980) and intervention (e.g. Leone, 1987) models, to multiple-equation specifications such as VAR (e.g. Moriarty, 1985) and SURARMA (Moriarty and Salamon, 1980) models. In spite of these studies, it is fair to say that time-series analysis has yet to experience widespread acceptance in the marketing research community. In a recent survey, Dekimpe and Hanssens (1995b) identified only 44 marketing studies that had used time-series concepts, several of which had appeared in non-marketing journals. Making abstraction of recent applications of long-run time-series techniques (discussed in more detailed in Section 3), this number is further reduced to 33 studies over a 20-year time span (1975-1995). By comparison, as early as 1976, a similar number of Koyck-model applications in marketing had already been identified in a meta-analysis of advertising effects duration (Clarke 1976).

We attribute the limited diffusion of time-series concepts to several factors: (1) marketing scientists' lack of training in time-series methods, (2) a resistance to data-driven approaches in model specification, (3) a lack of adequate data sources, and (4) the absence of a substantive marketing area where time-series modeling was adopted as primary research tool.

First, while most marketing scientists are well trained in standard econometric (e.g. GLS, ML, 2SLS) and experimental-design (e.g. ANOVA) techniques, only few have received a formal training in time-series analysis. For example, of the 43 applicants for a tenure-track marketing position at UCLA in Fall 1996, only 6 (14%) had taken a graduate course in time-series analysis, while 24 (56%) had received training in traditional econometrics and 28 (65%) in experimental-design methods.

Second, time-series techniques are data driven (e.g. lag structures are determined on the basis of sample summary statistics such as the autocorrelation function), and therefore said to "lack foundations in marketing theory" (Leeflang et al., 2000, p. 458). Many marketing researchers prefer to impose an *a priori* structure on the data, which could explain the frequent use of the Koyck model to capture lagged advertising effects, or the recent popularity of confirmatory – as opposed to exploratory – factor analysis. In contrast, data-driven methods such as time-series analysis and fully-extended market-share attraction models have often been met with a certain skepticism. While a similar debate has taken place in the economics literature (see e.g. Darnell and Evans, 1990; Granger, 1981; Sims, 1986), this has not prevented the widespread use of time-series techniques in that discipline.

Third, the application of time-series techniques in marketing settings has been hampered by data limitations.³ 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 data bases 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 ac-

³ The importance of data availability is illustrated by the fact that when the well-known Lydia Pinkham longitudinal data set became publicly available, it lead to several time-series publications (see e.g. Baghestani, 1991; Helmer and Johansson, 1977; Hanssens, 1980b; Moriarty, 1985; Zanas, 1994).

counting records. These were often highly aggregated, necessitating subjective allocations across time periods. By contrast, in both economics and finance, two fields of study where time-series analysis is more widespread, specialized agencies exist that for decades have recorded in a consistent way the over-time behavior of a variety of variables, including macro-economic indicators, stock prices and exchange rates.

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 time-series 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 time-series techniques. For example, the 2nd edition of two marketing-modeling textbooks (Hanssens et al., 2000, Chapters 5 and 6; Leeflang et al. 2000, Section 17.3) devotes considerable more attention to time-series techniques than their first edition, and the doctoral seminar series at the European Institute for Advanced Studies in Management (EIASM) has added a time-series module to the Doctoral Seminar on Measurement Models in Marketing.

As for the a-theoretical character of the approach, two recent developments offer more of a confirmatory potential: cointegration analysis 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 should give time-series techniques more credibility among advocates of a theory-driven specification of empirical models. In addition, 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 (Bass and Wind, 1995; Ehrenberg, 1995). Recent illustrations of the use of time-series techniques to derive EGs include Dekimpe et al. (1999), Lal and Padmanabhan (1995), Leeflang and Wittink (1992), Nijs et al. (2000), Srinivasan and Bass (2000) and Srinivasan et al. (2000), among others.

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 time-series techniques in marketing. To date, the best known marketing-transactions data bases in the research community are point-of-purchase scanner data for consumer products, and consumer-transaction data bases in relationship-intensive markets such as financial services (Balasubramanian et al. 1998). The cross-sectional heterogeneity of these data bases has lead to many effectiveness and segmentation studies, at the level of brand choice, purchase quantity and purchase timing (see e.g. Gupta, 1988; Chintagupta 1993). Over time, these data bases started to cover longer time spans, which made it possible to study their longitudinal dimension (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 applications).

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 (for extensive technical reviews, see Enders, 1995; Franses, 1998; or Harris, 1995). This provided a natural match between time-series analysis and one of marketing's long-lasting interest fields: quantifying the *long-run* impact of marketing's tactical and strategic decisions (Wind and Robertson, 1983; Marketing Science Institute, 1988, 1990). Dekimpe et al. (1999) reviewed the marketing applications of these techniques up to 1998, and the reader is referred to that study for a discussion on those applications. Since that review, Bronnenberg et al. (2000) used moving-window unit-root and cointegration tests along with the associated impulse-response functions to study the inter-relationship between market share and retail distribution during market-structure formation. Hanssens (1998) showed that only retail-demand induced order shocks are persistent, and therefore should be incorporated in long-run order forecasts for manufacturers, and that long-run retail demand can be influenced by the manufacturer's marketing mix. Dekimpe and Hanssens (1999) investigated the long-run profit-implications of temporary and sustained spending strategies, and identified four strategic scenarios: business as usual, evolving business practice, escalation and hysteresis. The fourth scenario, hysteresis, was studied in more detail in Hanssens and Ouyang (2000), who developed optimal spending rules in terms of both trigger and maintenance marketing. Srinivasan and Bass (2000) reconciled two empirical generalizations, stable market shares and evolving sales, by show-

ing empirically the existence of a cointegrating relationship between brand sales and category sales. Srinivasan et al. (2000) demonstrated that temporary, gradual and structural changes in prices have a different impact on market-share evolution. The over-time impact of price promotions on category sales was analysed for over 500 categories in Nijs et al. (2000), who (a) found limited evidence of persistent effects, and (b) tested the moderating impact of marketing intensity, competitive conduct and competitive structure on the short- and long-run primary-demand elasticity of price promotions. Primary-demand increases are just one potential source of the often-observed sales increases after a price promotion. Pauwels et al. (2000) investigated the long-term impact of price promotions on three components of brand sales, i.e. category incidence, brand choice, and purchase quantity, and found the relative importance of these components to differ from the short-term categorization made in Gupta (1988). On a more technical level, Franses et al. (1999) advocate the use of outlier-robust unit-root and cointegration tests when analysing weekly scanner series, while Franses et al. (2000) propose unit-root and cointegration tests that take the logical-consistency properties of market-share series into account.

An overview of marketing applications of different long-run time-series concepts is given in Table 1.

Insert Table 1 about here

4. FUTURE

We have described four developments that contributed to the recent surge in interest for time-series techniques in the marketing literature. In the current Section, we discuss several expected future developments, and discuss the potential opportunities and/or threats they offer to the continued use of time-series 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 in Section 3 as one of the main drivers for the growing popularity of time-series techniques in marketing. The question emerges, however,

whether a continued evolution towards ever-growing data sets will remain a blessing to time-series researchers. To focus our discussion, we will, in turn, 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 temporal aggregation, and at a smaller level of entity aggregation.

4.1.1. Number of variables. Traditionally, time-series 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 (Hanssens et al., 2000), we expect a growing use of Granger-causality tests to empirically determine (and subsequently impose) exclusion restrictions (see Leeflang and Wittink, 1992 for a recent application). Most Granger-causality tests in marketing are of a bivariate nature, however, which may lead to the erroneous imposition of some exclusion restrictions. It may therefore be advisable to test for Granger causality in higher-dimension VAR or error-correction models, but a trade-off will always have to be made between parsimony considerations on the one hand, and misspecification biases on the other hand.

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; Dekimpe et al., 1999; Srinivasan et al. 2000). However, a unique recursive system becomes harder to defend when the information set becomes larger. Using the multivariate normality property of the VAR residuals, Dekimpe and Hanssens (1999) therefore propose to derive the expected instantaneous values for the other variables once the focal variable is shocked, after which they trace the over-time impact of the entire shock vector. In large systems, however, this may involve taking along a considerable number of insignificant, yet non-zero, values.

The large set of potentially relevant variables may not only pose problems in the specification of the instantaneous and short-run dynamics of the VAR model, they may

also make the application and direct interpretation of cointegration analyses more difficult (see Lutkepohl and Reimers 1992 for an in-depth discussion). 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, or Nijs et al., 2000), or one could impose (and subsequently test) theory-based restrictions on some of the cointegrating coefficients (e.g. Juselius and Hargreaves, 1992). In competitive settings, however, few theoretical insights are available to help in this exercise (Leeflang and Wittink, 1992; Hanssens et al., 2000).

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 time series 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 time-series techniques on such variables. Some industries and specific companies have 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 time series of inferred consumer preference from conjoint measurement to estimate the elasticity of sales with respect to customer-defined product quality. 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 ?

In sum, we see two consequences of the increasing size of marketing information sets: (1) a growing need to select a priori the most relevant variables for inclusion in a model, where time-series based Granger-causality tests are of obvious help, and (2) new challenges for applied marketing researchers who want to use the confirmatory potential of recent techniques such as structural VARX and cointegration models. They are likely to notice that marketing theory is often of little help in specifying the necessary exclusion restrictions. This is ironical, as marketing theorists have often criticized "conventional" time series techniques for their a-theoretical character. We

hope that the demand for stronger a-priori insights created by larger datasets will spur new developments in marketing theory, especially on evolutionary market behavior. The recent paper by Heilman, Bowman & Wright (2000) on the evolution of consumer preference formation is an excellent example in this respect.

4.1.2. Length of the time span. As marketing data capture becomes automated and virtually costless, longer time series will become available for research⁴. This offers substantial opportunity for marketing research. 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 of certain marketing 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; Granger, 1998), while too long a time span may affect the managerial relevance of the findings (Dekimpe and Hanssens 1995b), and make the constant-parameter assumption used in most time-series models harder to defend (Franses 1998).

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 e.g. 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 should 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 time-series 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 ? These are but a few examples of strategically important questions that can be raised.

4.1.3. Level of temporal aggregation. Growth of marketing databases will also occur through finer time grids. While previous studies often used quarterly and/or

⁴ As indicated in Table 1, some prior studies already had access to long (multiple-decade) time series (column 5), in which case the data were invariably aggregated to the annual level (column 6). In the

monthly data, we see a recent movement towards weekly (scanner-based) observations (see Table 1, column 7). This development resulted, for instance, in a more accurate estimation of post-promotional dips (e.g. Nijs et al., 2000; Van Heerde et al. 2000) and competitive reaction patterns (e.g., Leeflang and Wittink, 1992), 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 data bases, 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 European diaper market is stable or evolving, sampling on an hourly basis does not increase the reliability of either unit-root or cointegration tests (see the statistical power discussion in Hakkio and Rush, 1991), nor does it offer additional managerial insights. To analyze eye-movement data (cf. Pieters and Warlop 1999), 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. Time-series studies have traditionally worked with more aggregated variables (see Table 1, column 8), 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 (see e.g., Christen et al., 1997). 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. The currently-available evidence is mixed. Pesaran and Smith (1995) illustrate the sensitivity of cointegration

future, we expect long time spans of temporally disaggregated data to become available (see also Section 4.1.3).

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. They therefore recommend to estimate the relationships of interest at a more disaggregate level, and to subsequently derive the averages and standard errors of the respective parameters (rather than estimate the average effect on aggregated data). While this approach seems reasonable to capture across-store differences in marketing effectiveness, it is less obvious how to use an a priori segmentation scheme to reduce (eliminate) across-consumer heterogeneity in long-run marketing responsiveness. Nijs et al. (2000), on the other hand, applied a non-linear (log-log) model to linearly aggregated data (aggregated across stores), and assessed the sensitivity of their results to aggregation biases by correlating their impulse-response functions with the ones obtained from the more robust (in terms of aggregation bias) linear model. All correlations were found to be very high (median correlation across 560 product categories higher than 0.9), suggesting a considerable robustness. This result is encouraging, especially in light of the observation that many time-series modelers work in log-log form (see Table 1, final column) to obtain direct elasticity estimates.

As indicated before, entity disaggregation may reflect a movement towards more analyses at the individual-*store* or SKU level, in which case traditional "aggregate" time-series techniques can still be applied, or at the individual-*consumer* (household) level, where individual-choice models seem more appropriate. Indeed, weekly data on the purchase occasions and/or quantities of an individual household may predominantly contain zeros, interrupted by an occasional positive spike, making them less appealing to time-series analysts. While this evolution towards more analyses at the individual consumer level may not seem to bode well to time-series modelers, it is interesting to note that recent developments in the individual-choice literature try to integrate the dynamic flexibility of time-series techniques into multinomial logit and probit models. Three approaches seem to emerge, i.e. (1) include a time-varying summary statistic of past purchases as an additional predictor variable in the choice model (along the tradition initiated by Guadagni and Little 1983), (2) allow the error terms in the utility function to follow a certain dynamic structure, such as a restricted VAR (Geweke et al. 1997; McCulloch and Rossi 1994), unrestricted VARMA (Haaijer and Wedel 1999) or error-correction specification (Paap and Franses 1999), or (3) to apply such a structure on the coefficients in the utility specification (see e.g. Haaijer and Wedel 1999). While

these approaches are very promising, more research is needed on the relative benefits of each approach relative to one another, the extension of the empirical applications to higher-order specifications (most illustrations to date consider first-order models), the reconciliation between the non-stationary focus in recent aggregate time-series models and the strict stationarity requirement in the time-series specification at the individual level (Paap and Franses 1999), and the data requirements to estimate these highly complex models (especially in case of multiple no-purchase events; Haaijer and Wedel 1999).

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. These long time windows made it virtually impossible to empirically assess marketing's role in such evolution (especially since only annual data were available in most of the studies covering multiple decades), with the possible exception of the primary demand expansion effects of falling prices. 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 (see e.g. Leeflang et al. 2000 or Hanssens et al. 2000 for recent reviews), but relatively little about how the marketing mix functions in a non-stationary environment. The question is important because simulations of product-life cycles have shown that markets can be evolving for years or even decades, and long after they have achieved a state of maturity (Midgley 1981).

The new reality of marketing decisions operates much more in rapidly changing and turbulent environments (Glazer and Weiss 1993), 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. Early examples of such work are the detailed diagnostics about the long-term im-

pact of price, sales call and advertising strategies used by two leading pharmaceutical companies competing in a therapeutic class in Dekimpe and Hanssens (1999), and Bronnenberg et al.'s (2000) study on how dynamic feedback relationships between market share and distribution are present in the early life-cycle stages, but disappear later on.

One area of study that will benefit 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 (Day and Fahey 1988; Srivastava et al. 1998). For example, one expanded definition of marketing is “marketing is the management process that seeks to maximize returns to shareholders by developing relationships with valued customers and creating a competitive advantage” (Doyle 2000). The finance discipline, with its inherent focus on growth and the valuation of assets over time, has long embraced time-series analytic techniques (see Mills 1994 for an extensive review). 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 marketing science literature 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 time series, that question may be addressed by expanding the scope of VAR market response 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 time-series 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 (4.1.3) at the individual consumer level (4.1.4). As such, internet data will easily and rapidly build up to long time series (4.1.2) with substantial cross-sectional detail. In much the same vain 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, in such a way that a complete *market monitoring system* emerges for marketing planning and academic research. Such databases enable superior repeated measurement of consumer attitudes and preferences, and set up a rich laboratory for experimentation. For example, VAR and intervention models can be used to infer the long-term effect of an awareness or preference increase on the revenue and profitability of a brand (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 time-series 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 (4.2). Moreover, 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 (Geyskens et al. 2000), and in terms of interactions with customers (Leeflang and Wittink 2000). From a time-series 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 recent review). Indeed, the constant-parameter assumption in many persistence-based models may not 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, time-series models have had limited use in marketing science because adequate data sources and PhD-level training were scarce, because researchers were reluctant to embrace a data-driven approach to model specification, and because a unique marketing problem that demands a time-series approach was lacking.

Recent developments have all but removed these obstacles to the diffusion of time-series methods in marketing science. Most notably, much progress has been made on the important yet difficult problem of assessing long-term marketing effectiveness, based on advances in unit-root econometrics. These methods not only provide descriptive measures of long-term marketing productivity, but they can also generate sales forecasts in function of marketing-control inputs, and they can help determine long-term optimal deployment of marketing resources.

The most productive use of time-series models in marketing science lies ahead, mainly because of the growth of marketing databases in various directions, such as number of variables, time span, and level of temporal and entity aggregation. This process is accelerated by the emergence of internet databases. For each of these expected evolutions, we have described how time-series models can provide unique contributions to marketing knowledge. 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. Indeed, for time-series models in marketing science, the best is yet to come.

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TABLE 1
APPLICATION OF LONG-RUN TIME SERIES CONCEPTS IN MARKETING

Study	Technique		Data Properties				
	Unit-root test*	Cointegration**	Persistence***	Sample length (in years)	Temp. aggreg. (in years)	Entity aggreg.****	Linear versus log
Baghestani (1991)	DF; ADF	EG	MV	54	1	S	Linear
Bronnenberg, Mahajan & Vanhonacker (2000)	ADF; SBUR; MWUR	FIML	MV	5 (257 weeks)	1/52	ms	Log
Chowdhury (1994)	ADF; O	EG	-	32	1	M	Log
Dekimpe (1992)	ADF	EG; FIML	UV; MV	6.3 (76 months); 23.5 (94 quarters)	1/12; 1/4	IS (Chain Linear); S; ms	Linear
Dekimpe & Hanssens (1995a)	ADF	FIML	UV; MV	6.3 (76 months)	1/12	IS (Chain Linear); S	Linear
Dekimpe & Hanssens (1995b)	ADF	-	-	-	-	-	-
Dekimpe & Hanssens (1999)	ADF	FIML	MV	5; 4.4	1/12; 1/12	S; S	Linear; Linear
Dekimpe, Hanssens & Silva-Risso (1999)	ADF; SBUR; MWUR; O	-	MV	2.2 (113 weeks)	1/52	IS; S	Linear
Dekimpe, Steenkamp, Mellens & Vanden Abeele (1997)	ADF; SBUR	-	-	1 or 2	1/12 and/or 2/12 (monthly/ bimonthly)	Estimated Brand Loyalty (S)	Linear
Franses (1991)	O	-	-	7 (42 bimonthly obs)	2/12	IS	Log
Franses (1994)	ADF	EG; O	MV	29	1	IS	Log
Franses, Kloek & Lucas (1999)	O	O	MV	2.2 (113 weeks)	1/52	ms	Log
Franses, Srinivasan & Boswijk (2000)	O	FIML	-	2 (104 weeks)	1/52	ms	Log
Hanssens (1998)	ADF	EG; FIML	MV	3.7 (44 months)	1/12	S	Linear; Log
Hanssens & Ouyang (2000)	ADF	FIML	MV	5	1/12	S	Linear; Log
Johnson, Oksanen, Veal & Frets (1992)	DF; ADF	EG	-	28 or 29	1	IS	Log
Jung & Seldon (1995)	DF; ADF	FIML	-	42	1	M	Log
McCullough & Waldon (1998)	DF	EG	-	34	1	M	log
Nijs, Dekimpe, Steenkamp & Hanssens (2000)	ADF; SBUR	FIML	MV	4	1/52	IS	Log
Pauwels, Hanssens & Siddarth (2000)	ADF; SBUR	FIML	MV	2.2	1/52	S; IS	Linear
Srinivasan & Bass (2000)	ADF	FIML	-	2 (104 weeks)	1/52	ms; S; IS	Linear
Srinivasan Popkowski Leszczyc & Bass (2000)	ADF; SBUR	FIML	MV	7 (365 weeks)	1/52	ms	Log
Zanias (1994)	DF; ADF; O	EG	-	27	1	S	Log

*: DF = Dickey & Fuller test; ADF = Augmented Dickey & Fuller test; O = other; SBUR = Structural-break unit-root test; MWUR = Moving-window unit root test.

**: EG = Engle & Granger Two-Step Procedure; FIML = Johansen's approach; O = other.

***: UV = Univariate persistence; MV = Multivariate persistence.

****: ms = market shares; S = brand sales; IS = industry sales; M = macro-variable.