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LONG-RUN MARKETING INFERENCES FROM SCANNER DATA

Abstract

Good marketing decisions require managers' understanding of the nature of the market-response function relating performance measures such as sales and market share to variations in the marketing mix (product, price, distribution and communications efforts). Our paper focuses on the dynamic aspect of market-response functions, i.e. how current marketing actions affect current and future market response. While conventional econometrics has been the dominant methodology in empirical market-response analyses, time-series analysis offers unique opportunities for pushing the frontier in dynamic response research.

This paper examines the contributions and the future outlook of time-series analysis in market-response modeling. We conclude first, that time-series analysis has made a relatively limited overall contribution to the discipline, and investigate reasons why that has been the case. However, major advances in data (transactions-based databases) and in modeling technology (long-term time-series modeling) create new opportunities for time-series techniques in marketing, in particular for the study of long-run marketing effectiveness. We discuss four major aspects of long-term time-series modeling, relate them to substantive marketing problems, and describe some early applications. Combining the new data with the new methods, we then present original empirical results on the long-term behavior of brand sales and category sales for four consumer products. We discuss the implications of our findings for future research in market response. Our observations lead us to identify three areas where additional research could enhance the diffusion of the identified time-series concepts in marketing.

1. INTRODUCTION

Marketing managers are principally concerned with the allocation of scarce marketing resources such as sales force, advertising and promotion, for the purpose of improving the market and profit performance of their products or brands. The quality of their decisions greatly depends on their understanding of the way in which customers will respond to these efforts, in the short run as well as the long run. More formally, they need to know the nature of the market-response function, in particular what the drivers are, what the magnitudes of the response parameters are, and how these parameters may vary across entities (e.g. brands or territories) and over time.

This market-response function is typically not formalized by marketing managers. Instead, they have often relied on accumulated business experience and intuition to derive a "vaguely right" sense of customer responsiveness to marketing efforts (Lodish 1982). However, in an era of increased competition - internally for marketing budgets and externally for customer revenue -marketing managers are being asked to justify their spending habits and plans, and indeed to demonstrate the profitability of their actions. These pressures accentuate the limits of "vaguely right" marketing management practice, and call for more objective, data-driven methods of marketing resource allocation.

It is a tribute to the discipline of econometrics that it has become the principal methodology for studying the shape of market-response functions. For approximately three decades, marketing researchers in industry and academia have used econometric techniques to develop a vast body of empirically-tested knowledge on the relationship between market performance and marketing investments. These methods and findings are summarized in research monographs such as Naert & Leeflang (1978) and Hanssens, Parsons & Schultz (1990), and a collection of empirical marketing generalizations, largely derived from econometric methods, may be found in Bass & Wind (1995).

We focus in our paper on the *dynamic* aspects of market-response models, which are motivated by questions about the future impact on sales of current and past marketing spending. While many econometric methods accommodate dynamic response patterns, they are often treated as "extensions" of the base models; for example, distributed-lag equations are multi-period versions of static response models. The discipline of *time-series analysis*, on the other hand, is dedicated to making inferences about the future from pattern recognition of the past. Since all managerial decisions are, by definition, aimed at controlling the future, the scientific goals of time-series analysis are very much aligned with those of practicing marketing managers. We therefore find it valuable to review the contributions of time-series analysis in market-response modeling to date, and, given our findings, to engage scholars in a new research stream that focuses on long-term marketing effectiveness.

The paper is organized as follows: first, we review the time-series analytic literature in marketing and draw several conclusions about its contributions to date (Section 2). We then argue that the research and managerial potential for these methods has yet to be unlocked, and that a major opportunity for this unlocking comes from two sources: (1) the availability of new, high-quality longitudinal marketing databases based on actual customer transactions, and (2) advances in long-term time-series analysis that clearly delineate the difference between temporary and permanent movements in a firm's market performance, and therefore offer a unique opportunity to distinguish tactical (short-run) vs. strategic (long-run) moves in marketing. Next, we will review the most important aspects of these long-term time-series modeling approaches (Section 3), and describe some pioneering applications in marketing (Section 4). Combining these new techniques and the new information sources, we present in Section 5 original, multi-category empirical results on one important type of transactions data, scanner-panel data for packaged foods. Finally, we will lay out an agenda of important future research in dynamic market-response modeling for the applied econometrician.

2. CONVENTIONAL TIME-SERIES ANALYSIS IN MARKETING

2.1. Introduction

As illustrated in Table 1, a wide variety of "conventional" time-series techniques has been applied to marketing problems, ranging from univariate forecasting models (ARIMA, exponential smoothing), single-equation transfer-function and intervention models, to multiple-equation specifications such as VAR, VARMA and SURARMA models.[1]

Table 1 about here

A first observation that emerged from our review is that many of these techniques have only been applied once or, at best, a limited number of times. For example, Moriarty & Salamon (1980) introduced the concept of SURARMA models, which was extended by Umashankar and Ledolter (1983) in their discussion of Diagonal Multiple Time Series (MTS-D) models. Similarly, Franses (1991) has introduced ARMAX modeling to the marketing literature, Bass & Pilon (1980) have discussed multiple time-series analysis (MTSA) as an alternative to transfer-function modeling, and Carpenter et al. (1988) have used the transfer-function identification technique advocated by Liu & Hanssens (1982). This suggests that, as new techniques become available in the time-series literature, there is a tendency to search for a marketing problem to which the technique can be applied. The main focus in a number of studies therefore seems to be on the illustration of a new tool,[2] rather than on developing substantive marketing knowledge.

Moreover, there does not seem to be a substantive marketing area where time-series modeling has been adopted as the primary research tool, such as structural-equation (LISREL) modeling in the satisfaction and channel-relationships literature, or discrete-choice (logit/probit) modeling in the promotions literature.[3] In Section 4, we will assess to what extent managers' and researchers' interest in long-run marketing effectiveness, combined with the recent availability of long-run time-series techniques (e.g. unit-root testing, cointegration and persistence modeling) could change this picture.

A corollary of the previous observations is that the overall number of time-series studies in marketing is fairly limited. After a broad survey of the marketing literature, Dekimpe and Hanssens (1995b)[4] identified only 44 marketing studies that used time-series concepts, several (7) of which had not yet been published, and several of which had appeared in non-marketing journals, such as *The Journal of Industrial Economics*, *Applied Economics* and *Review of Economics and Statistics*. This finding provides further evidence that time-series techniques have not gained widespread acceptance in the marketing research community. We attribute the limited diffusion of time-series concepts to several factors, such as (1) limited training of marketing scientists in time-series methods, (2) some resistance to data-driven approaches to model specification, and (3) a lack of adequate data sources.

2.2. Barriers to the diffusion of time-series techniques in marketing

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. Support for this contention is found in the fact that of the 43 applicants for a position as assistant professor with a leading business school in the Fall of 1996, only 6 (14%) had taken a graduate course in time-series analysis, while 24 (56%) had received a training in traditional econometric techniques, and 28 (65%) in experimental-design methods.

Second, some researchers may have a "philosophical" problem with data-driven approaches to model specification, as evidenced in occasional reviewer comments and discussions with colleagues. Many researchers prefer to impose *a priori* a certain structure on the data, which could explain the frequent use of the Koyck-model to capture lagged advertising effects, or the popularity of *confirmatory* - as opposed to exploratory - factor analyses. In contrast, data-driven methods such as time-series analysis or fully-extended market-share attraction models often face a certain skepticism. It is interesting to note, though, that a similar debate has taken place in the economics literature (see e.g. Granger 1981), but that this has not prevented the widespread use of time-series techniques in that discipline.

Finally, the application of time-series techniques in marketing settings has been hampered by data limitations. It is often easier for marketing researchers to obtain cross-sectional rather than longitudinal data sets. In the field of finance, on the other hand, long series are readily available, which helps explain why time-series modeling has become more popular in that discipline.[5] The importance of data availability is further illustrated by that 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 & Johansson 1977; Hanssens 1980a; Moriarty 1985; Zanias 1994). A major reason for the scarcity of longitudinal data sets in marketing relates to the firms' incentives 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. To quote a captain of industry, Henry Ford, in this context: "history is bunk". Moreover, assembling a data set of historical spending and performance typically requires the retrieval of old accounting records, which are often highly aggregated and may require subjective allocations across time periods. Marketing researchers often spend time digging through old company records to manually construct the time series used in their study, and it is our experience that many companies still cannot readily produce monthly or even quarterly spending and performance figures for the last five to ten years. In contrast, in both economics and finance, specialized agencies exist that have recorded in a consistent way the over-time behavior of a great variety of variables, including macro-economic indicators, stock prices and exchange rates.

2.3. Opportunities offered by new transactions-based data sources

We conjecture that the future of time-series modeling in marketing will be positively and significantly affected by the advent of new data sources that are based on the automatic, real-time recording of purchase or consumption transactions, as opposed to the retrieval of old accounting records. To date, the best known marketing-transactions databases in the research community are point-of-purchase scanner data for consumer products, and customer-transactions databases in relationship-intensive markets such as financial services.
Scanner panel data have already provided a major impetus to cross-sectional research in marketing, in particular the study of consumer heterogeneity in market response (see Chintagunta 1993 for a review). This heterogeneity forms the basis for the design of effective market segmentation strategies, and has been investigated at the level of brand choice (e.g. Bucklin & Gupta 1992; Gupta 1988), purchase quantity (e.g. Gupta 1988) and purchase timing (e.g. Gupta 1988; Jain & Vilcassim 1991). The dominant modeling approach has been the multinomial logit model, not only in published academic research, but also in commercial applications in the packaged-goods sector, according to a recent survey by Bucklin & Gupta (1996).

Recently, an interest has emerged in using the same scanner data sources to make inferences about marketing's long-run effectiveness (e.g. Mela et al. 1996; Papatla & Krishnamurthi 1996). However, these studies still use the conventional battery of statistical techniques to analyze long-run movements in longitudinal data. For example, Mela et al. (1996) use the Koyck specification to measure long-term marketing effects. These methods are appropriate for the study of multi-period sales response in stationary markets, where constant means and variances in performance have already been established, but as Dekimpe & Hanssens (1995a) argue, they are not well suited to address the more strategically-relevant questions about marketing's ability to affect the long-term evolution of a brand in a non-stationary market.

Fortunately, the time-series literature has contributed a number of new techniques that are designed to make specific inferences about the long run: unit roots, cointegration, error-correction, and persistence. In what follows, we briefly review these techniques and describe some pioneering applications in marketing. Next, we use some of these methods on scanner panel data in four product categories. We will investigate whether these scanner environments are indeed as stable/mature as many authors claim, and we will determine the potential for making long-run marketing inferences from these point-of-purchase data.

3. RECENT LONG-RUN TIME-SERIES TECHNIQUES: A BRIEF REVIEW

3.1 Unit-root testing

Unit-root tests allow one to identify the presence of a long-run or stochastic-trend component in a series' data-generating process. In the absence of a unit root, all observed fluctuations in a brand's performance or marketing support are temporary deviations from a deterministic component (such as a fixed mean or deterministic trend), whereas no complete (mean)[6] reversion occurs in unit-root processes, i.e. the series may wander widely apart from any previously-held position.

Within a marketing context, the presence of a unit root in performance has been shown to be a necessary condition for long-run marketing effectiveness (see e.g. Baghestani 1991; Dekimpe & Hanssens 1995a), and the absence of a unit root in most published market-share series has been interpreted as empirical evidence for the often-heard contention that many markets are in a long-run equilibrium where the *relative* position of the players is only temporarily affected by their marketing activities (Dekimpe & Hanssens 1995b). Unit-root tests can also be used to determine whether so-called "mature" markets are characterized by the absence of long-run movements in the *absolute* sales performance of all brands in the industry (cf. Section 5).

Apart from these substantive research issues, unit-root testing also deserves more attention in marketing research for statistical reasons. Indeed, it has long been recognized in econometrics that traditional hypothesis tests may be misleading when applied to non-stationary variables

(Granger & Newbold 1986). Within the marketing literature, however, one seldom tests for non-stationarity, even though this could result in spurious relationships between the variables of interest, or result in inconsistent specifications when not all variables are integrated of the same order (Granger 1981). Moreover, if based on a visual inspection, a prolonged up-or downward movement is found in the data, one tends to automatically include a deterministic trend (e.g. Rao & Bass 1985). The inappropriate use of deterministic trends may again create statistical problems,[7] however, a finding which has been largely ignored in the marketing field.

Numerous procedures have been developed to test for the presence of a unit root. One of the more popular tests (also in marketing, cf. infra) is the Augmented Dickey Fuller (ADF) test, which is based on the following test equation:[8]

$$X_t - X_{t-1} = \Delta X_t = a_0 + b\, S_{t-1} + \sum_{j=1}^{m} a_j\, \Delta X_{t-j} + u_t\,, \qquad (1)$$

The t-statistic of b is compared with the critical values in Fuller (1976), and the unit-root null hypothesis is rejected if the obtained value is smaller than the critical value. Clearly, substituting $b = 0$ introduces a random-walk component in the model, whereas $-1 < b < 0$ in (1) results in a mean-reverting process.

Other unit-root testing procedures have been advocated to test for seasonal unit roots (see e.g. Dickey, Hasza & Fuller 1984; Hasza & Fuller 1982), to correct for outliers (Franses & Haldrup 1994), for heteroskedasticity in the error terms (Phillips & Perron 1988), and for structural breaks (e.g. Perron & Vogelsang 1992). Clearly, all of these extensions may be highly relevant in marketing settings. For example, many product categories are subjected to seasonal fluctuations in demand, and many of the ARIMA and transfer-function models in Table 1 incorporated seasonal components to capture these fluctuations. Structural breaks may occur for a variety of reasons, such as new-product introductions, changes in distribution channels or patent expiration for pharmaceutical products. Outliers may be caused by strikes or unexpected supply shortages, and the growing turbulence in many competitive environments is expected to contribute to an increasing variability in performance and spending. In Section 4, we will review to what extent these more advanced unit-root tests have already found their way into the marketing literature.

3.2 Cointegration modeling

When unit roots are found in several variables, the question arises to what extent the underlying stochastic trends are related to each other, i.e. whether a systematic or long-run equilibrium relationship exists between the series that prevents them from wandering apart. Within a marketing setting, one has investigated whether a brand's sales and advertising are moving together (co-evolving) over time (e.g. Baghestani 1991; Zanias 1994), whether a product category's long-run evolution is linked to the evolution in some macro-economic variables (Franses 1994), and whether aggregate advertising spending is related to macro-economic fluctuations (Chowdhury 1994).

Formally, the existence of long-run equilibria is quantified through the cointegration concept. Consider, for example, two series which both have a unit root, so that they may both wander in any direction without mean reversion. Still, a systematic relationship could exist between the two that prevents them from moving too far apart in the long run. If an exact relationship existed between the two series, they would be tied together under a linear constraint of the form:

$$Y_t = b_0 + b_1 X_t \, . \tag{2}$$

In practice, however, it is unlikely for any equilibrium relationship to hold exactly in every single time period. Rather, one expects to see in every period some finite deviation from the perfect equilibrium. The actual relationship is then given by

$$Y_t = b_0 + b_1 X_t + e_t \, , \tag{3}$$

where e_t is called the ***equilibrium*** error. The existence of a long-run equilibrium relation between X_t and Y_t (which each have a unit root), requires e_t to be mean-reverting. Indeed, if e_t still had a unit root, X_t and Y_t could drift widely apart from one another, and they would not be tied together in the long run.

Engle & Granger (1987) formalized the above discussion through the following definition: An N-dimensional time-series vector $\vec{X}_t$ is said to be cointegrated of orders d and b, denoted as $CI(d,b)$, if it satisfies the following two conditions: (1) each component of $\vec{X}_t$, when considered individually, is integrated of order d (≥ 1), and (2) there exists at least one (and possibly $r \leq N\text{-}1$ cointegrating vectors β such that the linear combination $\beta'\vec{X}_t$ is integrated of order d-b (with b

> 0), i.e. the linear combination reduces the order of integration.

As was the case for unit-root testing, many different procedures have been proposed to test for and estimate cointegration vectors. Two of the more popular procedures are Engle and Granger's OLS approach and Johansen's FIML approach. The former procedure estimates equation (3) with OLS, and subsequently tests the residuals for the presence of a unit root. Its ease of implementation, combined with the super-consistency of the estimators, has made this approach one the more popular methods for estimating long-run equilibrium relationships. Its use has been criticized, however, since asymptotic unbiasedness does not imply the absence of small-sample biases, because the non-normal distribution of the estimators makes statistical inference difficult, and especially since OLS is not well designed to estimate more than one cointegrating vector. Indeed, when N is greater than two, more than one cointegrating vector may exist, while only one would be found with the OLS approach.

Johansen's (1988) FIML approach addresses these concerns, and has become the most widely used procedure. It starts from the following vector-autoregressive representation:

$$\vec{X}_t = \vec{c} + \Pi_1 \vec{X}_{t-1} + \dots + \Pi_k \vec{X}_{t-k} + \vec{u}_t \tag{4}$$

which can be reparameterized as:

$$\Delta\vec{X}_t = \vec{c} + \sum_{i=1}^{k-1} \Gamma_i \Delta\vec{X}_{t-i} + \Gamma_k \vec{X}_{t-k} + \vec{u}_t , \tag{5}$$

with $\Gamma_i = -I_N + \Pi_1 + \dots + \Pi_i$ ($i = 1, 2, \dots, k$). This model is mostly written in the levels, but all long-run information is still contained in the levels component $\Gamma_k \vec{X}_{t-k}$. The number of cointegrating vectors is determined by the rank of Γ_k, which can be written as the product of two full-rank matrices:

$$\Gamma_k = -\alpha \beta' , \tag{6}$$

where the rows of β' provide the base vectors for the r-dimensional cointegration space.

Several further extensions/refinements have been proposed, such as tests for seasonal cointegration (Lee 1994) and tests for cointegration between variables integrated of order d (>1). In section 4, we will review to what extent Engle and Granger's OLS approach, Johansen's FIML approach and some of these extensions have already been applied in a marketing context.

3.3 Error-correction models

If cointegration has been established between some of the variables, one should control for these long-run linkages in modeling the short-run relationships between them. Engle & Granger (1987) showed that this can be achieved through a special error-correction mechanism, which is a model in the differences augmented by the lagged equilibrium error. The latter's inclusion in the short-run model reflects that the system partially corrects for previous deviations from the long-run equilibrium.

Based on the significance of the error-correction term in respectively, the sales or advertising equation, Hanssens (1987) distinguished between a response and budgeting equilibrium, and Franses (1994) showed how the Gompertz model extends into an error-correction specification when a long-run equilibrium relationship is assumed between the varying saturation level and a set of integrated explanatory variables.

Engle and Granger's OLS approach to error-correction modeling saves the residuals of the equilibrium regression (3), and subsequently adds the lagged-residuals term e_{t-1} as an additional explanatory variable. Its associated coefficient can be interpreted as a measure for the speed of adjustment towards the long-run equilibrium. In Johansen's FIML approach, equation (5) is already written in error-correction form when Γ_k is expressed as $-\alpha\beta'$, and the α-coefficients reflect the speed of adjustment.

In marketing, time-series models are sometimes used for causality testing (cf. Section 2) or for their superior forecasting performance. In both instances, error-correction models are advisable over conventional transfer-function or VAR models on the differences: when cointegration exists between two variables, Granger causality is bound to exist in at least one direction, and the error-correction representation will offer a more comprehensive causality test than traditional approaches. From a forecasting perspective, the addition of the error-correction terms ensures that information on the system's long-run equilibrium is taken into account. Because of this additional piece of long-run information, a higher forecasting accuracy is obtained, especially for longer forecasting horizons (Engle & Yoo 1987).

3.4. Persistence modeling

The presence of a unit root implies that a portion of a shock to the series will persist through time and affect its long-run behavior. The magnitude of this retained portion determines, for example, how much an estimate of the brand's long-run sales or market-share forecast should be changed when its current performance is ten percent lower than expected on the basis of its past history. In the absence of a unit root, this continuing effect is zero. For a pure random-walk process, 100% of the original shock persists, so the long-run forecast is lowered by ten percent. For series that are neither stationary nor a pure random walk, this portion can take on any value greater than zero, and measures the relative importance of the unit root.

Three different approaches have been taken to quantify the relative importance of a single unit root: (1) the sum of the moving-average coefficients in the infinite-shock representation of the first-differenced series (Campbell & Mankiw's (1987) $A(1)$ measure); (2) the normalized variability of the underlying stochastic trend (Cochrane's (1988) V measure); and (3) the normalized spectral density at zero frequency (Huizinga 1987). As will be indicated below (Section 4), only the first approach has been applied in the marketing literature to date.

The above persistence measures are all univariate. However, brands operate in a multivariate environment, and managers' main interest may be in the differential long-run effect of alternative marketing-mix variables. For example, a manager may ask if an (unexpected) 10% increase in advertising has a larger long-run impact on sales than an (unexpected) 10% price reduction. Multivariate persistence measures address this question (Dekimpe & Hanssens 1995a). Here, too, a number of different operationalizations have been proposed. First, Campbell and Mankiw's $A(1)$ measure is easily generalized to the multivariate case by working with an infinite-shock VMA. Unfortunately, this approach does not capture instantaneous cross-effects, which are very important in most marketing settings. To address this limitation, Evans (1989) proposed to work with a transformed model specification in which a temporal ordering is imposed on the data (e.g. advertising may have an immediate impact on sales, but there can only be a lagged feedback effect of sales on advertising). When the temporal ordering is hard to justify on a priori grounds, Evans & Wells (1983) proposed to derive the long-run impact of a vector of shocks, composed of the original shock and the *expected* magnitudes for the shocks in the other variables. Pesaran et al. (1993) extended the other two univariate persistence measures through the (normalized) variance-covariance matrix between the respective random-walk parts in the series, and through the cross-spectrum at frequency zero. The use of these techniques in marketing is reviewed in Section 4.

4. MARKETING APPLICATIONS OF LONG-RUN TIME-SERIES TECHNIQUES

Table 2 summarizes the published marketing applications of the long-run time-series concepts discussed in Section 3. Several observations emerge from this table.

Insert Table 2 about here

First, in spite of their frequent use in other disciplines such as economics and finance, these techniques have yet to gain widespread acceptance in marketing. For example, only seven studies on the use of cointegration could be located, even though an "ABI/INFORMS" search revealed more than 580 published studies with this term in the title or abstract. Even more studies will have used unit-root tests, but only 9 published studies were located in the marketing literature. Moreover, as with the "conventional" time-series methods, several of those were again not published in a mainstream marketing journal.

Second, the simpler and easier-to-implement procedures seem to be preferred. For example, the (Augmented) Dickey-Fuller test is the most frequently used unit-root test, while some of the more robust specifications (e.g. the tests proposed by Phillips & Perron 1988 or Franses & Haldrup 1994) have yet to be applied in a marketing context. The same is true for unit-root tests that allow for a structural break in the data-generating process (see e.g. Perron & Vogelsang 1992). Still, these procedures may prove to be useful in many marketing applications, e.g. to account for the entrance of a major new competitor. Unlike many studies in finance and economics, there also does not seem to be a tradition to apply a variety of different test statistics to the same series before deciding on the presence or absence of a stochastic trend. With respect to cointegration modeling, Engle and Granger's two-step approach is still the most frequently used procedure in marketing, even though the FIML approach has now become well established in other disciplines. Finally, multivariate persistence applications that do not impose a prior causal (temporal) ordering on the variables, such as the procedures described in Evans & Wells

(1983) or Pesaran et al. (1993), have yet to be used in a marketing context.

Most of the marketing applications deal with data at the macro- or product-class level: Chowdhury (1994) and Jung & Seldon (1995) both study the relationship between aggregate advertising spending and macro-economic variables, while Franses (1994) and Johnson et al. (1992) try to explain the long-run evolution in the primary demand for, respectively, Dutch cars and Canadian alcoholic beverages. Only Baghestani (1991) and Zanias (1994), who both use the well-known Lydia-Pinkham data, and Dekimpe & Hanssens (1995a) have used these concepts to study long-run marketing effectiveness at the managerially more relevant store and brand level. As such, more research is needed to fully translate the identified long-run insights into *actionable* managerial guidelines.

5. AN EMPIRICAL STUDY OF LONG-RUN MOVEMENTS IN INDUSTRY AND BRAND SALES FOR FREQUENTLY-PURCHASED CONSUMER GOODS

5.1. Motivation

Using scanner panel data on four different consumer product categories (liquid laundry detergent, soup, yogurt and catsup), we perform unit-root tests and calculate the univariate persistence in sales for each brand (21 in total) and for the total category. As discussed earlier, the statistical distinction between mean-stationary and evolving (or unit-root) sales behavior has important ramifications for marketers. If sales are mean-stationary, marketing actions can produce at most temporary deviations from average sales performance. If sales are evolving, a necessary condition for long-term marketing effectiveness is met, and further research should establish whether or not marketing actions actually drive the observed sales evolution.

A priori, expanding the unit-root results to industry vs. brand sales gives rise to four possible scenarios, seen from the perspective of a brand whose manager uses marketing resources to improve sales and profit performance:

- *stationary brand sales in a stationary industry*: all sales gains and losses are of a temporary nature, and brand marketing is therefore *tactical* in nature. In such environments, also the brand's relative position or market share will be stationary, and all marketing effects will either be intrinsically short-lived, or will be self-canceling in the long run (cf. infra).

- *stationary brand sales in an evolving industry*: implies a lack of long-run marketing effectiveness, as the brand is unable to establish permanent gains in spite of operating in an evolving category. While marketing activities can have long-run primary demand effects in such markets, the additional sales do not accrue to the brand, but rather benefit its competitors!
- *evolving brand sales in a stationary industry*: this scenario implies that the brand is locked into a strategic battle for long-run position. Moreover, as the category is not moving away from its historical mean, firms are involved in a zero-sum game in which the long-run sales gain for one the players will always come at the expense of a long-run loss for at least one of the other players.
- *evolving brand sales in an evolving industry*: depending on the relative importance of the identified long-run components in, respectively, brand and industry sales, firms may be able to improve not only their absolute long-run performance, but also their relative position. Moreover, if cointegration can be established between its own performance and the combined performance of its competing brands, brands can be seen as riding long-run market waves that could actually be driven by its marketing spending.

5.2 Data description

A.C. Nielsen household scanner panel data on the purchases of liquid laundry detergent, soup, yogurt and catsup in the Sioux Falls market (South Dakota) were used to construct time-series of weekly sales and primary-demand figures. These data sets were made available to the academic research community through the Marketing Science Institute, and have been used extensively in the recent marketing literature; see e.g. Bucklin et al. 1995 (yogurt); Cooper et al. 1996 (catsup) or Bucklin and Gupta 1992 (detergents), among others.

As some markets have seen a proliferation of brands and sizes (e.g. each brand in the detergent market is typically offered in several sizes ranging from 32 to 128 ounces), we expressed sales in number of ounces sold, and aggregated all different sizes of a particular brand into one figure. For the catsup, yogurt and soup market, we considered all brands with a minimum share of 2%, and in the detergent market, we considered the set of brands used in previous studies (e.g. Bucklin and Gupta 1992). This resulted in a total of 21 brand-level series:

7 in the detergent market and yogurt market, 4 in the catsup market and 3 in the soup market. The considered brands represent approximately 80% of category sales in the detergent market, and more than 90% in the three other categories.

113 weekly observations were available, from the first week of 1986 until the 9th week of 1988. We are aware of the fact that, from a statistical point of view, longer time spans would have been preferred. However, (1) we wanted to determine whether long-run inferences could be made from the data which are publicly available to the marketing community, and (2) we feel that there may even be a trade-off between managerial relevance on the one hand, and statistical-power considerations on the other hand (see Section 6 for a more elaborate discussion on this issue).

5.3 Unit-root test results

We adopted the ADF procedure in Eq. (1) to test for the presence of a regular unit root in the four primary-demand and 21 brand-level series, and used the AIC criterion to determine the number of lagged difference terms in the test equation. Test results are presented in Table 3. In one instance (Solo sales), two specifications resulted in the same AIC value. Based on a top-down approach, the higher-order model was selected which indicated a unit-root. For the unit-root series, Campbell and Mankiw's univariate persistence measures were calculated for different low-order ARMA models (i.e. p= 0, .., 4 and q= 1, ..., 4), and the median value of all models which reached convergence is reported in the last column of Table 3.

Table 3 about here

At the primary-demand level, a unit root was found in two instances, the catsup market and the soup market, while the other two industries, yogurt and detergents, were found to be mean-stationary.[9] Thus, even though all four of these product categories have existed for many years, long-run evolution is still possible in some cases! Hence, *the term "market maturity" should not be equated with lack of permanent change in market conditions.* Moreover, the univariate persistence estimates (0.2 for the catsup market, and 0.43 for the soup market) further underline the importance of the long-run movements in those product categories.

At the brand level, the empirical results are a mixture of mean-reversion and evolution, representing all four of the quadrants described earlier.[10]

Table 4 about here

Of the twelve stationary brands, eight are operating in a stationary category as well. Of the nine evolving brands, six may experience permanent change in spite of their category being stationary. While a detailed investigation of each case is beyond the scope of this paper, these univariate results already demonstrate that *the long-run behavior of brand sales is quite different across and within categories*, and that *marketing investments may have permanent effects on brand sales, even in stable markets*. Clearly, multivariate persistence estimates would be needed to quantify the actual extent of long-run *marketing* effectiveness, but our univariate results already underscore that in many instances, there is *a potential* for long-run effectiveness, while in a number of other cases, the necessary conditions for long-run marketing effectiveness are not fulfilled. This mixture of results, especially within a given product category, also indicate that special care should be exerted to ensure consistent model specifications (Granger 1981).

It is also interesting to observe that the long-run behavior of brands belonging to a common manufacturer (which might induce similarities in marketing support) may be quite different. For example, both Wisk and Surf are Lever-Brother brands. No unit-root was found for the Wisk series, while Surf had the largest univariate persistence estimate of 0.64. Put differently, shocks (which could be due to sales promotions or competitive activities) to Wisk do not result in an update of its long-run performance, while 2/3 of a shock to Surf persists in the long run!

Recent research has focused on the marketing of private labels, which are generally viewed to be a threat to the long-run viability of the more expensive national brands (Raju et al. 1996). However, Table 3 further indicates that in two of the three product categories with private-label brands (i.e. Catsup and Soup), the private-label brand is showing a mean-reverting sales pattern. It appears, then, that *the long-run threat of private labels may be exaggerated*, and that further research should investigate the conditions under which private label-brands affect the long-term sales performance of named brands.

Finally, we observe that in some markets (e.g. the detergent market), the sales behavior of major players (such as Tide and Wisk, belonging to respectively Procter & Gamble and Lever Brothers) is mean reverting. Given that the managers of these brands are motivated to improve their market positions and profitability, the question emerges whether this mean reversion is due to the fact that

(a) the marketing-mix variables of these brands, as well as the cross-effects from their competitors, have only short-run (temporary) effects on sales, or

(b) they intrinsically have long-run effects, but because of competitive activities they cancel each other out in the long run. Marketing managers which observe mean reversion in performance could then erroneously conclude that neither their own nor their competitors' activities have any long-run impact, and fail to react to changes in the latter.

Under case (b), a brand manager has no choice but to respond to an aggressive action of a competitor, such as a price cut, lest (s)he wants to risk the permanent loss of sales. Under case (a), competitive reaction may or may not be desirable, depending on the trade-off between lower sales/same marketing costs versus same sales/higher marketing costs. In Appendix A, we address this issue analytically, and consider whether or not brand actions and counteractions which intrinsically have long-run effects can produce a time series of sales that is mean-stationary. We consider three competitive scenarios: firms set their advertising budget independently, a leader/follower scenario, and both firms set their budget as a function of the other brand's decisions, and we show that case (b), where the stationarity of the performance series would "mask" competing long-run effects, *cannot* occur in the first two competitive-reaction scenarios, and is *very unlikely* to occur in the third scenario. We can therefore conclude on a positive note that marketing researchers are unlikely to observe stationarity in the data if indeed there are negative permanent effects of competitive marketing activities.

6. CONCLUSIONS AND AREAS FOR FUTURE RESEARCH

This paper has examined the contributions and future outlook of time-series analysis in market-response modeling. We conclude, first, that time-series analysis has made a relatively *limited* overall contribution to the discipline, and we investigate reasons why that has been the case. However, major advances in data (transactions-based databases) and in modeling technology (long-term time-series modeling) create new opportunities for time-series techniques in marketing, in particular for the study of long-term marketing effectiveness. We discuss four major aspects of long-term time-series modeling, relate them to substantive marketing problems, and describe some early applications. Combining the new data with the new methods, we then present original empirical results on the long-term behavior of brand sales and category sales for four consumer products. Our observations lead us to identify three areas where additional research could enhance the diffusion of the identified time-series concepts in marketing research.

The trade-off between statistical power and managerial relevance. Many applications in economics and finance deal with time series covering multiple decades, which ensures good statistical power for the test procedures. From a managerial perspective, however, data points that far in the past are not very relevant, and time series in the marketing discipline, especially at the brand level, are typically much shorter. In a recent meta analysis, Dekimpe & Hanssens (1995b) identified 419 published time-series models in marketing. Focusing on data at the product or brand level, the median time span for these variables was 5 years. On the other hand, while macro-economic data are typically collected on a monthly or quarterly basis, marketing information now can be sampled much more frequently, for example at the daily or weekly level. Unfortunately, unlike many conventional hypothesis tests, unit-root and cointegration tests depend less on the number of observations per se, but instead on the length of the time span (see e.g. Hakkio & Rush 1991; Shiller & Perron 1985). Put differently, additional observations obtained by sampling more frequently result only in a marginal increase in power. Therefore, more research is needed on the small-sample (and more specifically, the small time-span) properties of these tests to reconcile managerial relevance and statistical rigor. At the same time, firms should realize the importance of storing and retaining market- performance and marketing-investment data for longer periods than they have done in the past.

The interpretation of multiple cointegrating vectors. When dealing with multiple (N) time series, a maximum of N-1 cointegrating vectors may exist. Within a marketing context, the number of variables in the system (and hence, the potential number of cointegrating vectors) may rapidly become excessive. In a competitive environment with four major players competing on the basis of price, advertising and promotion, 15 cointegrating or long-run equilibrium relationships may (but need not) exist between the four performance and twelve control variables. From a statistical point of view, the information in the data needed to accurately determine the number of cointegrating relationships r may be weak, especially when the sample is rather short. Juselius & Hargreaves (1992, p. 259) therefore suggest to "use any prior economic insight ... to make sure that the choice of r is consistent with both the statistical information and the economic insight concerning the number of long-run relations and common trends." Unfortunately, few marketing theories exist to assist in this respect.

Furthermore, the *interpretation* of the cointegrating relationships may prove to be difficult, especially when $r > 1$ (Lütkepohl & Reimers 1992). Within the economics and finance literature, cointegration analysis is often used to empirically test the existence of theoretically expected long-run equilibria, for example as predicted by the neo-classical growth model (Neusser 1991) or models of exchange-rate determination (MacDonald & Taylor 1994). In those applications, the number of variables is often limited, and one typically tests whether at least one of the cointegrating vectors satisfies the restrictions imposed by the considered theory. As mentioned before, few such theories are available in marketing, making the long-run analyses more *exploratory* in nature, and making it more difficult to "ignore" certain cointegrating vectors because they do not support the underlying theory. More research is needed on methods that can assist applied researchers in selecting the most relevant cointegrating vectors out of a potentially large set of such vectors, and/or on "exclusion" procedures to separate the subset of variables that will determine a market's long-run steady-state solution from those that are only relevant in explaining short-run fluctuations around that equilibrium. Recent exogeneity research (e.g. Juselius & Hargreaves 1992) is useful in this respect, but more work is needed on the value of the proposed tests in typical marketing settings, where the researcher is confronted with (1) limited prior information, (2) a large potential information set, and (3) relatively short time spans.

Because of these interpretational difficulties and because of a lack of long-run equilibrium theories in marketing, we do not foresee a dramatic increase in the number of *cointegration* applications. By contrast, impulse-response functions and their associated multivariate persistence estimates do not have these interpretation problems (Dekimpe & Hanssens 1995a; Lütkepohl & Reimers 1992), and they clearly illustrate how the long run emerges out of a "sequence of short runs". We therefore expect to see more marketing applications of this technique. Still, error-correction models may be used to simulate the impulse-response functions and to reflect the gradual adjustment of the system to underlying cointegrating relationships. However, the main focus of the analysis is on the interpretation of the persistence estimates, rather than on the non-unique and sometimes misleading cointegrating coefficients. Hence, we expect cointegration analyses to be used in marketing more for "statistical correctness" than for a direct interpretation of the cointegration coefficients.

Sensitivity to functional forms. Several functional forms have been used in the marketing literature to link a brand's performance to its marketing support, including the linear, multiplicative (log-log), semi-logarithmic and logistic specifications (Hanssens, Parsons & Schultz 1990). When unit-root and cointegration tests are applied to assess the existence of a long-run relationship between marketing and performance, one would expect the test results to be insensitive to such monotone transformations. As shown in Granger & Hallman (1991), however, this is not always the case. The popular ADF test, for example, is found to be sensitive to most monotone transformations, and a cointegrating relationship between sales and advertising in the linear model may be preserved when working with a multiplicative model, but not necessarily in a semi-logarithmic model. As such, test statistics that are invariant to a broad class of transformations, and especially to the logarithmic transformation, are important in applied time-series analysis in marketing research.

In conclusion, our key assessment on the contribution of time-series analysis in marketing to date is limited, but our key expectation for future contributions is high. On the *demand* side, marketing managers have always been intrigued by the potential long-run effectiveness of their marketing investments, and the increased competition for scarce marketing resources requires that they demonstrate these effects. On the *supply* side, the limited statistical methods for assessing long-term patterns in and among time series have been substantially expanded and improved by unit-root modeling and its extensions. At the same time, new transactions-based marketing databases are gradually removing obstacles of data scarcity that have impeded the use of time-series analysis in the past. The new analytical and empirical results in this paper illustrate these opportunities.

The conditions for a widespread diffusion of time-series techniques in marketing are right, and new working papers and research presentations on long-term marketing effectiveness have already begun to appear (e.g. Bharadwaj & Bhattacharya 1996; Dekimpe & Hanssens 1996; Dekimpe et al.; Popkowski-Leszczyc 1996). We hope that the framework set forth in this paper will communicate and hopefully accelerate the dissemination of these important techniques in the marketing research and marketing management communities.

Footnotes

1. We consider in a separate section recent developments (e.g. unit-root tests, persistence calculations, and cointegration and error-correction models) which focus on the series' long-run properties.

2. This may also be reflected in the titles of the articles, which often contain "An illustration/application of ... in marketing" (see e.g. Barksdale & Guffey 1972; Helmer & Johansson 1977).

3. One exception may be the use of Granger-causality tests. Indeed, it has become fairly common (see e.g. Leeflang & Wittink 1992; Roy et al. 1994) to perform preliminary causality tests when the amount of prior knowledge is limited, as when studying competitive reaction patterns.

4. It should be noted that their review did not include frequency-domain applications. These studies are included in the last panel of Table 1. Again, the number of marketing applications in this research tradition is very limited, and restricted to the illustration of some new techniques which have not gained much popularity in later work.

5. See e.g. Mills (1993) for a recent review.

6. In what follows, the mean-stationary model is (unless explicitly stated otherwise) used as alternative hypothesis, since this may be a more realistic marketing scenario than the trend-stationary model (see Dekimpe 1992 for an extensive discussion on conceptual problems with deterministic-trend models in marketing settings).

7. See e.g. Nelson & Kang (1984).

8. The m ΔX_{t-j} terms are added to the test equation to make sure the residual series u_t is white noise. In equation (1), the deterministic component only consists of a constant, but can be augmented with a deterministic-trend term.

9. Similar results were found when a deterministic trend was added to the test equation. Also in the univariate persistence estimates (where we always included a moving-average component), no evidence of over-differencing was found.

10. When a deterministic trend was added to the test equation, our conclusion w.r.t. the presence/absence of a unit root in the data was not affected in all but one instance (Yogurt market -- WBB). Hence, our substantive findings were robust to the choice of alternative hypothesis. In the univariate persistence calculations, some evidence of over-differencing was found in only two cases: Solo and WBB, the two cases where also the unit-root test results were not clear-cut.

APPENDIX A

An important question faced by brand managers whose sales performance is found to be mean-stationary, is whether it is possible that this stationarity "conceals" or "masks" all kinds of long-run effects, both positive and negative. For expository purposes, we consider whether advertising (A) can have a positive and competitive advertising (CA) a negative long-run effect which cancel one another. Three scenarios will be considered, which each have an intuitive marketing interpretation and which have been observed repeatedly in empirical research (see e.g. Hanssens, Parsons & Schultz 1990; Roy et al. 1994):

- the two firms set their advertising spending independently of each other;
- one firm is the leader, the other the follower;
- both firms set their advertising spending as a function of their competitor's current and past advertising effort.

We will show that the "masking" of long-run effects *cannot* occur in the first two scenarios, and is *very unlikely* to occur in the third scenario. For the sake of simplicity, we will assume that both A and CA are mean-reverting, but a similar reasoning applies when the control variables are evolving.

Case 1: Independent advertising spending

Consider the following situation, which is the simplest case of independent advertising spending:

$$S_t = \alpha_S + \beta_1(L)\,A_t + \beta_2(L)\,CA_t + e_{S,t}\,, \tag{A.1a}$$

$$A_t = \alpha_A + e_{A,t}\,, \tag{A.1b}$$

$$CA_t = \alpha_{CA} + e_{CA,t}\,, \tag{A.1c}$$

where $e_{S,t}$, $e_{A,t}$ and $e_{CA,t}$ are white-noise residuals, and where $\mathrm{cov}(e_{A,t}, e_{CA,t+i})=0$, $\forall i$. After appropriate substitutions, we get:

$$S_t = \alpha^* + \beta_1(L)e_{A,t} + \beta_2(L)e_{CA,t} + e_{S,t}\,. \tag{A.2}$$

A temporary advertising increase will have a continuing impact if the partial derivative of S_{t+k} ($k\rightarrow\infty$) with respect to $e_{A,t}$ is non-zero. Obviously, this can only occur if $\beta_1(L)$ is an infinite-lag polynomial whose coefficients do not converge to zero. In that case, however, the variance of the right-hand side of equation (A.2) will grow without bound, while the left-hand side (S_t) is a stationary (and hence, finite-variance) variable, which would create an inconsistent model specification (Granger 1981). Hence, β_1(L) cannot be an infinite-order polynomial whose weights do not converge towards zero, and advertising nor competitive advertising can have a continuing impact.

Case 2. One firm is the leader, the other the follower

In this second scenario, Equation A.1 is changed to reflect the fact that the competitor sets his/her advertising spending as a function of our current and/or past advertising expenditures.

$$S_t = \alpha_S + \beta_1(L)\, A_t + \beta_2(L)\, CA_t + e_{S,t}\ , \tag{A.3a}$$

$$A_t = \alpha_A + e_{A,t}\ , \tag{A.3b}$$

$$CA_t = \alpha_{CA} + \kappa(L)\, A_t + e_{CA,t}\ , \tag{A.3c}$$

with cov($e_{A,t}$, $e_{CA,t+i}$)=0, $\forall$i. After appropriate substitutions, we get

$$S_t = \alpha^* + [\beta_1(L) + \beta_2(L)\kappa(L)]\ e_{A,t} + \beta_2(L)e_{CA,t} + e_{S,t}\ . \tag{A.4}$$

Using a similar reasoning, *A* and *CA* can only have a continuing (and supposedly canceling) impact if β_1(L) and β_2(L) are infinite-lag polynomials whose coefficients do not convergence towards zero. This situation again leads to an inconsistency, in that the right-hand side would be of infinite variance, while the left-hand side would be of finite variance. Even in the unlikely event that the κ( ) coefficients cancel "an infinite number of contributions to the total variance" in the term between square brackets, the β_2-terms would still cause an infinite-variance right-hand side.

Case 3. Both firms react to the other firm's (current and/or past) advertising

Equation (A.3) is again updated to reflect this new scenario:

$$S_t = \alpha_S + \beta_1(L)\, A_t + \beta_2(L)\, CA_t + e_{S,t}\,, \tag{A.5a}$$

$$A_t = \alpha_A + \kappa_1(L)\, CA_t + e_{A,t}\,, \tag{A.5b}$$

$$CA_t = \alpha_{CA} + \kappa_2(L)\, A_t + e_{CA,t}\,. \tag{A.5c}$$

After appropriate substitutions, (A.5) can be rewritten as:

$$S_t = \alpha^* + \frac{[\beta_1(L)\kappa_1(L) + \beta_2(L)]}{1 - \kappa_1(L)\kappa_2(L)}\, e_{AC,t} + \frac{[\beta_2(L)\kappa_2(L) + \beta_1(L)]}{1 - \kappa_1(L)\kappa_2(L)}\, e_{A,t} + e_{S,t}\,. \tag{A.6}$$

In this case, it is possible that, even when β_1(L) and β_2(L) are infinite-lag polynomials (and thus reflect underlying long-run effects), both the left- and right-hand side have a finite variance. However, this masking of long-run effects would only occur if both competitors react in such a way that they *completely* cancel out the other firm's advertising effect for an *infinite* number of periods to come.[4] It is only if this very stringent (and therefore unlikely) condition is met, that one would see a masking of underlying long-run or continuing effects.

At this point, one could argue that in the different models (i.e. equations A.1-A.3-A.5), we did not include lagged sales terms to capture purchase-reinforcement effects, autoregressive spending patterns or feedback effects. It is easy to show, however, that the addition of any of these effects would not alter the spirit of our argumentation, nor any of our substantive findings. We can therefore conclude on a positive note that marketing researchers are very unlikely to observe stationarity in their data (and therefore conclude that long-run competitive cross-effects can be precluded), when these competitive activities indeed have permanent effects.

4 To give a specific example, if $\beta 1(L)$ is an infinite-lag polynomial, it is not sufficient that the competitive reactions result in a net zero effect in period 1, period 2 , ..., period 20; they must cancel the firm's advertising effect in so many periods that there are only a finite number of periods which offer a contribution to the variance on the right-hand side.

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TABLE 1
APPLICATIONS OF "CONVENTIONAL" TIME-SERIES TECHNIQUES IN MARKETING

TECHNIQUE	STUDY
Univariate ARIMA modeling	Dalrymple (1978); Didow and Franke (1984); Geurts and Ibrahim (1975); Kapoor et al. (1981); Moriarty and Adams (1979, 1984).
Multivariate single-equation models	
- Transfer-function/multiple time-series/ARMAX modeling	Aaker et al. (1982); Adams and Moriarty (1981); Bass and Pilon (1980); Carpenter et al. (1988); Doyle and Saunders (1985, 1990); Franses (1991); Moriarty (1985); Hanssens (1980a,b); Helmer (1976); Helmer and Johansson (1977); Somers et al. (1990).
- Intervention analysis	Krishnamurthi et al. (1986); Leone (1983; 1987); Mulhern and Leone (1990); Narayan and Considine (1989); Wichern and Jones (1977).
- Granger-causality tests	Aaker et al. (1982); Bass and Pilon (1980); Batra and Vanhonacker (1988); Doyle and Saunders (1990); Hanssens (1980a,b); Jacobson and Nicosia (1981); Leeflang and Wittink (1992); Roy et al. (1994);...
Multiple-equation models (e.g. VAR, VARMA, SURARMA)	Granger and Newbold (1986); Heuts and Bronckers (1988); Kleinbaum (1988); Moriarty and Salamon (1980); Umashankar and Ledolter (1983).
Spectral-density models	Barksdale and Guffey (1972); Chatfield (1974); Parsons and Henry (1972); Reinmuth and Geurts (1977).

MTSA: Multiple Time Series Analysis (Bass and Pilon 1980); SURARMA: Seemingly Unrelated ARMA (Moriarty and Salamon 1980); ARMAX: ARMA model for endogenous dependent variable with additional explanatory exogonous variables (Franses 1990). VARMA: Vector AutoRegressive Moving Average Model (Granger and Newbold 1986).

TABLE 2
APPLICATION OF LONG-RUN TIME-SERIES CONCEPTS IN MARKETING

A. Unit-root testing

	STUDY	TEST STATISTIC
Tests for regular unit root	Baghestani (1991)	DF; ADF
	Chowdhury (1994)	ADF; Kwiatkowski et al. (1992)
	Dekimpe and Hanssens (1995a)	ADF
	Franses (1991)	Hylleberg and Mizon (1989)
	Franses (1994)	DF
	Johnson et al. (1992)	DF, ADF
	Jung and Seldon (1995)	DF; ADF
	Zanias (1994)	DF; ADF; CRDW (Sargan and Bhargava 1983)
Tests for seasonal unit root	Dekimpe and Hanssens (1995a)	Dickey, Hasza and Fuller (1984): Hasza and Fuller (1982)
	Heuts and Bronckers (1988)	Hasza and Fuller (1982)
Tests allowing for structural break	None	-
Tests accounting for outliers		

* DF = Dickey and Fuller test; ADF = Augmented Dickey and Fuller test; CRDW: Cointegrating Regression Durbin Watson test

B. Cointegration / Error correction models

	STUDY	APPLICATION AREA
Engle and Granger's OLS approach	Baghestani (1991)	Advertising-sales relation at the brand level (Lydia Pinkham)
	Chowdury (1994)	Relationship between aggregate advertising spending and macro-economic variables
	Franses (1994)	Primary demand for Dutch cars
	Johnson et al. (1992)	Primary demand for alcoholic bevarages
	Zanias (1994)	Advertising-sales relation at the brand level (Lydia Pinkham)
Johansen's FIML approach	Jung and Seldon (1995)	Relationship between aggregate advertising spending and consumption
	Dekimpe and Hanssens (1995a)	Advertising-sales relationship for a home-improvement chain
Boswijk approach	Franses (1994)	Primary demand for Dutch cars
Stock and Watson approach	Chowdhury (1994)	Relationship between aggregate advertising spending and macro-economic variables
Seasonal CI / CI between series integrated of higher order	None	-

C. Persistence modeling

	STUDY	APPLICATION AREA
Univariate persistence		
Campbell and Mankiw's $A(1)$	Dekimpe and Hanssens (1995a)	Advertising-sales relationship for a home-improvement chain
Cochrane's V-measure	None	-
Spectral-density measure	None	-
Multivariate persistence with prior causal ordering	Dekimpe and Hanssens (1995a)	Advertising-sales relationship for a home-improvement chain
Multivariate persistence without prior causal ordering	None	-

TABLE 3
EMPIRICAL FINDINGS

A. Primary demand

Product Category	Test Statistic	m	Unit root?	A(1) (median)
Detergent	-2.97	2	No	0.00
Yogurt	-4.29	0	No	0.00
Catsup	-2.41	5	Yes	0.20
Soup	-2.11	2	Yes	0.43

B. Brand sales: Liquid detergent market

Brand	Test Statistic	m	Unit Root?	A(1) (median)
Tide	-3.58	2	No	0.00
Wisk	-7.35	0	No	0.00
Era	-6.76	0	No	0.00
Cheer	-3.48	3	No	0.00
Bold	-5.77	0	No	0.00
Solo	-2.18	8	Yes	0.08
Surf	-2.71	0	Yes	0.64

C. Brand sales: Yogurt market

Brand	Test Statistic	m	Unit Root?	A(1) (median)
Dannon	-3.04	2	No	0.00
Yoplait	-4.44	0	No	0.00
Weight Watchers	-4.09	0	No	0.00
Nordica	-2.32	2	Yes	0.26
WBB	-2.50	2	Yes	0.17
QCH	-0.96	9	Yes	0.20
Private label	-2.84	3	Yes	0.30

D. Brand sales: Catsup market

Brand	Test Statistic	m	Unit Root?	A(1) (median)
Hunts	-6.55	2	No	0.00
Del Monte	-5.44	1	No	0.00
Heinz	-2.86	5	Yes	0.21
Private label	-7.91	0	No	0.00

E. Brand sales: Soup market

Brand	Test Statistic	m	Unit Root?	A(1) (median)
Campbells	-2.27	2	Yes	0.39
Swanson	-2.53	6	Yes	0.54
Private label	-7.65	0	No	0.00