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EMPIRICAL GENERALIZATIONS ABOUT MARKET EVOLUTION AND STATIONARITY

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We present empirical generalizations about conditions under which marketing variables evolve or remain stationary. We first define evolution statistically and make the case why it is an important concept for increasing our understanding of long-run marketing effectiveness. We then briefly review ways in which evolution can be tested empirically from readily available data. We present a database of over 400 prior analyses and catalog the relative incidence of stationarity versus evolution in market performance and marketing spending. We find that evolution is the dominant characteristic for sales and marketing-mix spending, but that stationarity is the dominant characteristic for market share. Thus we find strong support for the conjecture that many markets are in a long-run equilibrium where the relative position of the players is only temporarily disturbed by their respective marketing activities. We assess the impact of a number of covariates on the likelihood of finding stationarity/evolution in sales and market share, and discuss the managerial implications of our findings.
(Econometric Models; Marketing Mix; Evolution; Stationarity)

1. Introduction

Companies' marketing practices and market performance often change over time. Since deregulation, airlines have increasingly used fare discounting as a way to attract new passengers, but they have also adopted a new focus on building customer loyalty by offering a variety of perks to frequent fliers. Over the last decade, there has been a growing emphasis on sales promotions in the consumer-goods industry (Simon and Sullivan 1993), in contrast to the seventies, which witnessed ever-increasing advertising budgets (Metwally 1978). As marketing strategies evolve, so may sales and their distribution across competitors. Johnson et al. (1992), for example, observed an upward trend in the real price of several Canadian alcoholic beverages and assessed its impact on the evolution of their consumption levels, while Hanssens and Johansson (1991) discussed the gradual share erosion of U.S. manufacturers in the domestic automobile market. Such up- and downward evolutions in a brand's performance may also be caused by external factors (e.g., demographic changes and/or macro-economic fluctuations), which may in turn translate into gradually changing marketing budgets and spending practices.

Not all markets show clear trends, however. Several authors have argued that many markets reach a long-run equilibrium where the relative position of the different players changes only temporarily as a result of their respective marketing activities. Ehrenberg (1991, 1994) claims in this respect that stationary markets are observed most frequently,

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and Bass and Pilon (1980) argue that competitive reactions often prevent long-run market-share gains. Supporting evidence for these points of view is found in Lal and Padmanabhan (1994) who regress the volume share of 233 products against time, and find a significant relationship in only 33 instances. Moreover, in only eight cases could these share trends be linked to the brands' promotional expenditures.

Our paper contributes a methodology and empirical generalizations that distinguish evolving from stationary markets. We first provide formal definitions of "stationarity" and "evolution" that allow us to empirically separate the two. We then provide a large-scale meta-analysis on their relative incidence in marketing, and we test a number of hypotheses on what factors affect their likelihood of occurrence.

Our empirical findings are of value to both marketing managers and researchers. Indeed, the effectiveness of alternative marketing strategies critically depends on the nature of the competitive environment (Aaker and Day 1986, Dekimpe and Hanssens 1995). A gradual increase in advertising support may, for example, stimulate sales growth in evolving markets, but may be self-canceling (and escalating) in stationary environments (see also Metwally 1978).

The distinction between stationary and evolving environments poses important challenges to the marketing scientist. Indeed, most implementable marketing models implicitly assume that a brand's performance fluctuates around a predetermined level from which marketing can create temporary deviations. These models allow precise estimates on marketing's short-term effectiveness in stationary environments, but do not provide insights into the underlying causes (be they marketing or nonmarketing related) of prolonged up- or downward trends in a brand's performance. Still, such insights are crucial when trying to improve the brand's long-run position in ever-changing environments, or when assessing the long-run effectiveness of alternative marketing strategies. Put differently, the short run is full of rich data and precise estimation methods, but may lack strategic relevance; the analysis of long-run fluctuations is full of strategic relevance, but still imprecise on measurement.

In earlier work, we discussed the concept of persistence as a way to bridge these two domains (Dekimpe and Hanssens 1995).[1] Persistence is a measure of the extent to which changes in current conditions (say, sales levels or marketing budgets) lead to permanent future changes. It reflects the impact of six marketing factors: instantaneous effects, delayed response, purchase reinforcement, performance feedback, decision rules, and competitive reactions.[2] By calculating persistence, we can derive to what extent our long-run forecasts should be adjusted when short-term changes occur in market performance and/or marketing control.[3] As shown in Dekimpe and Hanssens (1995), persistent marketing effects can *only* occur in evolving environments, i.e., where the performance fluctuations are not just temporary deviations from a pre-determined (i.e., deterministic) level. As an example, a sales promotion may induce a thousand consumers to switch to our brand at the promotion price. If these consumers return to their previous purchase habits once

[1] For other applications of the persistence concept, see Campbell and Mankiw (1987) and Evans (1989). Campbell and Mankiw introduced the concept in a univariate setting, while Evans extended their measure to multivariate scenarios.

[2] Most previous studies on the over-time effectiveness of marketing focus on only a subset of these dimensions (e.g., Clarke 1976, Lal and Padmanabhan 1994), and therefore do not quantify the *total* long-run impact of a given marketing action.

[3] Persistence measures therefore quantify the hysteresis concept discussed by Little (1979) and Simon (1994). Simon recently emphasized the need for more research on hysteresis, especially on generalizations that will help us predict its occurrence (p. 1). As indicated below, our research is a first step in this direction. Persistence measures also operationalize the two long-run goals of marketing activity elucidated by Bass et al. (1984): "One purpose of marketing activity is to make behavior nonstationary in a direction which is favorable to a brand. Another purpose is to prevent behavior from becoming nonstationary in a direction which is not favorable to a brand." (p. 285).

the promotion has ended, then our brand's performance will not be fundamentally altered as a result of this marketing effort. Instead, we will observe stationary sales, and the fluctuations due to the promotion will be temporary in nature. On the other hand, if two hundred of the promotion-induced customers stick with our brand, then the original promotion would have a persistent effect and the observed sales would deviate permanently from pre-promotion levels, i.e., there would be no mean reversion and sales would evolve.

In general, marketing is said to have a persistent effect on performance if it can be shown that it affects the evolution in market performance. A *necessary* condition for the existence of long-run (persistent) marketing effectiveness is therefore the presence of evolution in performance.[4] Our meta-analytic results on the relative incidence of evolution/stationarity therefore provide an *upper bound* for the presence of long-run marketing effectiveness. They complement Lal and Padmanabhan's work in a number of ways: our perspective is broader in that we do not limit ourselves to the long-run effectiveness of sales promotions alone, we consider both long-run market share as well as primary-demand effects, we define trends stochastically rather than deterministically, and we test a number of formal hypotheses on when evolution is most likely to be observed. On the other hand, our study does *not* quantify the magnitude of long-run marketing effectiveness. This would require the persistence measures on a large number of marketing data, which is left as an important area for future research.

The remainder of the paper is organized as follows. In §2, we formalize the notion of evolution and indicate two approaches to empirically distinguish stationary from evolving patterns. Section 3 describes our database, and §4 introduces our main hypotheses. Empirical results are presented in §5, and §6 summarizes the managerial implications of our findings.

2. Evolution versus Stationarity

The distinction between stationarity and evolution can be illustrated through the following first-order autoregressive model of a brand's sales performance:

$$(\quad - \phi L)S_t = c + u_t, \qquad \text{with} \qquad S_0 = 0,$$

where ϕ is an autoregressive parameter, L the lag operator (i.e., $L^k S_t = S_{t-k}$), u_t a series of zero-mean, constant-variance (σ_u^2) and uncorrelated random shocks, and c a constant. Applying successive backward substitutions allows us to write equation (1) as

$$S_t = [c/(\quad - \phi)] + u_t + \phi u_{t-1} + \phi^2 u_{t-2} + \cdots$$

in which the present value of S_t is explained as a weighted sum of past random shocks. Depending on the value of ϕ, two scenarios can be distinguished. When $|\phi| < 1$, the impact of past shocks diminishes and eventually becomes negligible. Hence, each shock has only a temporary impact. In this case, the series has a fixed mean $c/(1 - \phi)$ and a finite variance $\sigma_u^2/(1 - \phi^2)$. Such a series is called stationary. When $|\phi| = 1$, however, (1) becomes:

$$(1 - L)S_t = \Delta S_t = c + u_t,$$

which can be written as

$$S_t = (c + c + \cdots) + u_t + u_{t-1} + u_{t-2} + \cdots, \tag{4}$$

implying that each random shock has a permanent effect on the brand's sales. In this

[4] Pesaran et al. (1993) recently introduced a somewhat different persistence operationalization: the normalized cross-spectrum at frequency zero. Here, too, evolution is a necessary condition for nonzero persistence, and our results still apply when adopting their measure.

case, no fixed mean is observed, and the variance increases with time. Sales do not revert to a historical level, but instead wander freely in one direction or another, i.e., they *evolve*.

A number of approaches have been used in the marketing literature to distinguish both scenarios (Hanssens et al. 1990). First, the $\phi = 1$ case corresponds to the presence of an integrated component in traditional ARIMA models, and the pattern of the series' autocorrelation function has often been used to determine whether or not the series should be differenced as in equation (3).[5] More recently, unit-root tests have been developed to formally test whether or not the autoregressive polynomial $(1 - \phi L)$ has a root on the unit circle.[6,7] Such tests can be performed with or without controlling for deterministic trends in the data.

The previous discussion used a first-order autoregressive model to introduce the distinction between stationarity and evolution.[8] The findings can easily be generalized to more complex data-generating processes, however, as the stationary/evolving character of a series is still determined by its level of integration. Evolving patterns may also arise because of seasonal factors. Consider, for example, the seasonal equivalent of model (1):

$$(- \phi_d L^d) S_t = c + u_t, \qquad \text{with} \qquad S_0, S_{-1}, \ldots, S_{-d+1} = 0. \tag{5}$$

Equation (5) represents a seasonal process where $d = 4$ for quarterly observations and $d = 12$ for monthly data. Sales are seasonally integrated or seasonally evolving when $\phi_d = 1$ (Osborn et al. 1988, Osborn 1990). As before, both ARIMA identification tools (see, e.g., Hanssens 1980a) and formal unit-root tests (see, e.g., Dekimpe 1992, Franses 1991) have been used to determine the level of seasonal integration of marketing variables. In what follows, we do not make a distinction between series that are "regularly" or "seasonally" integrated; both are classified as evolving.

3. Database

We collected all univariate time-series models published between 1975 and 1994 in the following leading journals: *International Journal of Forecasting*, *International Journal of Research in Marketing*, *Journal of Advertising Research*, *Journal of Business*, *Journal of Business Research*, *Journal of Marketing*, *Journal of Marketing Research*, *Management Science* and *Marketing Science*. The reference lists of the identified articles were used to trace other studies, and an extensive computer search of the ABI/Inform data base (period 1987–1994) was performed to further augment our sample. Finally, when we were aware of ARIMA models in other journals, working-paper series and/or doctoral dissertations, we added these models to our data set. In total, we identified 44 studies which reported

[5] See, e.g., Helmer and Johansson (1977) or Hanssens (1980b).

[6] See Diebold and Nerlove (1990) for a review, and Dekimpe and Hanssens (1991, 1995) or Franses (1991, 1995) for marketing applications.

[7] Lal and Padmanabhan (1994) do not formally test for the presence of a unit root. Instead, they *uniformly* difference all series in one set of analyses, and work *uniformly* with the original data (i.e., the share levels) in another set. As such, they do not make the distinction between stationary and evolving performance series in their study on the long-run effectiveness of sales promotions. They also test for the presence of a deterministic trend in 233 share series. The unit-root concept, on the other hand, defines trends stochastically, which may result in more plausible long-run forecasts (Pesaran and Samiei 1991). Unit-root analysis is also managerially more appealing in that it does not restrict marketing's effectiveness to creating temporary deviations from a predetermined trend line.

[8] More technically, stationarity is used to describe the behavior of a time series where all observed fluctuations are temporary deviations from a deterministic component. This component could, for example, consist of a fixed mean (as in Eq. (1)), a set of seasonal means, or a deterministic trend (so-called trend stationarity). In contrast, nonstationarity or evolution is used to describe behavior that is not reverting to such a deterministic component.

TABLE 1

Description of the Data Set

Study	Product Description	Performance Series	Control Series	Method: Unit Root Test?
Aaker et al. (1982)	Cereal	6	6	No
Adams and Moriarty (1981)	?	10	0	No
Baghestani (1991)	Vegetable juice			Yes
Bass and Pilon (1980)	Catsup		1	No
Carpenter et al. (1988)	Detergents	11	22	No
Dalrymple (1978)	Variety of ind. and cons. prod.	27	0	No
Dekimpe (1992)	Gifts	12	3	Yes
Dekimpe and Hanssens (1991)	Private airplanes	12	0	Yes
Dekimpe and Hanssens (1995)	House improvement chain	1	3	Yes
Didow and Franke (1984)	Aggregate sales and adv.	3	6	No
Doyle and Saunders (1985)	Gas appliances	1	6	No
Doyle and Saunders (1990)	Supermarket departments	12	0	No
Franses (1991)	Beer	1	2	Yes
Franses (1994)	Cars	1	0	Yes
Geurts and Ibrahim (1975)	Holiday reservations		0	No
Geurts and Whitlark (1992)	Cookies		3	Yes*
Hanssens (1980a)	Vegetable juice			No
Hanssens (1980b)	Domestic airline industry	7 (+14)	6 (+12)	No (Yes**)
Hanssens (1987)	Coffee, refrigerators, domestic airline industry	20	26	Yes
Helmer (1976)	Response to direct mailing of not-for-profit company			No
Helmer and Johansson (1977)	Vegetable juice			No
Heuts and Bronckers (1988)	Trucks		0	Yes
Jacobson and Nicosia (1981)	Aggregate adv. expend. + consumption			No
Johnson et al. (1992)	Alcoholic beverages	30	30	Yes
Kapoor et al. (1981)	Cons. product with back-to-school and Christmas peaks	1	0	No
Kleinbaum (1988)	Trucks	4	0	No
Krishnamurthi et al. (1986)	Freq. purch. consumer product	2	2	No
Leeflang and Wittink (1992)	Nonfood consumer products	0	28	No
Leone (1983)	Grocery product	3	3	No
Leone (1987)	Cat food, toothpaste	3	0	No
Leong and Ouliaris (1991)	Cars, apparel, planes, food, supermarket sales	6	0	Yes
Moriarty (1985a)	Vegetable juice	1	1	No
Moriarty (1985b)	Household regulator device	1	0	No
Moriarty (1990)	Durable; Househ. regul. device	2	0	No
Moriarty and Adams (1979)	Cleaning aid	10	0	No
Moriarty and Adams (1984)	Durables	2	0	No
Moriarty and Salamon (1980)	Freq. purchased branded good	4	0	No
Mulhern and Leone (1990)	Grocery sales	8	0	No
Narayan and Considine (1989)	Passengers on transit system		0	No
Somers et al. (1990)	Furniture	0	2	No
Takada (1988)	Grocery product	3	15	No
Umashankar and Ledolter (1983)	Freq. purchased branded good	5	0	No
Wichern and Jones (1977)	Toothpaste	2	0	No
XX (1994)	Orange juice	0	13	Yes

* Analyzed by Dr. K. Powers.

** Data on two other routes were analyzed by Dr. K. Powers

XX Anonymous study for which one of the authors was a reviewer.

more than 400 different models. A summary of the included studies is given in Table 1.[9]

Two hundred thirteen series were classified using formal unit-root tests, while 206 were classified using the more traditional ARIMA approach. It may well be that some authors who used a visual inspection of the (partial) autocorrelation function over- or underdifferenced their data, but we see no reason why one error would be more prevalent than others. As such, we feel that our subsequent results would hold up directionally if all series had been classified using formal unit-root tests. To partially validate this assumption, we asked an independent researcher, Dr. Keiko Powers, to analyze 46 marketing and 10 psychology time series using both methods. In more than 90 percent of the cases, the same classification was obtained, and there was no significant difference in the proportion of variables classified as evolving by the two methods.

The relative incidence of evolution and stationarity is given in the following table:

	Evolving	Stationary
All models	227 (54%)	192 (46%)
Market performance only	131 (60%)	89 (40%)
Marketing mix only	96 (48%)	103 (52%)

We find evolution in a majority of the cases, in all marketing series in general as well as in market performance alone. As such, our results suggest that in many cases the necessary conditions exist for making a long-run impact. This is good news for the marketing scientist and the marketing manager alike, though it also invites close scrutiny of the approximately 40% of the cases where market performance does *not* evolve over time. Note also that escalating marketing spending can only be observed in less than half of the cases, as a slight majority of the control series is stationary.

With respect to the performance series, it is useful to make a distinction between sales and market-share measures. Indeed, sales can be affected by external market growth and decline, while market share is not. Also, competitive reactions may be less severe when a firm's strategy aims at expanding the market rather than attacking competitors' relative positions. The meta-analysis by performance measure is:

Market performance measure (*)	Evolving	Stationary
Sales (revenues or units)	122 (68%)	58 (32%)
Market share	9 (22%)	31 (78%)

(*) Test of equality of proportions is rejected at $p < 0.05$.

A striking result is that a vast majority of the market-share series is stationary. This confirms the argumentation of, among others, Bass and Pilon (1980), Ehrenberg (1991, 1994), and Lal and Padmanabhan (1994) that many markets are in a long-run equilibrium where the *relative* position of the players is only temporarily affected by their marketing activities. An important implication of this finding is that, unless there are primary-demand effects, marketing expenditures tend to be self-canceling in the long run. In contrast, sales (i.e., the brand's *absolute* performance levels) are indeed evolving in a majority of the cases. Future research is needed, however, to determine whether the observed sales evolutions are driven by the firms' marketing efforts, or whether they result

[9] A number of the studies in Table 1 used the same data set (e.g., Baghestani 1991, Helmer and Johansson 1977, and Moriarty 1985a). In those instances, the data base was adjusted to avoid double counting in our analyses.

from macro-economic and/or demographic fluctuations beyond management's control. Multivariate persistence may be calculated to address this issue, as illustrated by Dekimpe and Hanssens (1995) in their study on the sales evolution of a large home-improvement chain.

Further research is also needed to investigate under what circumstances one is most likely to observe evolution or stationarity. Indeed, even though stationarity is the dominant characteristic for market share, we find evolutionary behavior in quite a few cases. Similarly, while one could expect evolution in sales from product-life-cycle or diffusion theory, the incidence of stationary sales patterns is far from negligible. Sections 4 and 5 will investigate the moderating impact on evolution of (1) the level of entity aggregation (brand/firm versus category/industry level), (2) the nature of the product category (durable or not), (3) the level of temporal aggregation, (4) the recency of the series, (5) the length of the considered time span, and (6) the country of origin. Section 4 provides the theoretical background for the hypotheses, and §5 discusses the empirical results. Given the differences in results between market share and sales, we will, whenever relevant, test the impact separately for each variable.

4. Hypotheses

Primary-demand effects may be most prominent when dealing with category/industry sales. We therefore expect to observe a higher proportion of evolving series at that level of aggregation than at the brand/firm level. The impact of this covariate is considered only for sales data, since shares are, by definition, brand related.

The nature of the product (durable or not) may also have an impact on the likelihood of finding evolution. The direction of this effect is not clear a priori, though. On one hand, switching costs may be higher for durables, suggesting longer-lasting effects of an initial purchase. Also, the impact of word-of-mouth communications is often more important when dealing with durables, suggesting that each individual purchase is more likely to become a trend setter (Mowen 1990, Urban 1993). On the other hand, for frequently purchased low-involvement products customers may stick with the first brand they find satisfactory (Lieberman and Montgomery 1988). Because of this higher purchase-reinforcement effect, one could hypothesize that long-run effects are more likely to occur for nondurables.

Next, we examine the important issue of temporal data aggregation. Within the current framework, data-aggregation bias would occur when the presence/absence of evolution depends on the data interval. As shown in Cogger (1981), aggregation does not affect the level of integration of an ARIMA model, and hence does not change the classification of a variable as either stationary or evolving. The question remains, however, whether the power of the testing procedures increases when using a smaller data interval. Put differently, even though the level of integration of the underlying data-generation process is not affected, does an increase in the sample size affect the proportion of correctly classified series? Conventional wisdom would suggest that more observations are better; for example, 120 monthly observations are preferred over 40 quarterly observations. When using unit-root tests to classify the series, though, little power is gained by merely sampling more frequently (see, e.g., Perron 1989 or Shiller and Perron 1985 for simulation evidence), and the critical variable is the length of the sample period rather than the frequency within a given time span. Also, when traditional ARIMA modeling techniques are used, it is not obvious that a mere increase in the sampling frequency will substantially facilitate the modeler's task of deciding on the level of integration. The underlying intuition can be clarified by considering an annual AR(1) model with $\phi = 0.9$. On one hand, the modeler has more data points when using quarterly data, and should therefore be able to obtain more precise inferences on the magnitude of the autoregressive parameter. On the other hand, the quarterly ϕ value is no longer 0.9 but much closer to one (Hakkio and Rush 1991), which intuitively makes it more difficult to make a correct classification. Based on the above discussion, we hypothesize no relationship between a series' level of temporal aggregation and its classification as stationary or evolving.

The length of the time sample may also be an important moderating variable (Perron 1989). Diffusion theory and product-life-cycle (PLC) theory suggest that evolution becomes more likely when the entire performance history of the brand is included in the sample. This implies that the likelihood of finding evolution increases when the sample period becomes longer. On the other hand, Shiller and Perron (1985) find that one is more likely to correctly reject a unit-root null hypothesis when the time span increases. Moreover, PLC theory suggests that a brand's performance and control variables go through distinct stages of growth, maturity and decline. If the series is truly evolving (stationary), a shorter sampling span may increase the likelihood of finding a seemingly stationary (evolving) pattern (Banerjee et al. 1992). In sum, the length of the time span may affect how a series is classified, but we have no strong priors on the direction of the effect.

A number of authors have argued that the PLC has become shorter over time (see Bayus 1992 for a review), which may affect the probability of finding evolution in more recent time series. We will therefore test the hypothesis that data recency affects the likelihood of evolution, while controlling for the length of the time sample.

Conventional wisdom suggests that some cultures are more brand loyal or long-term oriented than others, and that differences in the legal environment or competitive structure may affect the likelihood of finding evolution/stationarity.[10] Moreover, previous meta-analyses found significant cross-country differences in the short-term effectiveness of advertising and price (Assmus et al. 1984, Tellis 1988). Our analysis will investigate whether or not these differences carry over in the long run.

5. Empirical Findings

The following empirical generalizations are derived from the database.

5.1. *Sales evolution is more likely to occur at the industry/category level than at the individual brand/firm level.*

Sales (*)	Evolving	Stationary
Brand/firm Level	77 (59%)	53 (41%)
Category/industry Level	45 (92%)	4 (8%)

(*) Test of equality of proportions is rejected at $p < 0.05$.

This finding implies that, all else equal, strategies aimed at category expansion are more likely to have long-run effects than those aimed at brand-sales expansion.

5.2. *Sales and market-share evolution in durables is as likely as in non-durables.*(*)

Sales (Market Shares)	Evolving	Stationary
Durables	14 (0)	11 (4)
Nondurables[11]	84 (9)	41 (27)

(*) Based on 150 sales and 40 share series that could be classified from the authors' description.

[10] Leeflang et al. (1991), for example, describe how the Dutch government kept the maximum airing time for television commercials at a fixed level for more than a decade.

[11] This category contains both frequently purchased branded goods and services.

The absence of a significant difference suggests that neither explanation we described earlier is powerful enough to make the sales level of durables more likely to evolve than that of nondurables. The same holds for market share, with the following caveat. All nine evolving market shares dealt with nondurable goods or services, so the absence of a *statistically significant* relationship may well be due to the small sample size.

5.3. *Temporal aggregation affects the likelihood of finding evolution.*

A logit model (0 = stationary / 1 = evolving) was estimated on the total sample with two dummy variables for the level of aggregation, and with the length of the sample period as control variable. Annual series were used as the base group, and the two dummy variables referred to, respectively, quarterly / bimonthly and monthly-or-smaller data intervals. Contrary to our expectations, we find that the level of aggregation has an impact on the resulting classification: *evolution becomes more likely when the data are sampled more coarsely.*

Limiting the sample to, respectively, the sales and market-share series, the same substantive results were obtained: even though aggregation does not affect the *true* order of integration of the data-generating process, the *testing* procedures used to infer that order are sensitive to the sampling frequency.

5.4. *Sales evolution was most frequently observed in the seventies.*

A logit model was used to test for the presence of a recency effect in, respectively, the total sample and the set of sales series. Series that started before 1970 were used as the base group, and two dummy variables were used to denote, respectively, a starting point in the seventies and the eighties. As before, we included the length of the sample period as a control variable. In both samples, series starting in the seventies were more likely to be classified as evolving, but no significant difference was found between series starting before 1970 and series starting after 1980. The latter finding corroborates to some extent the results of Bayus (1992), who found that diffusion rates have not significantly accelerated over time.

To make some inferences on the presence of a recency effect in market share, a dummy variable was created to distinguish series originating before and after 1980. It was found that *the more recent share series were more likely to be stationary*. This may reflect that competitive reactions have intensified in recent history, making it more difficult for a brand to create long-run market share gains.

5.5. *The longer the sample, the more likely one is to find evolution in sales, but not in market share.*

In the previous analyses (§§5.3. and 5.4), we found that the length of the sample period (which we used as a control variable) had a significant and positive impact on the probability of finding evolution, both when looking at the total sample and when considering sales only.[12] This dependence on the length of the observation period was also observed by Ehrenberg (1994), who argued that most marketing phenomena appear to be stationary when the window of observation is relatively small (e.g., up to two years). Our findings raise an important question, though, on the optimal length of the sample when trying to make inferences about the long-run effectiveness of marketing on sales. Too short a time period may make it more difficult to capture the underlying long-term movements (Hakkio and Rush 1991). A very long observation period (e.g., two decades), on the other hand, may make the findings less managerially relevant, and the assumption that the data-generating process did not change over time may become harder to defend. Further research along the lines of Banerjee et al. (1992) is therefore desirable. They used moving-window unit-root tests to empirically assess possible transition points in the data-generating process.

For the market-share series, on the other hand, the length of the time series did not

[12] These results were obtained in both logit and stepwise discriminant analyses.

have a significant impact. In a stepwise discriminant analysis, for example, this variable was never included. This insensitivity to the sample length, which should again be interpreted with some caution because of the smaller sample size, provides further evidence of the fact that, even when looking at prolonged periods of time, market shares tend to be in a long-run equilibrium position.

5.6. *There is a significant difference between North America and Europe in their proportion of evolving sales variables.*

Region (*)	Evolving Sales	Stationary Sales
United States & Canada	117 (72%)	46 (38%)
Europe	5 (29%)	12 (71%)

(*) Test of equality of proportions is rejected at $p < 0.05$.

This implies that the potential for long-run effectiveness is different in the two continents, which may be caused by differences in their legal and competitive structure. No European market-share data were available, but for the market-share series, a comparison could be made between the United States and Canada on the one hand, and Australia and New Zealand on the other hand.

Region (*)	Evolving	Stationary
United States & Canada	8 (29%)	20 (71%)
Australia & New Zealand	1 (8%)	11 (92%)

(*) Test of equality of proportions cannot be rejected at $p < 0.05$.

In this case, no significant differences could be observed, with a vast majority of the share series being stationary in both continents.

6. Conclusions

We have made the case that marketing scientists and managers should pay close attention to factors that cause market performance to evolve. Evolution is empirically tractable and provides a much needed link between readily observable short-run fluctuations and important long-run movements on which strategic thinking should be based.

We derived a number of empirical generalizations about conditions under which markets are likely to evolve. Among them, we highlight our finding that sales evolution is the rule rather than the exception, but that market shares tend to be stationary. Also, observing evolution becomes more likely when sampling data more coarsely and over longer time periods.

Focusing on market-share stationarity, we further find that this condition is equally prevailing in long vs. short time samples, but more prevailing when time periods are measured more finely and more recently.

Taken together, these generalizations provide a foundation for the study of long-run marketing effectiveness. When we find evidence of evolution, we establish an upper bound for the existence of long-run marketing effectiveness, i.e., when evolution is present, it *can* (but need not) be influenced by marketing actions. As such, an understanding of when evolution takes place guides the manager and the marketing scientist toward those conditions where a long-run impact can be made. The logical next research steps are (1) to extend the set of moderating variables, (2) to calculate multivariate persistence estimates that quantify the impact of specific marketing activities on the brand's performance evolution, and (3) to build empirical generalizations about factors that influence these persistence levels.

A few specific areas for future research emerge from our work. One is the relationship between the structure of the competitive environment and the long-run effectiveness of alternative marketing strategies. Second, we should investigate the need to react to competitive moves, not only in function of their immediate impact, but also in function of their long-run effects on a brand's performance. Finally, empirical generalizations are needed on what strategies are best suited to *create* or *maintain* a positive long-run evolution. For example, should one gradually increase the brand's communications support, or should one opt for periodic, more drastic changes in several marketing-mix instruments (see, e.g., Simon 1994)? From a defensive point of view, what strategies should the market leader in a stationary market adopt to maintain this favorable equilibrium position? We hope that these and other questions will be pursued, for the benefit of enhancing our understanding of long-run marketing effectiveness.

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References

Aaker, D. A., J. M. Carman, and R. Jacobson (1982), "Modeling Advertising Sales Relationships Involving Feedback: A Time-Series Analysis of Six Cereal Brands," *Journal of Marketing Research*, 19, 116–125.

——— and G. S. Day (1986), "The Perils of High Growth Markets," *Strategic Management Journal*, 7, 409–421.

Adams, A. J. and M. M. Moriarty (1981), "The Advertising-Sales Relationships: Insights from Transfer-Function Modeling," *Journal of Advertising Research*, 21, 41–46.

Assmus, G., J. U. Farley, and D. R. Lehmann (1984), "How Advertising Affects Sales: Meta Analysis of Econometric Results," *Journal of Marketing Research*, 21, 65–74.

Baghestani, H. (1991), "Cointegration Analysis of the Advertising-Sales Relationship," *Journal of Industrial Economics*, 34, 671–681.

Banerjee, A., R. L. Lumsdaine, and J. H. Stock (1992), "Recursive and Sequential Tests of the Unit Root and Trend Break Hypotheses: Theory and International Evidence," *Journal of Business and Economic Statistics*, 10, 271–287.

Bass, F. M., M. M. Givon, M. V. Kalwani, D. Reibstein, and G. P. Wright (1984), "An Investigation into the Order of the Brand Choice Process," *Marketing Science*, 3, 267–287.

——— and T. L. Pilon (1980), "A Stochastic Brand Choice Framework for Econometric Modeling of Time Series Market Share Behavior," *Journal of Marketing Research*, 17, 486–497.

Bayus, B. L. (1992), "Have Diffusion Rates Been Accelerating Over Time?" *Marketing Letters*, 3, 215–226.

Carpenter, G. S., L. G. Cooper, D. M. Hanssens, and D. F. Midgley (1988), "Modeling Asymmetric Competition," *Marketing Science*, 7, 393–412.

Campbell, J. Y. and N. G. Mankiw (1987), "Are Output Fluctuations Transitory?" *Quarterly Journal of Economics*, 102, 857–880.

Clarke, D. G. (1976), "Econometric Measurement of the Duration of Advertising Effect on Sales," *Journal of Marketing Research*, 13, 345–357.

Cogger, K. D. (1981), "A Time-Series Analytic Approach to Aggregation Issues in Accounting Data," *Journal of Accounting Research*, 19, 285–298.

Dalrymple, D. J. (1978), "Using Box-Jenkins Techniques in Sales Forecasting," *Journal of Business Research*, 6, 133–145.

Dekimpe, M. G. (1992), "Long-run Modeling in Marketing," unpublished Ph.D. thesis, Los Angeles, UCLA.

——— and D. M. Hanssens (1991), "Assessing the Evolution of Competitive Relationships: Do Long-Run Market Equilibria Really Exist?", Center for Marketing Studies Working Paper No. 209, Anderson Graduate School of Management, UCLA.

——— and ——— (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1–21.

Didow, M. N. and G. R. Franke (1984), "Measurement Issues in Time-Series Research: Reliability and Validity Assessment in Modeling the Macroeconomic Effects of Advertising," *Journal of Marketing Research*, 21, 12–19.

Diebold, F. X. and M. Nerlove (1990), "Unit Roots in Economic Time Series: A Selective Survey," in T. B. Fomby and G. F. Rhodes (Eds.), *Advances in Econometrics*, 8, 3–69.

Doyle, P. and J. Saunders (1985), "The Lead Effect of Marketing Decisions," *Journal of Marketing Research*, 22, 54–65.

Doyle, P. and J. Saunders (1990), "Multiproduct Advertising Budgeting," *Marketing Science*, 9, 97–113.

Ehrenberg, A. S. C. (1991), "New Brands and the Existing Market," *Journal of the Market Research Society*, 33, 285–299.

——— (1994), "Theory or Well-Based Results: Which Comes First?" in G. Laurent, G. L. Lilien and B. Pras (Eds.), *Research Traditions in Marketing*, Boston: Kluwer Academic Publishers.

Evans, G. W. (1989), "Output and Unemployment Dynamics in the United States," *Journal of Applied Econometrics*, 4, 213–237.

Franses, P. H. (1991), "Primary Demand for Beer in the Netherlands: An Application of ARMAX Model Specification," *Journal of Marketing Research*, 28, 240–245.

——— (1994), "Modeling New Product Sales; An Application of Cointegration Analysis," *International Journal of Research in Marketing*, 11, 491–502.

Geurts, M. D. and I. B. Ibrahim (1975), "Comparing the Box Jenkins Approach with the Exponentially Smoothed Forecasting Model: Application to Hawaii Tourists," *Journal of Marketing Research*, 12, 182–188.

——— and D. Whitlark (1992), "Forecasting Market Share," *The Journal of Business Forecasting*, Winter, 17–22.

Hakkio, C. S. and M. Rush (1991), "Cointegration: How Short is the Long Run," *Journal of International Money and Finance*, 10, 571–581.

Hanssens, D. M. (1980a), "Bivariate Time Series Analysis of the Relationship Between Advertising and Sales," *Applied Economics*, 12, 329–340.

——— (1980b), "Market Response, Competitive Behavior, and Time Series Analysis," *Journal of Marketing Research*, 17, 470–485.

——— (1987), "Marketing and the Long Run," Center for Marketing Studies Working Paper No. 164, The Anderson Graduate School of Management, UCLA.

——— and J. K. Johansson (1991), "Rivalry as Synergy? The Japanese Automobile Companies Export Expansion," *Journal of International Business Studies*, 22, 503–526.

———, Leonard J. Parsons, and R. L. Schultz (1990), *Market Response Models: Econometric and Time Series Analysis*, Boston: Kluwer Academic Publishers.

Helmer, R. M. (1976), "New Experimental and Quasi-Experimental Designs for Estimating Lagged Effects of Advertising Directly," 1976 *Educators' Proceedings, American Marketing Association*, 478–482.

——— and J. K. Johansson (1977), "An Exposition of the Box Jenkins Transfer Function Analysis with an Application to the Advertising-Sales Relationship," *Journal of Marketing Research*, 14, 227–239.

Heuts, R. M. J. and J. H. J. M. Bronckers (1988), "Forecasting the Dutch Heavy Truck Market: A Multivariate Approach," *International Journal of Forecasting*, 4, 57–79.

Jacobson, R. and F. M. Nicosia (1981), "Advertising and Public Policy: The Macroeconomic Effects of Advertising," *Journal of Marketing Research*, 18, 29–38.

Johnson, J. A., E. H. Oksanen, M. R. Veall, and D. Fretz (1992), "Short-run and Long-run Elasticities for Canadian Consumption of Alcoholic Beverages: An Error-Correction Mechanism/Cointegration Approach," *The Review of Economics and Statistics*, 74, 64–74.

Kapoor, S. G., P. Madhok, and A. M. Wu (1981), "Modeling and Forecasting Sales Data by Time Series Analysis," *Journal of Marketing Research*, 18, 94–100.

Kleinbaum, R. M. (1988), *Multivariate Time Series Forecasts of Market Share*. Marketing Science Institute Report 88-102, Cambridge, MA.

Krishnamurthi, L., J. Narayan, and S. P. Ray (1986), "Intervention Analysis of a Field Experiment to Assess the Buildup Effects of Advertising," *Journal of Marketing Research*, 23, 337–345.

Lal, R. and V. Padmanabhan (1994), "Competitive Response and Equilibria," Working Paper, Stanford Graduate School of Business.

Leeflang, P. S. H., K. H. Alsem, and J. C. Reuyl (1991), "Diagnosing Competition for Public Purposes: A Case Study," Working Paper No. 207, The Anderson Graduate School of Management, UCLA.

——— and D. R. Wittink (1992), "Diagnosing Competitive Reactions Using (Aggregated) Scanner Data," *International Journal of Research in Marketing*, 9, 39–57.

Leone, R. P. (1983), "Modeling Sales-Advertising Relationships: An Integrated Time Series Econometric Approach," *Journal of Marketing Research*, 20, 291–295.

——— (1987), "Forecasting the Effect of an Environmental Change on Market Performance: An Intervention Time-Series Approach," *International Journal of Forecasting*, 3, 463–478.

Leong, S. M. and S. Ouliaris (1991), "Applying the Econometrics of Cointegration to Time Series Data in Marketing Research," Working Paper, National University of Singapore.

Lieberman, M. B. and D. B. Montgomery (1988), "First-Mover Advantages," *Strategic Management Journal*, 9, 41–58.

Little, J. D. C. (1979), "Aggregate Advertising Models: The State of the Art," *Operations Research*, 29, 629–667.

Metwally, M. M. (1978), "Escalation Tendencies of Advertising," *Oxford Bulletin of Economics and Statistics*, 40, 153–163.

Moriarty, M. M. (1985a), "Transfer Function Analysis of the Relationship Between Advertising and Sales: A Synthesis of Prior Research," *Journal of Business Research*, 13, 247–257.

——— (1985b), "Design Features of Forecasting Systems Involving Management Judgments," *Journal of Marketing Research*, 22, 353–364.

——— (1990), "Boundary Value Models for the Combination of Forecasts," *Journal of Marketing Research*, 27, 402–417.

——— and A. J. Adams (1979), "Issues in Sales Territory Modeling and Forecasting Using Box-Jenkins Analysis," *Journal of Marketing Research*, 16, 221–232.

——— and ——— (1984), "Management Judgment Forecasts, Composite Forecasting Models, and Conditional Efficiency," *Journal of Marketing Research*, 21, 239–250.

——— and G. Salamon (1980), "Estimation and Forecasting Performance of a Multivariate Time Series Model of Sales," *Journal of Marketing Research*, 17, 558–564.

Mowen, J. C. (1990), *Consumer Behavior*, New York: MacMillan Publishing Company.

Mulhern, F. J. and R. P. Leone (1990), "Retail Promotional Advertising: Do the Number of Deal Items and Size of Deal Discounts Affect Store Performance," *Journal of Business Research*, 21, 179–194.

Narayan, J. and J. Considine (1989), "Assessing the Impact of Fare Increases in a Transit System by Using Intervention Analysis," *Journal of Business Research*, 19, 245–254.

Osborn, D. R. (1990), "A Survey of Seasonality in UK Macroeconomic Variables," *International Journal of Forecasting*, 6, 327–336.

———, A. P. L. Chui, J. P. Smith, and C. R. Birchenhall (1988), "Seasonality and the Order of Integration for Consumption," *Oxford Bulletin of Economics and Statistics*, 50, 361–377.

Perron, P. (1989), "Testing for a Random Walk: A Simulation Experiment of Power when the Sampling Interval is Varied," in B. Raj (Ed.), *Advances in Econometrics and Modeling*, Boston: Kluwer Academic Publishers.

Pesaran, M. H., R. G. Pierse, and K. C. Lee (1993), "Persistence, Cointegration and Aggregation: A Disaggregated Analysis of Output Fluctuations in the U.S. Economy," *Journal of Econometrics*, 56, 57–88.

Shiller, P. J. and P. Perron (1985), "Testing the Random-Walk Hypothesis: Power versus Frequency of Observation," *Economics Letters*, 18, 381–386.

Simon, H. (1994), "Hysteresis in Marketing," Working Paper No. 04-1994, Johannes Gutenberg Universitat, Mainz.

Simon, C. J. and M. W. Sullivan (1993), "The Measurement and Determinants of Brand Equity: A Financial Approach," *Marketing Science*, 12, 28–52.

Somers, T. M., Y. P. Gupta, and S. C. Herriot (1990), "Analysis of Cooperative Advertising Expenditures: A Transfer-Function Modeling Approach," *Journal of Advertising Research*, 30, 35–49.

Takada, H. (1988), "Analysis of Competitive Market Behavior Using Multiple Time Series Analysis and Econometric Methods," Working Paper, University of California, Riverside.

Tellis, G. J. (1988), "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research*, 25, 331–341.

Umashankar, S. and J. Ledolter (1983), "Forecasting with Diagonal Multiple Time Series Models," *Journal of Marketing Research*, 20, 58–63.

Urban, G. L. (1993), "Pretest Market Forecasting," in J. Eliashberg and G. Lilien (Eds.), *Handbooks in Operations Research and Management Science (Marketing)*, Amsterdam: Elsevier Science Publishers.

Wichern, D. W. and R. H. Jones (1977), "Assessing the Impact of Market Disturbances Using Intervention Analysis," *Management Science*, 24, 329–337.