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An intuitively appealing decision rule is to allocate a company's scarce marketing resources to where they have the greatest long-term benefit. This principle, however, is easier to accept than it is to execute, because long-run effects of marketing spending are difficult to estimate. The authors address this problem by examining the behavior of market response and marketing spending over time and identify four common strategic scenarios: business as usual, hysteresis in response, escalation, and evolving business practice. The authors explain and illustrate why each scenario can occur in practice and describe its positive and negative consequences for long-term profitability. The authors propose to use multivariate persistence measures to identify which of the four strategic scenarios is taking place and illustrate this approach in the pharmaceutical and packaged-food industries. The results substantiate the authors' proposition that the strategic scenario is a major determinant of marketing effectiveness and long-term profitability. This conclusion sets up a substantial agenda for further research.

Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability

The question of optimal long-run marketing resource deployment continues to receive wide interest among marketing academics and practitioners alike (Lodish et al. 1995; Mantrala, Sinha, and Zoltners 1992; Slywotzky and Shapiro 1993). Academics understandably are surprised by reported empirical results that 85% of all promotions are losing money to the promoters and that only half of the advertising expenditures generate economic benefits to the advertisers (Abraham and Lodish 1990). Practitioners are concerned to observe virtually entire industries go through prolonged money-losing periods, such as the U.S. airlines in the early 1990s, and increasingly feel the pinch of demonstrating the long-run revenue generation of their marketing budgets (Cressman 1996; Gopalakrishna et al. 1995; Slywotzky and Shapiro 1993).

A key, and perhaps the most difficult, challenge is that only short-term results of marketing actions are readily ob-

servable, yet short-term profit maximization is not the best paradigm for allocating resources. Businesses in the United States in general, and the marketing discipline in particular, repeatedly have been criticized for their short-run orientation (for example, see Hansen and Hill 1991; Wind and Robertson 1983). Long-term profit maximization is considerably more difficult to operationalize, however, because there is little or no consensus of what constitutes the long run and because market conditions continuously change, making it difficult to relate future outcomes to current actions (Dekimpe and Hanssens 1995a, b; Wind and Robertson 1983).

Do marketing investments themselves help shape the future by contributing to changing market conditions or by affecting the competitors' long-run position? Certain well-publicized marketing events have been suggested to have changed market conditions forever. For example, in the early 1990s, Compaq launched an aggressively priced, high-quality line of products, which is widely believed to have opened up the home market for personal computers. Johnson and colleagues (1992) observe an upward trend in the real price of several Canadian alcoholic beverages and assess its impact on the evolution of beverage consumption levels. Slywotzky and Shapiro (1993) describe how a sustained and consistent marketing campaign caused Zantac to gain a 50% market share in the antiulcer medication market, whereas Tagamet's share gradually eroded to 23% over the

same six-year time span. Bronnenberg, Mahajan, and Vanhonacker (1998) illustrate how the evolution of market structures is related closely to the respective players' distribution evolution, and Hanssens and Johansson (1991) discuss the gradual share erosion of U.S. manufacturers in the domestic automobile market, which has been attributed in part to the differential effectiveness of the U.S. and Japanese manufacturers' marketing strategies. Much of this evidence is anecdotal though, and there is no broad body of knowledge that enables us to measure precisely the degree to which marketing efforts affect the long-term evolution of the marketplace.

Currently available managerial tools have been of little help in increasing our understanding of observable long-term marketing effects or offering guidelines for long-term resource allocation in evolving or changing markets. Marketing's focus has been on "short-run forecasting and optimization procedures, while assuming an essentially stable environment" (Wind and Robertson 1983, p. 13). However, recent empirical research suggests that 60% of market performance variables and 68% of sales variables are not stable but rather evolve over time (Dekimpe and Hanssens 1995a, p. G114). Moreover, we (1995b) have demonstrated how persistence models can quantify marketing effectiveness in such evolving environments. In a nutshell, marketing actions have persistent effects on sales if (1) the sales environment is evolving (as opposed to stable or stationary) and (2) this sales evolution depends on marketing actions. In our (1995b) empirical example, a home-improvement chain's price-oriented print advertising was shown to have a high short-run impact with limited sales persistence (mainly short-run benefits), whereas television spending had a low short-run impact with substantial sales persistence (mainly long-run benefits). The application illustrates that marketing can have persistent performance (*in casu*, sales) effects that can be quantified empirically. However, when assessing the long-run revenue implications, we should consider not only the output (response) implications, but also the input (spending) side of the equation.

In this article, we examine the long-run profitability implications of marketing decisions by comparing the ensuing spending strategies with their persistent results. We classify both marketing effort and market response as either short-lived (temporary) or persistent (evolving) and derive four strategic scenarios: business as usual, escalation, hysteresis, and evolving business practice. We examine the reasons these scenarios exist and their consequences for the long-run profitability of temporary, as well as sustained, marketing actions. We then turn our attention to two case studies that illustrate these strategic scenarios in the pharmaceutical and packaged-goods sectors. In each case, we diagnose a company's long-run marketing profitability on the basis of historical market performance and marketing mix data. We conclude with strategic recommendations based on long-run marketing profitability and address some areas for further research.

TEMPORARY VERSUS SUSTAINED EFFORT AND RESPONSE

Companies continually adjust their marketing mix in response to perceived changes in the market environment or in their goals. Some of these adjustments are temporary, in that

the company abandons the change in favor of the previous level after a finite time period. For example, a brand that offers a two-week discount off an otherwise fixed price engages in such a temporary effort. Other changes are permanent (sustained) if there is no return to the previous level. If the preceding discount policy leads to a regular practice of discount policies, it would be an example of a sustained effort. From a strategic perspective, the important question is whether temporary and sustained marketing efforts result in persistent market response that leads to long-run competitive advantage.

In Figure 1, we show the four scenarios that can exist in terms of temporary versus sustained effort and response. In each of the four graphs, we trace what happens to a brand's future performance and marketing spending after a one-unit spending increase in period t. The graphs depict the incremental impact compared with a situation in which this initial increase had not happened. If the impact converges to zero, the initial increase had only a temporary impact, whereas if it converges to a nonzero level, it has initiated a permanent deviation from previous performance and/or spending levels. In the business as usual cell, we only find a temporary increase in sales and marketing support; that is, the incremental impact disappears after a few periods. Suboptimal decision making therefore will have no long-run damaging impact on the firm's profitability. In the evolving business practice case, however, the initial budget increase leads to persistent changes in both spending and performance. The relative magnitude of these changes, along with the brand's long-run profit margin, will determine the long-run revenue implications of the extra dollars spent in period t. In contrast, only the long-run sales level is affected in the hysteresis case, and only the long-run spending level is updated in the case of escalation, which clearly translate to, respectively, positive and negative changes in the brand's long-run profitability.

There are many real-world illustrations of and explanations for the four scenarios described in Figure 1.[1] For example, empirical evidence from scanner panel data suggests that the performance and spending behavior of several frequently purchased consumer brands and categories is predominantly stationary (e.g., Dekimpe, Hanssens, and Silva-Risso 1999; Lal and Padmanabhan 1995). Yet companies resort repeatedly to promotional tactics to create temporary sales gains. This case can be classified as temporary marketing activity that creates temporary incremental results, a scenario we refer to as *business as usual*. Such scenarios often exist in market shares, which have been shown to fluctuate predominantly around fixed means over time (Dekimpe and Hanssens 1995a, p. G114; Srinivasan and Bass 1998). Ehrenberg (1988) argues that consumers' habitual buying propensities explain such stationary behavior, in both repeat buying and brand switching. Companies that can profitably play the repeated business as usual game can sustain their positions for a long time; for example, the alternating price promotions by leading national brands (e.g., Pepsi and Coca-Cola) can be regarded as a long-run strate-

Figure 1
STRATEGIC SCENARIOS RESULTING FROM TEMPORARY VERSUS PERMANENT EFFORT/RESPONSE

Key: ♦ Sales ■ Marketing mix
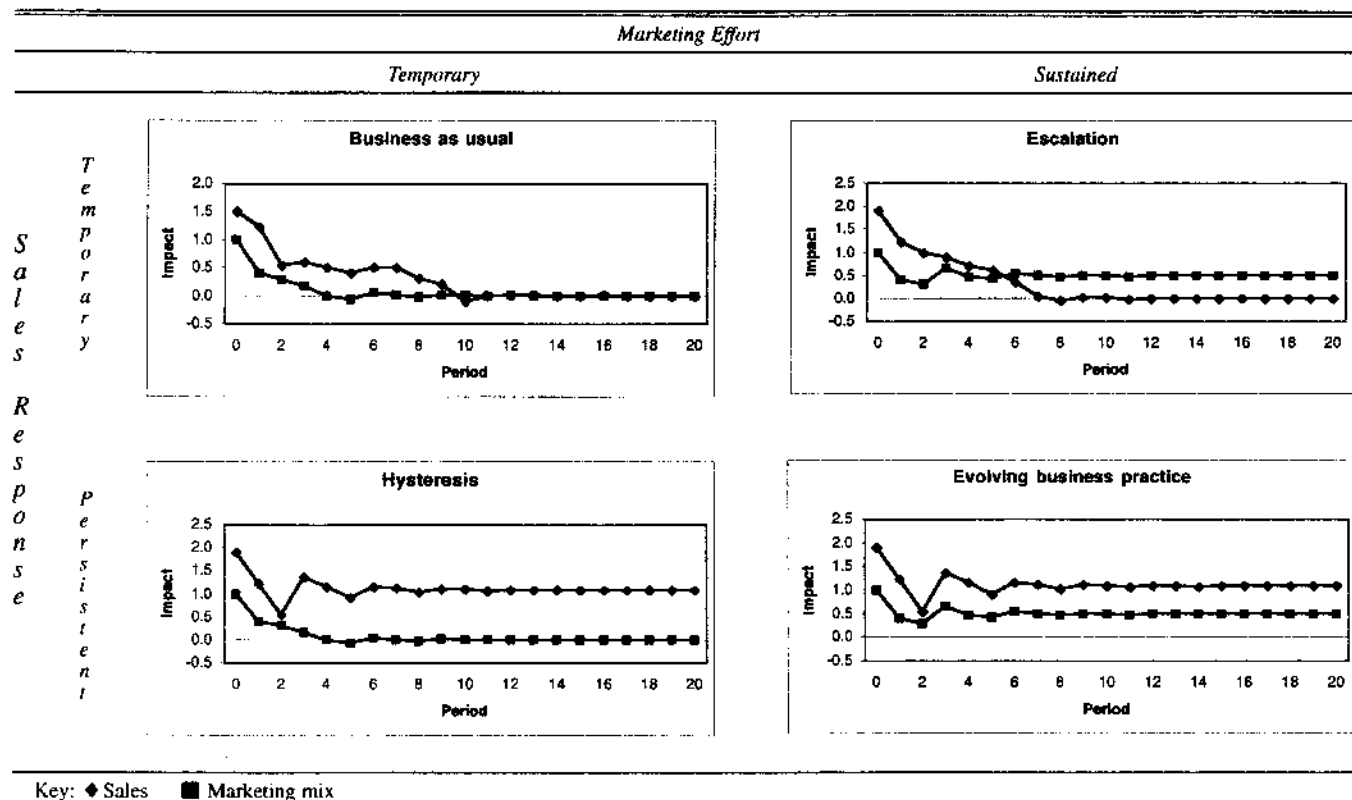
gy to defend their stable market shares from possible encroachment by a third firm (Lal 1990).

Other markets are characterized by the *escalation* of marketing expenditures or prices without long-run performance movements. Leeflang and Wittink (1996a), for example, provide empirical evidence that many managers tend to react to changes in a competitor's marketing instrument even when the brand's performance is not affected by that competitive change. Such overreaction also is observed in a replication study by Brodie, Bonfrer, and Cutler (1996). Using a detailed study of the market-share and reaction elasticities in six Australian product categories, Metwally (1978) finds that a substantial fraction of the brands' advertising expenditures was self-cancelling and escalating. A similar escalation recently has been observed in the film industry, in which advertising costs are believed to be out of control (Eller 1996).

Marketing escalation suggests that competitive action and reaction creates sustained marketing engagements without persistent sales or market-share gains for any of the players. Although they may be profitable at the onset, spending escalation scenarios typically are not sustainable for the players, and neither are prolonged price wars. However, if companies gradually can increase prices or reduce marketing spending without a persistent loss in customer patronage, substantial long-run profit gains can be realized.

Hysteresis is a phenomenon of temporary marketing action that causes sustained sales change. Little (1979) first uses the term in marketing, and Simon (1997) describes various phenomena, including loyalty after brand switching and

organizational inertia, that can lead to hysteresis. Simon also uses empirical examples of how temporary actions involving price and marketing communications created sustained change in the competitive positions of pharmaceutical, cigarette, dessert, and liquor brands. Similarly, in a scanner market environment, Dekimpe, Hanssens, and Silva-Risso (1999) find that temporary price reductions by a private-label soup brand created hysteretical primary demand effects.

Marketing actions that exhibit hysteresis are particularly attractive to companies because temporary investments generate permanent benefits. By the same token, hysteresis can become a barrier to entry or position improvement to competitors.

The 1970s and 1980s witnessed a gradual increase in the market performance of Japanese automobile makers worldwide (e.g., Hanssens and Johansson 1991). At the same time, Japanese firms invested sustained efforts in quality improvement, image building, distribution channels, and aggressive pricing. This is an example of sustained marketing effort that leads to persistent results, which we call the *evolving business practice* scenario. This scenario has been verified empirically by Baghestani (1991) in the context of advertising spending and sales performance for a consumer product. Similarly, Bronnenberg, Mahajan, and Vanhonacker (1998) show that the evolutions of distribution and market share are interrelated in the early phases of the life cycle and that this relationship helps determine long-term market structure. At the strategic level, Johnson and Russo (1997) argue that competitors coevolve, or adapt interdependently, to everchanging market conditions. In their view, principles

of (co)evolution augment those of game and behavioral theory in an understanding of the dynamics of competitive strategy.

SUSTAINED MARKETING EFFORT AND PERSISTENT SALES

Because marketing consumes scarce human, financial, and time resources, there are good reasons companies would limit their efforts to periodic short-term or temporary spending. Among them, marketing budgets may be limited because of low commitment to marketing at the senior executive level, or management may believe that quick-fix solutions exist to improve the market position of their products. Indeed, 52% of the observed marketing mix spending patterns consist of only temporary fluctuations around a fixed mean (Dekimpe and Hanssens 1995a, p. G114). Why, then, in the remaining 48% of cases, would companies engage in sustained change in marketing spending, which can be more costly and implies a higher level of engagement? This question has been addressed in the strategy literature, most notably by Ghemawat (1991). In his view, *commitment*, which is defined as the tendency of strategies to persist over time, is a general explanation for sustained differences in organizational performance. When this commitment is oriented toward sustained change, it can give rise to evolving behavior in marketing, such as lower prices, quality improvement, and reduced cycle time. However, commitment also can be oriented toward a stationary goal, including the status quo, in which case mean-reverting marketing behavior may result.

According to Ghemawat (1991), commitment is generated by the following four driving factors: First, lock-in, which is investment in durable, specialized, and/or untradeable "sticky" factors (Harrigan and Porter 1983). Production facilities are a good example of a sticky factor. In marketing, brand equity can be considered a sticky factor, because it has been shown to be a major driver of sales performance (e.g., Aaker 1991) and to create brand loyalty that erodes only slowly, if at all (e.g., Dekimpe et al. 1997). Other examples of lock-in include contractual agreements that prohibit the discontinuation of existing channel relationships and the shift in power from manufacturers to distributors, which has made it more difficult for the former to discontinue certain product varieties. A leading pet-food manufacturer, for example, was hesitant to stop the production of some of its unprofitable varieties for fear of losing shelf space for its other, more successful products, though it also sensed the competitive pressure to continue adding new varieties to its assortment. In a similar vein, Broniarczyk, Hoyer, and McAlister (1998) discuss the reluctance of retailers to reduce the number of items carried in their outlets. In conclusion, when committed to a certain practice, companies may find it difficult to reverse their marketing behavior.

Second, in lock-out, disinvestment creates forgone opportunities because of difficulties in reacquiring and redeploying the allocated factors. Also, the scarcity of certain marketing resources may preempt potential contenders or put them at a competitive disadvantage. The French automaker Renault's decision to abandon the U.S. market after several unsuccessful entry attempts is not likely to be reversed anytime soon because of the formidable barriers of entry and marketing resource requirements. In a distribution context, Rao and McLaughlin (1989) show that small firms have a harder time acquiring shelf space for their new products than do larger, more established competitors. Similarly, first movers often occupy the most attractive locations in product characteristics space and extend their assortment to preempt entry into product differentiation niches (Lieberman and Montgomery 1988). Such lock-outs may prevent some brands from lifting their performance to higher levels and others from turning around a negative performance evolution.

Third, lags in adjusting the firm's stocks of sticky factors to desired levels can occur. For many years, Coors was a successful regional brewing company in the United States. When the company decided to become nationally distributed, it took approximately a decade to implement that strategy. Even when adjusting the most flexible marketing instrument, price, marketers can be confronted with substantial lags. Leeflang and Wittink (1992), for example, indicate how manufacturer-induced price reactions to competitive activities require cooperation between retailers and manufacturers; in their Dutch example, it takes on average five to ten weeks to implement the desired changes in a price or promotion plan. When the lags in adjusting marketing behavior are strong, the existing patterns (whether stationary or evolving) tend to be prolonged.

Fourth, with inertia, firms have built-in biases to maintain the status quo. They may be locked in to a specific set of fixed assets (cf. supra), be reluctant to cannibalize existing product lines, or lack the flexibility to adapt quickly to changing conditions (e.g., Rumelt 1995). As an illustration, Leeflang and Wittink (1996b) report that firms' promotional calendars are set, in part, on the basis of previous promotions that are believed to have been successful. Still, the speed of reaction to competitive moves or changing market conditions has been found to be a major determinant of a firm's performance (Bowman and Gatignon 1995). For example, in spite of clear market signals favoring fuel-efficient automobiles in the 1970s, the market leader, General Motors, was slow in making the necessary adjustments to design and market large numbers of small cars and eventually lost approximately 15 share points. We conclude that inertia in marketing behavior contributes to the continuation of prior spending and pricing patterns, whether stationary or evolving.

Ghemawat (1991) argues that the commitment resulting from these four forces is a main factor associated with companies' performance across industries. His explanation, however, is restricted to the input or investment aspect of management. To use the commitment paradigm in a marketing framework, we also must consider the output or performance aspect of management, that is, market responsiveness to temporary versus sustained marketing effort. What good is a sustained policy of quality improvement if customers' behavior is not responsive to quality changes?

Previous research has shed some light on this important issue. In particular, we (1995a, b) have listed six major reasons there might be a long-run or persistent customer response to marketing effort. The first three of these are due to customer behavior; immediate response and delayed response provide same- and subsequent-period lifts to sales because of the added value in the marketing effort. Furthermore, purchase reinforcement generates repeat purchases and word-of-mouth effects that can be traced to the original marketing effort.

The sequence of immediate and delayed customer response and purchase reinforcement may be sufficient in it-

self to create enduring changes to a company's sales. However, because these changes are not likely to go unnoticed in the company and industry, subsequent managerial behavior may prolong or accelerate them. According to our (1995b) previous work, such behavior can take on three possible forms. Performance feedback, especially encouraging short-term sales response, can cause the firm to maintain or increase its marketing effort. Next, decision rules may cause a given marketing effort to be accompanied by other company efforts; for example, price promotions regularly are accompanied by increased advertising spending. Performance feedback and decision rules may both result from and contribute to a firm's commitment to certain marketing practices. Last but not least, competitive reaction often takes place, either for damage prevention (defensive marketing) or as an opportunistic copycat reaction to what is perceived to be a good idea.

In conclusion, several behavioral phenomena explain the existence of sustained or persistent change in both marketing effort and customer response. The resulting chain reaction of events may be complex, but it is important (1) to disentangle them analytically and (2) to interpret their long-run implications correctly. Consider, for example, the following two hypothetical scenarios:

1. A company (A) engages in a marketing campaign that generates immediate positive market response but no long-term purchase reinforcement. The short-term success of the campaign, however, causes the organization to lock itself into future campaigns. Competitors, fearful of damage to their market positions, react forcefully. Such a chain of events could lead to marketing escalation with no net benefits to the industry participants. The fare wars among U.S. airlines in the early 1990s and their disastrous effects on profitability are a good illustration of this scenario.
2. A second company (B) starts a campaign for which market response is slow in materializing. However, the gained customers engage in repeat purchase and positive word of mouth. Because the company exceeds budget before campaign profitability is established, the effort is halted, and the negative experience locks the company out of future campaigns of this kind. Such a chain of events leads to a missed opportunity due to short-sightedness in decision making.

What both strategic mistakes have in common is that the readily observable short-term market response effects were misinterpreted. Company A attributed persistence to only temporary results and spent too much, whereas company B failed to acknowledge such persistence and spent too little. In both cases, the decision makers would be characterized as myopic, or short-term–oriented. However, had they correctly read the persistence levels of their marketing efforts, they would have been able to implement a long-term productivity strategy; that is, they could have compared the persistent benefits of their actions with their costs.

Our discussion so far has made the distinction between permanent and temporary effects of shocks in marketing spending and market performance. In empirical work, it may be important to recognize an intermediate step as well—the "dust-settling" period between immediate and permanent effects. We define and illustrate the *dust-settling phase* as the number of time periods between the first occurrence of significant impact and the first occurrence of stable long-run impact. For example, dust settling in the

evolving business practice scenario in Figure 1 takes approximately eight periods.

Marketing effects during the dust-settling period can fluctuate widely and therefore should be accumulated (i.e., computing the total incremental expenditures and revenues that emerge because of the initial shock) for the purpose of assessing their impact. In contrast, the initial effect can be derived from single-period impulse response estimates. The quantification of the persistent or sustained impacts involves a single figure, because time subscripts no longer are needed when the impulse response functions have stabilized. Our empirical illustration reflects these distinctions and calculates separate profitability values for immediate, dust-settling, and persistent effects of marketing investments.

LONG-RUN PROFITABILITY CONSEQUENCES

The four strategic scenarios in Figure 1 have widely different consequences for the long-term profitability of marketing effort. In business as usual, inferring marketing profitability is straightforward from the short-run data: We conduct a conventional cost–benefit analysis, possibly over several periods but with no long-term consequences, and conclude that the market response and profit margins are either sufficient or insufficient to cover marketing costs (for example, see Hanssens, Parsons, and Shultz 1999, Chapter 9). In hysteresis, the long-term profitability of the marketing action that caused the hysteresis (assuming it is positive) is infinite, and it is only a matter of time before the short-run marketing investment is recuperated. The number of time periods until cost recovery also can be calculated from the data. Likewise, in escalation, the long-run profitability of marketing grows to negative infinity, because every period adds to the spending total but not to the response total. Finally, the case of evolving business practice could produce either positive or negative long-run profits, depending on the relative magnitude of evolving sales and costs. This is perhaps the most interesting scenario to study because deriving long-run marketing profitability is intricate, and the long-run results could become gradually better or worse than the readily observable short-run effects.

Long-run marketing profitability can be measured in several ways. A stock variable such as persistent surplus would subtract sustained costs from persistent income streams. This metric is managerially intuitive and can be used in net present value calculations. It is especially useful for evaluating long-run consequences of price changes, as we examine subsequently. However, persistent surplus accrues to positive or negative infinity in all resource allocation problems except the business as usual scenario. A flow variable such as long-run profit margin, in contrast, does not have this problem and lends itself well to comparisons over different time horizons, including the infinite time horizon. Furthermore, when exact profit margins are not known, because of, for example, confidentiality, we can express empirical results in terms of long-run break-even margins (LBMs) and thus develop thresholds for long-run profitability.

Long-Run Profit Margin Analysis for Marketing Resource Allocation

The short-run break-even margin (SBM) of a marketing investment is simply the profit margin (PM) on additional sales that is required to recover the marketing costs that gen-

erated these additional sales plus, if applicable, the erosion of baseline revenues if lower prices are involved. The LBM is the same construct for long-run response and cost effects, namely, after the dust settles. In a subsequent section, we detail the measurement of LBM, following the persistence framework we (1995b) previously introduced.

In Figure 2, we show the strategic consequences of the relative location of SBM and LBM in any particular marketing case. Suppose, first, that LBM < SBM, which means that the long-run outlook is more positive than the short-run. If PM < LBM, immediate disinvestment is called for; if PM > SBM, marketing is profitable, and the profitability will be amplified in the long run. The ambiguous zone, in which LBM < PM < SBM, suggests that profitability requires patience and sustained spending. Although there are short-run losses, the amplification of profit eventually pushes the company over the LBM hurdle.

If, however, SBM < LBM, the long-run outlook is not as advantageous as the short-run, and the company should be careful in its marketing investments. Again, if PM < SBM, immediate disinvestment is called for, because the future will only get worse. When PM > LBM, sustained profits can be expected; however, there is an attenuation of profit. Finally, the ambiguous zone, in which SBM < PM < LBM, sends potentially dangerous false hope signals. Although short-run profitability is achieved, it is not sustainable, and the company is on a course toward long-run losses. The two aforementioned hypothetical scenarios can be interpreted as belonging to the two ambiguous zones in Figure 2.

Persistent Surplus Analysis for Evaluating Price Changes

Deriving long-run profit consequences of price changes under coevolution is more intricate, because a price change usually affects all subsequent sales, namely, baseline volume plus additional sales attributed to the price change. To derive the persistent gains or losses from a sustained price change, let q denote the currently anticipated long-run sales volume at an anticipated long-run price of p, namely, the baseline scenario. Then, a change in p with sustenance Δp

produces a change in volume with persistence Δq. Long-run profitability of this price change occurs in the following condition:

(1a) $(p + \Delta p)(q + \Delta q) > p \times q$,

or, after some math,

(1b) $\Delta p \times q + \Delta q \times p + \Delta p \times \Delta q > 0$.

If the action is a price increase, the long-run profit condition implies that the persistent revenue increase from retained baseline sales is greater than the persistent sales loss valued at the new price. Similarly, a sustained price cut is long-run profitable if the persistent sales gain valued at the new price is greater than the baseline sales erosion (revenue loss from baseline sales).[2]

In conclusion, the derivation of long-run market response and marketing spending patterns in the data enables us, first, to assign a brand or product to one of four possible strategic scenarios. Second, by comparing current or anticipated profit margins with LBMs or deriving the persistent surplus of price changes, we can make important inferences about the long-run outlook for the company's profitability as well.

MEASURING EFFORT SUSTENANCE AND RESPONSE PERSISTENCE

To derive the long-run (output and input) implications of marketing actions, a firm should be able to (1) capture the complex interplay of the different contributing factors and (2) translate the underlying short-run dynamics into their long-run consequences, because the long run emerges out of a sequence of short runs.

We (1995b) introduced, in this respect, temporally ordered vector-autoregressive (VAR) models and their associated impulse response functions. Assume, for ease of exposition and without loss of generality, a three-variable system that describes the dynamic interrelationships among a brand's sales performance (S), its marketing budget (M), and its competitors' marketing spending (CM), in which all variables are evolving.[3] Prior to the imposition of a temporal ordering, the VAR model would be specified as[4]

$$(2) \quad \begin{bmatrix} \Delta S_t \\ \Delta M_t \\ \Delta CM_t \end{bmatrix} = \begin{bmatrix} \pi_{11}^1 & \pi_{12}^1 & \pi_{13}^1 \\ \pi_{21}^1 & \pi_{22}^1 & \pi_{23}^1 \\ \pi_{31}^1 & \pi_{32}^1 & \pi_{33}^1 \end{bmatrix} \begin{bmatrix} \Delta S_{t-1} \\ \Delta M_{t-1} \\ \Delta CM_{t-1} \end{bmatrix}$$

$$+ \dots + \begin{bmatrix} \pi_{11}^J & \pi_{12}^J & \pi_{13}^J \\ \pi_{21}^J & \pi_{22}^J & \pi_{23}^J \\ \pi_{31}^J & \pi_{32}^J & \pi_{33}^J \end{bmatrix} \begin{bmatrix} \Delta S_{t-J} \\ \Delta M_{t-J} \\ \Delta CM_{t-J} \end{bmatrix} + \begin{bmatrix} u_{S,t} \\ u_{M,t} \\ u_{CM,t} \end{bmatrix},$$

Figure 2
LONG-RUN PROFITABILITY SCENARIOS*

*The intermediate "dust-settling" period makes the transition between short- and long-run results. For clarity of exposure, we do not acknowledge this explicitly in this figure.
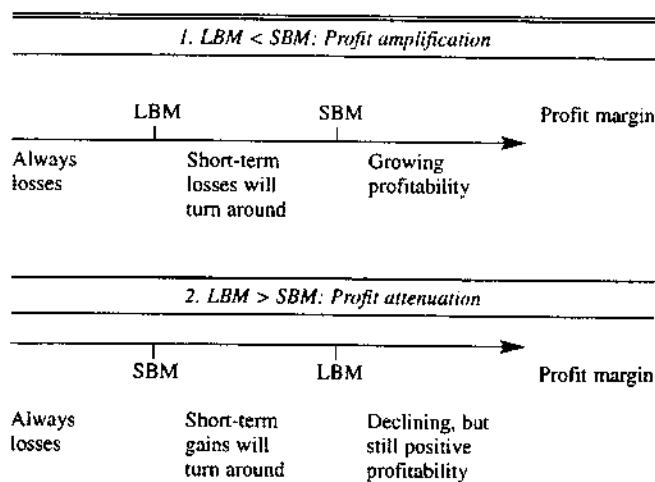
[2]In the preceding derivations, we make abstraction from any long-run changes in the marginal cost curves. If such changes can occur (e.g., because of experience curve effects), the vector-autoregressive specification should be augmented with a cost equation to capture the dependence of costs on volume.

[3]When dealing with stable variables, the level of the variable (X_t) is used rather than its first difference $\Delta X_t = X_t - X_{t-1}$ (for an in-depth discussion, see Dekimpe and Hanssens 1995b).

[4]For ease of exposition, we have omitted any deterministic components from the model. When needed, constant terms, seasonal dummy variables, and/or deterministic trends can be added to the specification easily.

where J is the order of the model, and $\bar{u} = [u_{S,t}, u_{M,t}, u_{CM,t}]'$ $\sim N(0, \Sigma)$. This specification directly captures all but one of the aforementioned factors: delayed response $(\pi^j_{12}, j = 1, ..., J)$, purchase reinforcement (π^j_{11}), performance feedback (π^j_{21}), inertia in decision making (π^j_{22}), and competitive reactions (π^j_{32}). Only instantaneous effects are not included directly, but these are reflected in the variance–covariance matrix of the residuals (Σ). This matrix, however, only can establish the presence of an effect, not its direction. That is, it cannot distinguish among $M_t \rightarrow S_t$ (marketing has an instantaneous effect on performance), $S_t \rightarrow M_t$ (there is an immediate feedback relationship of sales to marketing spending), and $M_t \leftrightarrow S_t$ (both effects occur simultaneously). To circumvent this ambiguity, we (1995b) proposed to work with a transformed VAR model in which we impose a certain ordering on the variables. For example, we could posit, on the basis of managerial judgment, the following ordering: $M_t \rightarrow CM_t \rightarrow S_t$, which implies that a brand's performance can be influenced instantaneously by both its own and its competitor's marketing spending but that there are no immediate feedback relationships. Moreover, in this causal ordering, competitors can react immediately to a change in the brand's spending, but the brand can react only with some delay to a change in the competitor's spending. Technically, the "transformed" VAR model is obtained through a Cholesky decomposition of the Σ matrix and can be written as

$$
(3) \quad
\begin{bmatrix} \Delta S_t \\ \Delta M_t \\ \Delta CM_t \end{bmatrix}
=
\begin{bmatrix} 0 & \gamma^0_{12} & \gamma^0_{13} \\ 0 & 0 & 0 \\ 0 & \gamma^0_{32} & 0 \end{bmatrix}
\begin{bmatrix} \Delta S_t \\ \Delta M_t \\ \Delta CM_t \end{bmatrix}
$$

$$
+ \sum_{j=1}^{J}
\begin{bmatrix} \gamma^j_{11} & \gamma^j_{12} & \gamma^j_{13} \\ \gamma^j_{21} & \gamma^j_{22} & \gamma^j_{23} \\ \gamma^j_{31} & \gamma^j_{32} & \gamma^j_{33} \end{bmatrix}
\begin{bmatrix} \Delta S_{t-j} \\ \Delta M_{t-j} \\ \Delta CM_{t-j} \end{bmatrix}
+
\begin{bmatrix} v_{S,t} \\ v_{M,t} \\ v_{CM,t} \end{bmatrix},
$$

in which the covariances between the error terms equal zero (for a detailed discussion, see Dekimpe and Hanssens 1995b; Evans 1989) and the instantaneous effects are given by the parameters γ^0_{12}, γ^0_{13}, and γ^0_{32}. Impulse response functions and the associated persistence estimates (derived from the level at which the impulse response functions stabilize) subsequently were derived by simulating, in Equation 3, the impact of one-unit shocks over time, which is given by, for example, $[v_{S,t} \ v_{M,t} \ v_{CM,t}]' = [0 \ 1 \ 0]'$.

In this article, we extend the approach we (1995b) previously advocated in three ways. First, we relax the need to impose an a priori temporal ordering on the variables. Second, the use of VAR models in the differences may result in a loss of relevant, long-run information when an equilibrium or cointegration relationship exists between the variables of interest. We introduce error correction models to account for short-run corrections toward this equilibrium relationship in the derivation of the impulse response functions. Third, we (1995b) previously did not provide confidence intervals for persistence estimates beyond the bivariate case. We provide an estimate for the respective standard deviations here.

Relaxation of the Need to Impose an A Priori Temporal Ordering

Often, clear managerial insights on the appropriate temporal ordering are missing, especially when the information set becomes elaborate or incorporates competitive marketing mix variables. This is especially applicable in instances in which the leader–follower roles are not identified clearly. If the instantaneous effect size is small (i.e., when the residual correlations in Equation 2 are small), the substantive findings are expected to be robust to the selected ordering, as was the case in our (1995b) and Dekimpe, Hanssens, and Silva-Risso's (1999) work. However, instances may exist in which the resulting impulse response functions and their associated persistence and sustenance estimates are sensitive to the imposed ordering. Moreover, when dealing with temporally aggregated data, a bidirectional instantaneous influence may exist between the variables, in which case no temporally ordered VAR model would describe the system's dynamics adequately.

We therefore propose to use the information in the residual variance–covariance matrix of Equation 2 to derive a vector of expected shock values and simulate this vector's impact over time (Evans and Wells 1983). Specifically, rather than simulating the impact of a shock vector [0 1 0]' in a transformed VAR model (in which the residual correlations are zero by construction), we now (1) use the original, untransformed model (i.e., Equation 2) to derive the expected values of the instantaneous shocks occurring to S and CM because of the one-unit shock to M and (2) derive the impulse response functions corresponding to this expected shock vector (which involves the simultaneous nonzero shocking of multiple variables). Assuming multivariate normality of the residuals of the VAR model, it is easy to show that the expected shock values in the other variables after a one-unit shock to the ith variable are given by $[\sigma_{ij}/\sigma_{ii}]$ $(i \neq j)$ (Johnson and Wichern 1988).[5]

Long-Run Equilibria and Corresponding Error Correction Mechanisms

In some cases, the use of VAR models specified in the (first) difference of the evolving variables may result in a loss of relevant long-run information and, therefore, provide biased estimates of both the included parameters and the persistence/sustenance estimates derived from them. Specifically, some of the evolving variables may be cointegrated with one another, in which case Equation 2 should be augmented with error correction terms to reflect the system's gradual adjustment toward an underlying long-run equilibrium.

Evolving variables are cointegrated when a linear combination exists between them that results in stable residuals. Even though each of the individual variables can move far away from its previously held positions, a long-run equilibrium exists that prevents them from wandering apart. Such

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[5]See Buckle and Meads (1991), Evans and Wells (1983), or Wells and Evans (1989) for other applications of this simultaneous shocking procedure.

long-run equilibria can emerge because of a variety of reasons. Among them, certain budgeting rules (e.g., percentage of sales allocation rules; Hulbert 1981) imply that sales successes eventually translate into higher marketing spending. Similarly, competitive decision rules (Hanssens, Parsons, and Schultz 1999, Chapter 4) can result in firms' marketing spending levels never deviating too far from one another. Finally, customers' limited budgets may cause different price levels to be associated with different long-run demand levels, which would imply a cointegration relationship between sales and prices.

Consider again, without loss of generality, our three-variable example. The existence of a perfect equilibrium relationship between the variables implies (for a more in-depth discussion, see Powers et al. 1991) the following:

$$(4) \qquad S_t = \beta_0 + \beta_1 M_t + \beta_2 CM_t.$$

In practice, however, we are unlikely to observe a perfect equilibrium in every period. A more realistic requirement is that its deviations are mean-reverting (stable) around zero; that is, $e_{S,t}$ in Equation 5 no longer should be evolving, even though each of the other variables in the equation is

$$(5) \qquad S_t = \beta_0 + \beta_1 M_t + \beta_2 CM_t + e_{S,t}.$$

As Engle and Granger (1987) show, an error correction model should be used to describe the full data-generating process, rather than a VAR model on the differences. The error correction model is obtained by augmenting Equation 2 with the lagged residuals of Equation 5, as follows:[6]

$$(6) \quad \begin{bmatrix} \Delta S_t \\ \Delta M_t \\ \Delta CM_t \end{bmatrix} = \begin{bmatrix} \alpha_S & 0 & 0 \\ 0 & \alpha_M & 0 \\ 0 & 0 & \alpha_{CM} \end{bmatrix} \begin{bmatrix} e_{S,t-1} \\ e_{M,t-1} \\ e_{CM,t-1} \end{bmatrix}$$
$$+ \sum_{j=1}^{J} \begin{bmatrix} \pi_{11}^j & \pi_{12}^j & \pi_{13}^j \\ \pi_{21}^j & \pi_{22}^j & \pi_{23}^j \\ \pi_{31}^j & \pi_{32}^j & \pi_{33}^j \end{bmatrix} \begin{bmatrix} \Delta S_{t-j} \\ \Delta M_{t-j} \\ \Delta CM_{t-j} \end{bmatrix} + \begin{bmatrix} u_{S,t} \\ u_{M,t} \\ u_{CM,t} \end{bmatrix}.$$

The addition of the error correction terms $[\alpha_S e_{S,t-1} \ \alpha_M e_{M,t-1} \ \alpha_{CM} e_{CM,t-1}]'$ implies that in every period there is a partial adjustment toward restoring the underlying, temporarily disturbed, long-run equilibrium. That is, the system partially corrects for the previously observed deviations $[e_{S,t-1} \ e_{M,t-1} \ e_{CM,t-1}]'$, and the respective α coefficients reflect the speed of adjustment of the corresponding dependent variable toward the equilibrium. Many testing procedures have been proposed to test for the existence of such long-run equilibrium relationship(s). In our empirical applications, we use Johansen's (for a detailed discussion of the procedure, see Johansen 1988; Johansen and Juselius 1990)

Full Information Maximum Likelihood (FIML) approach to test for cointegration and construct the lagged error terms.[7]

As we (1995b) indicated, VAR or error correction models may result in the estimation of many parameters. To avoid a potential overparameterization, we follow the practice of setting all parameters with a t-value less than one equal to zero and add the lagged cointegrating errors (estimated from the full model) as exogenous covariates to this more parsimonious model specification (for a formal motivation, see Harris 1995). In case of further degrees-of-freedom problems, the same solutions as found in traditional econometric and time series models in the marketing literature may be used (for a review, see Hanssens, Parsons, and Schultz 1999), such as limiting the information set to the most important competitors, using a combined competition variable, or working with relative price or spending variables.

Accuracy Assessment for the Persistence Estimates

We (1995b) previously did not provide an indication of the accuracy of our persistence estimates beyond the bivariate case. Following Mark (1990), Monte Carlo simulations can be performed to derive the persistence estimates' standard errors. Using the initial start-up values of the different variables as given, we repeatedly sample from the multivariate normal distribution $N(0, \hat{\Sigma})$, with $\hat{\Sigma}$ the estimated residual variance–covariance matrix of the parsimonious VAR or error correction model. Using these sampled residuals and the estimated equations, we create new ("artificial") performance, marketing spending, and price series. Using these artificial data as input, we subsequently reestimate the (parsimonious) VAR or error correction model and recompute the associated impulse response functions and persistence and sustenance levels. This procedure is repeated 1000 times, and the sample standard error of the resulting 1000 persistence and sustenance estimates provides an indication of their accuracy.

EMPIRICAL ILLUSTRATIONS

We present two case studies that illustrate different combinations of persistent response and sustained marketing spending. In the first example, we study the sales erosion of a pharmaceutical product and illustrate how a failure to read correctly the long-run price and advertising dynamics may have led its management to harvest the brand prematurely. We also compute the long-term marketing profitability of different marketing investments. The second example focuses on the sales history of a frequently purchased branded good and relates it to the stationary or evolving behavior of advertising, promotions, and prices. The first example illustrates an evolving business scenario, whereas the second illustrates a mixture of stationarity and evolution, which leads to a profitable price escalation opportunity.

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[7]Because of its interpretation as a long-run equilibrium, several authors have suggested the use of the parameter estimates in Equation 3 as a direct estimate of the long-run elasticities (e.g., Baghestani 1991). However, recent evidence suggests that a direct interpretation of the cointegrating coefficients may be misleading (e.g., Lutkepohl and Reimers 1992), especially because up to $N - 1$ cointegrating vectors could exist between N evolving variables. We therefore concur with Lutkepohl and Reimers (1992) and use the impulse response functions derived from the vector error correction models to capture both the short-run dynamics (which, as we previously indicated, also reflect the partial adjustments toward the long-run equilibrium) and the resulting persistence levels.

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[6]$e_{M,t}$ and $e_{CM,t}$ are obtained after appropriately normalizing Equation 5 to have, respectively, M_t and CM_t on the left-hand side of the equation.

Understanding Sales Erosion for a Pharmaceutical Product

The pharmaceutical industry is characterized by intense rivalry in the areas of new product development and pricing. When a new drug is approved for commercialization, its maker receives a handsome reward for years of research and development and clinical testing in the form of patent protection, which usually results in a price premium. However, competitors often try to improve on the medical performance of the patented product and offer a "new and improved" version at comparable price points. An example could be the advent of second-generation antidepressant medicines, such as Zoloft, that compete with the highly successful pioneer, Prozac, on the premise of same effectiveness with fewer side effects.

We obtained a monthly sample of five years of market performance (number of prescriptions from a panel of several thousand physicians, projected to national levels), marketing support (national advertising in real dollars and number of sales force visits to doctors), and pricing data for the major competitors in a prescription drug market. We focused on the two major players in the market: brand A, the pioneer, and brand B, a successful challenger offering a product with similar performance and fewer side effects. Therefore, a major strategic question for brand A management was how to allocate its marketing resources and determine its price path relative to the challenger to overcome its intrinsic quality disadvantage.

As Figure 3, Part A, illustrates, brand B was able to establish market leadership. The interesting research question is therefore to what extent brand A's chosen pricing and spending (advertising and detailing contacts) strategy delayed or accentuated this long-term erosion in its market position. If our models reveal persistent sales response to pricing and/or marketing support, the increase in brand A's relative price (see Figure 3, Part B) coupled with a reduction in its marketing budget (Figure 3, Parts C and D) would be evidence of a premature harvesting of the brand that undermined the brand's long-run position in the marketplace. A significant strength of our modeling approach is that we can examine the potential trade-off of strategies that aim at long-term sales gains (at the risk of undermining profitability) versus those that aim at long-term profit gains (at the risk of undermining market viability).

The univariate test statistics from the augmented Dickey-Fuller test reveal evolutionary behavior in brand A's sales, advertising support, sales force contacts, and relative price (price differential with brand B), as we show in Table 1.[8] Therefore, a VAR market response model for prescriptions, detailing, advertising, and relative price was estimated on differences, augmented with lagged error correction terms, because Johansen's (1988) FIML test indicated the presence of one cointegrating relationship among the variables:[9]

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[8]Even though individual unit root tests may not be overly powerful, the subsequent multivariate analyses offer convergent validity on the resulting classifications. For example, the erroneous classification of a variable as evolving would have caused an additional cointegrating vector (in which only one coefficient in the equilibrium regression is significant) to be found in Johansen's (1988) FIML test, and the absence of any significant persistence estimates (irrespective of the variable being shocked) would have pointed toward stability. None of these effects occurred, however.

[9]The λ_{max} statistic provided equivalent results.

Figure 3
DATA PHARMACEUTICAL EXAMPLE

A. Pharmaceutical Sales

B. Pharmaceutical Prices

C. Pharmaceutical Advertising

D. Pharmaceutical Detailing
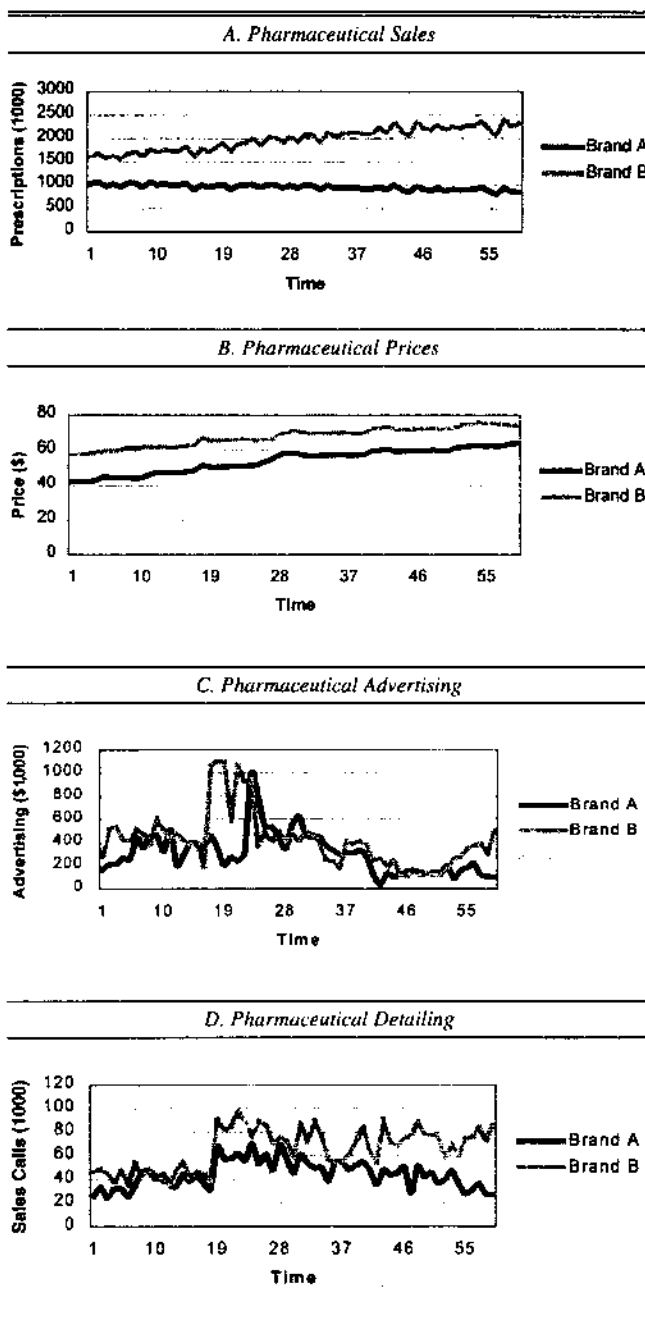
Table 1
UNIT ROOT TEST RESULTS FOR THE PHARMACEUTICAL EXAMPLE

	m	t-value	Unit root?
Prescriptions (P_t)	2	-.109	Yes
Price differential (PD_t)	0	-.446	Yes
Advertising (A_t)	0	-2.041	Yes
Sales calls (SC_t)	1	-1.804	Yes

Notes: m = number of lagged difference terms, selected on the basis of the Schwarz criterion. t-value = t-statistic for the parameter estimate associated with the lagged level in the augmented Dickey-Fuller equation, to be compared with the 5% critical value of -2.93.

H_0: At most, zero cointegrating vectors,

$$\lambda_{trace} = 49.154 > \lambda_{crit,0.95} = 47.21.$$

H_0: At most, one cointegrating vector,

$$\lambda_{trace} = 19.836 < \lambda_{crit,0.95} = 29.68.$$

The resulting equilibrium equation, normalized on P_t, is given by[10]

(7) $\quad P_t = 742.605 - 14.175PD_t + .220A_t - 1.019SC_t + e_{P,t},$

$\qquad\qquad$ (3.944) $\quad$ (.051) $\quad$ (.704)

which subsequently was used to construct the lagged error correction terms for the Vector Error Correction Model (VECM). The parameter estimates of the restricted VECM used in the impulse response derivations are provided in Table 2.

This VECM is not temporally ordered, and therefore, no direct instantaneous effects are estimated. However, following the procedure outlined in the previous sections, the residual variance–covariance matrix Σ was used to derive the expected instantaneous shock values in the other variables triggered by an initial shock in price, advertising, or detailing:

$$\Sigma = \begin{bmatrix} 454.655 & -.130 & 696.256 & 44.775 \\ -.130 & +.242 & -2.938 & -.122 \\ 696.256 & -2.938 & 10003.438 & 65.079 \\ 44.775 & -.122 & 65.079 & 54.943 \end{bmatrix}$$

For example, the instantaneous shock vector when advertising is the initiating instrument is given by $[u_{P,t}, u_{PD,t}, u_{A,t},$

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[10]Standard errors are added in parentheses.

$u_{SC,t}] = [.069, -.0003, 1.000, .007] = [696.256/10,003, -2.938/10,003, 1.000, 65.079/10,003]$, whereas the instantaneous shock vector after an initial detailing shock is given by $[.815, -.002, 1.184, 1.000]$.

The sales persistence graphs for shocks to brand A's marketing support variables are shown in Figure 4, Parts A–C, and the corresponding sustenance graphs are given in Figure 4, Parts D–F. Depending on the variable, dust settling took between four and seven months. Similar graphs for the cross-effects between the support variables are available from the authors on request. The persistence and sustenance estimates, including potential cross-effects and along with their associated standard errors, are provided in Table 3.

We begin our substantive interpretation of these figures with a profitability assessment of the long-run effects of marketing spending on journal advertising. As indicated in Table 4, journal advertising has relatively small but persistent (and significant) effects on prescriptions; each $1,000 advertising shock generates immediate prescription increases of 70, which amplify to 83 in the long run. With advertising sustenance of approximately 48%, this implies that advertising's profitability gradually improves over time: The break-even margins drop from $14.29 in the short run to $9.68 in dust settling to $5.73 in the long run. Therefore, for observed margins greater than $14.29, journal advertising is an attractive resource allocation whose profitability even gets amplified over time. For margins between $14.29 and $5.73, the company should not cut advertising prematurely on the basis of short-term lack of profitability. The profit amplification eventually will generate positive returns to advertising. If margins drop below $5.73, even the response amplification is insufficient to generate positive returns to advertising.

In contrast, the sales response to changes in sales calls is stronger in the short run: 815 additional prescriptions per 1000 calls. The data do not provide a detailed cost allocation

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Table 2
VECM PARAMETER ESTIMATES FOR THE PHARMACEUTICAL EXAMPLE

	Equation			
	ΔP_t	ΔPD_t	ΔA_t	ΔSC_t
ΔP_{t-1}	-.361 (.074)	—	.590 (.514)	.020 (.023)
ΔPD_{t-1}	-12.809 (4.908)	.286 (.112)	-36.657 (23.768)	-3.779 (1.666)
ΔA_{t-1}	-.104 (.022)	-.001 (.0006)	—	—
ΔSC_{t-1}	—	—	-2.631 (1.837)	-.523 (.098)
$e_{P,t-1}$	-.293 (.088)	—	—	—
$e_{PD,t-1}$	—	-.067 (.026)	—	—
$e_{A,t-1}$	—	—	-.302 (.092)	—
$e_{SC,t-1}$	—	—	—	—

Notes: Standard errors are in parentheses. All values with $|$ t-statistic $| \leq 1$ are restricted to zero. Deterministic components (e.g., seasonal dummies, intercept) are not presented because of space limitations. P= prescriptions, PD = price differential, A = advertising, and SC = sales calls.

of sales calls to individual products, but if we assume a reasonable 15% time allocation off the typical $90 cost of a call, we obtain a cost attribution of $13.50 per call and an SBM of $16.50 per prescription. The readily observable positive sales response may explain the high sustenance levels (71%) in sales calls (see also Figure 4, Part E); that is, positive feedback in the form of higher short-run prescriptions motivated the company to maintain high levels of sales calling. However, there is no sales response persistence to match, and consequently, the short-run gains from extra sales calls eventually are eroded. In every subsequent period, additional costs of $13.50 per call occur that should be debited against any initial profit gains. In terms of Figure 2, this implies that the short-term gains from sales calls eventually will turn around. This may explain the gradual reduction of brand A's detailing from period 20 onward as part of an overall harvesting strategy.

We now address long-term relative pricing effects. As indicated in Figure 4, Part F, changes in price differential are sustained over time; a $1 increase in this differential results in a permanent increase of $1.22. Customer reaction to such price changes is strong and quick to materialize, estimated

Figure 4
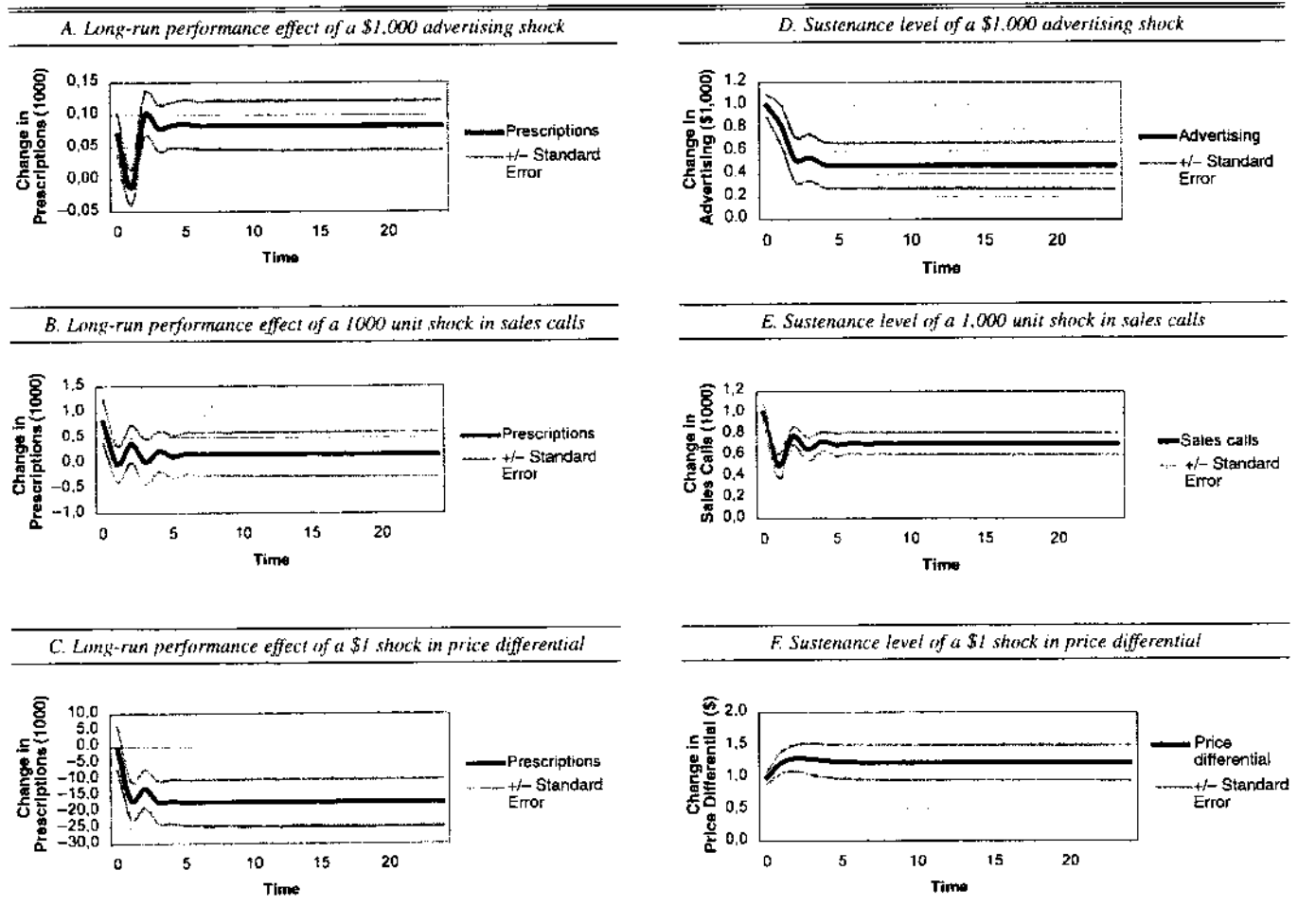### PERSISTENCE AND SUSTENANCE LEVELS IN THE PHARMACEUTICAL EXAMPLE

A. Long-run performance effect of a $1,000 advertising shock

B. Long-run performance effect of a 1000 unit shock in sales calls

C. Long-run performance effect of a $1 shock in price differential

D. Sustenance level of a $1,000 advertising shock

E. Sustenance level of a 1,000 unit shock in sales calls

F. Sustenance level of a $1 shock in price differential

Table 3
PERSISTENCE AND SUSTENANCE ESTIMATES FOR THE PHARMACEUTICAL EXAMPLE

| | Long-Run Impact on | | | |
Shock to	Prescriptions (1000)	Price Differential ($1)	Advertising ($1,000)	Sales Calls (1000)
Price Differential ($1)	-17.219 (7.229)	1.223 (.273)	-16.046 (36.273)	-3.594 (2.290)
Advertising ($1,000)	.083 (.038)	.001 (.002)	.476 (.204)	.002 (.010)
Sales calls (1000)	.169 (.449)	-.020 (.019)	2.755 (2.175)	.708 (.104)

Table 4

SHORT- AND LONG-RUN BREAK-EVEN MARGINS FOR ADVERTISING AND SALES CALLS FOR A PHARMACEUTICAL PRODUCT

Immediate				Dust Settling				Long Run			
Adver-tising	Sales Calls	Sales Response	Break-Even Margin	Adver-tising	Sales Calls	Sales Response	Break-Even Margin	Adver-tising	Sales Calls	Sales Response (1000)	Break-Even Margin
$1,000	0	70	$14.29	$678	0	70	$9.68	$476	0	83	$5.73
0	1000	815	$16.50	0	725	0	N/A	0	708	0	N/A

Notes: In the break-even calculations, all insignificant (cross)-effects have been set to zero. The first line reads as follows: A $1,000 shock in advertising is not associated with changes in sales calling but increases prescriptions in the same time period by 70. It therefore requires a margin of $14.29 per prescription to recover these marketing costs. During the dust-settling periods, advertising increases on average by $678 per month, which augments unit sales by 70 prescriptions (average per month). The break-even margin for the dust-settling period is $9.68 per prescription. In the long run, the same initial $1,000 advertising shock causes a sustained spending increase of $476, which is associated with a long-run sales response of 83 prescriptions. This requires a break-even margin of $5.73 per prescription. The second line makes similar calculations for a shock of 1000 sales calls at an assumed cost allocation of $13.50 per call.

at −16,500 prescriptions per dollar after one period. Furthermore, these losses are permanent; in every subsequent period, the prescription level is approximately 17,200 units lower than the level that would have been obtained without the price change.[11] Whether the resulting volume versus margin trade-off is profitable to brand A depends on the anticipated long-run sales and price (or margin) levels, absent the price change. The associated break-even margin for different values of the long-run base forecast, with the assumption that positive price shocks are absorbed fully in the profit margin (i.e., that they do not affect the marginal cost curve), is given as break-even margin = −1.22 + (1.22/17,200) × base forecast.

The actual base forecast of brand A's prescriptions is linked to its long-run advertising and pricing strategy, as is evidenced by the existence of a cointegrating relationship. Using the last observed values for the price differential (−10.05), advertising ($101,386), and contacts (27,000), the long-run sales forecast in equilibrium (Engle and Yoo 1987) would be 880,000, and the corresponding LBM for a $1 price increase would be $61.20 per prescription. Given the observed price values (and thus, range of plausible margins), brand A's policy of gradually reducing the price differential with its challenger increased its long-run profitability while lowering its long-run sales level.

In summary, the following strategic diagnosis emerges from our analyses: When the superior brand B entered the market, it gradually took over prescription sales of the pioneer, brand A (Figure 3, Part A). The pioneer's initial reaction, to increase its calling effort, not only failed to produce persistent sales gains, but also was costly in the long run. Brand A subsequently reduced sales calls, which, our analysis shows, improved its long-run profitability. This profitability also was enhanced through its pricing strategy of gradually narrowing the price differential with brand B, even though this strategy contributed to the long-run sales erosion of the brand. Long-run sales further were affected negatively by the sharp reductions in advertising support. Although actual profit margins are needed to assess the prof-

it consequences of this decision, our results indicate that the reduction in advertising may have been premature (i.e., as long as margins exceed $5.73). The ultimate wisdom of a harvesting strategy depends on the full portfolio of alternative investment opportunities for brand A's management, but this consideration is beyond the scope of our article.

Price Escalation for a Frequently Purchased Consumer Product

One of the early published marketing mix models focused on the relative effectiveness of pricing, advertising, and promotion to stimulate the sales of a well-known packaged-food product in a competitive environment (Little 1975). The BRANDAID project provided management with econometric estimates of these instruments' relative effectiveness and offered recommendations for improved resource allocation.

In our second illustration, we reanalyze the BRANDAID data using our long-run time-series models (Figure 5). Pre-

Figure 5
DATA CONSUMER-PRODUCT EXAMPLE

A. Consumer-Product Sales

B. Consumer-Product Prices

[11]These results also can be expressed as long-term price elasticities, as follows: At the end of the observation period, brand A's price was approximately $60. Therefore, a $1 price shock represents a 1.7% change, and the sustained change of $1.22 represents 2%. This change results in sustained sales losses of 17,200, or 1.9% when measured against brand A's last sales level (900,000). Therefore, the long-run price elasticity is close to unity.
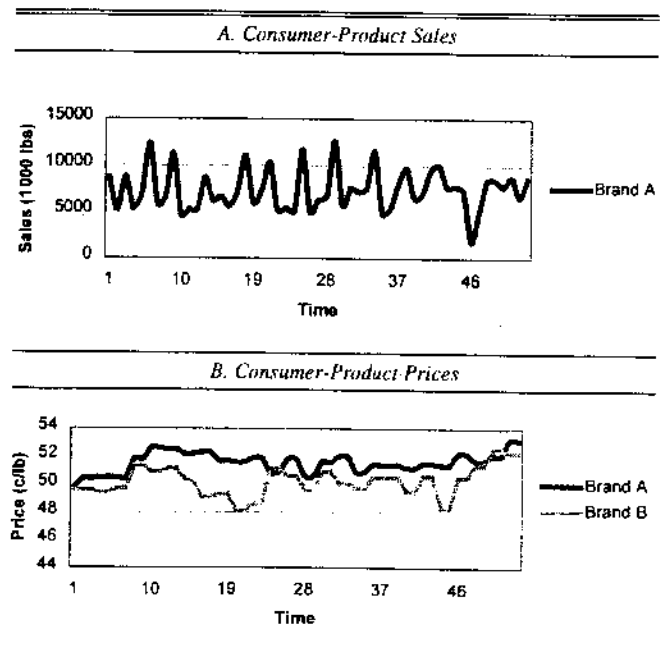
liminary unit root tests revealed that only prices were evolving over time, in terms of both the absolute prices and the price differential relative to competition, whereas sales (in pounds), advertising, and promotion support were stationary (Table 5).

From a strategic perspective, such a model implies that the company is operating in a business as usual condition, except for prices, which are escalating. We therefore estimated a five-equation response model in the levels of sales, advertising, and promotion but in changes of prices. Because seasonal fluctuations were observed in the data (cf. Little 1975, p. 663), we added seasonal dummy variables to the model specification. No error correction term was added to the model specification, because the two evolving price series were found not to be cointegrated ($\lambda_{trace} = 14.506 <$ $\lambda_{crit, .95} = 15.41$). Finally, a strike dummy variable was used to correct for the outlier effect of this exogenous event. The relevant parameter estimates for the impulse response calculations are given in Table 6.

The mixed level changes VAR model shows, first of all, that there is no evidence of any long-run brand building effects of advertising and promotion. Even though they have some short-run effects, with promotions exhibiting the familiar positive immediate effect followed by a postpromotional dip, they do not result in any incremental long-run sales or expenditures (see Figure 6, Part A). With respect to the price fluctuations, however, almost 100% (.993, stan-

dard error [s.e.] = .160) of the initial price shock is sustained. These price shocks have a predictable negative short-run impact on sales. However, sales levels quickly recover and return to their original level in three to four periods (see Figure 6, Part B).

The combination of evolving prices and stable performance creates a long-run profit opportunity for the firm in the form of price escalation. Even though price hikes are sustained over time, customers quickly adjust to these higher prices. Unlike the previous example, in which the long-run base forecast of the evolving performance series was dependent on the time path of the marketing control variables, the stationary nature of this sales series enables us to derive an unconditional base forecast—the sample mean of 7,477,200 pounds. Our price sustenance results then enable us to derive the long-run profit implications of an unexpected price increase of 1 cent per pound—$74,249, which is an

Table 5
UNIT ROOT TEST RESULTS FOR THE FREQUENTLY PURCHASED CONSUMER PRODUCT

	m	t-value	Unit root?
Own price (OP_t)	0	-1.939	Yes
Competitor price (CP_t)	0	-1.110	Yes
Price differential (PD_t)	0	-2.040	Yes
Advertising (A_t)	0	-7.146	No
Promotion (PR_t)	0	-8.726	No
Sales (S_t)	0	-9.657	No

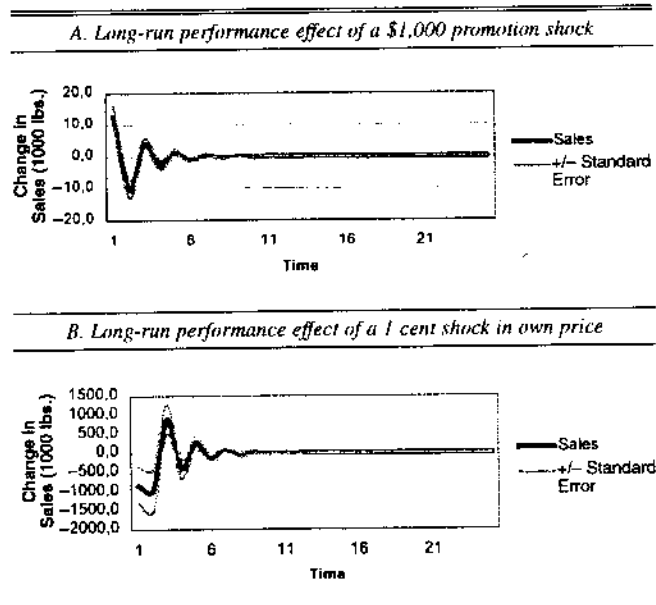Notes: m = number of lagged difference terms, selected on the basis of the Schwarz criterion. t-value = t-statistic for the parameter estimate associated with the lagged level in the augmented Dickey-Fuller equation, to be compared with the 5% critical value of -2.93.

Figure 6
PERSISTENCE LEVELS IN THE CONSUMER-PRODUCT EXAMPLE

A. Long-run performance effect of a $1,000 promotion shock

B. Long-run performance effect of a 1 cent shock in own price

Table 6
VAR PARAMETER ESTIMATES FOR THE FREQUENTLY PURCHASED CONSUMER PRODUCT

	Equation				
	ΔOP_t	ΔCP_t	A_t	PR_t	S_t
ΔOP_{t-1}	-.007 (.127)	—	-45.529 (13.556)	-111.976 (22.171)	-1745.203 (369.958)
ΔCP_{t-1}	—	—	24.885 (8.043)	33.395 (13.164)	1006.643 (235.647)
A_{t-1}	—	—	—	—	—
PR_{t-1}	—	—	—	-.262 (.132)	-11.185 (1.669)
S_{t-1}	—	—	-.011 (.004)	-.015 (.006)	—

Notes: Standard errors are in parentheses. All values with |t-statistic| ≤ 1 are restricted to zero. Deterministic components (e.g., seasonal dummies, intercept, strike dummy) are not presented because of space limitations. OP = own price, CP = competitor price, A= advertising, PR = promotion, and S = sales.

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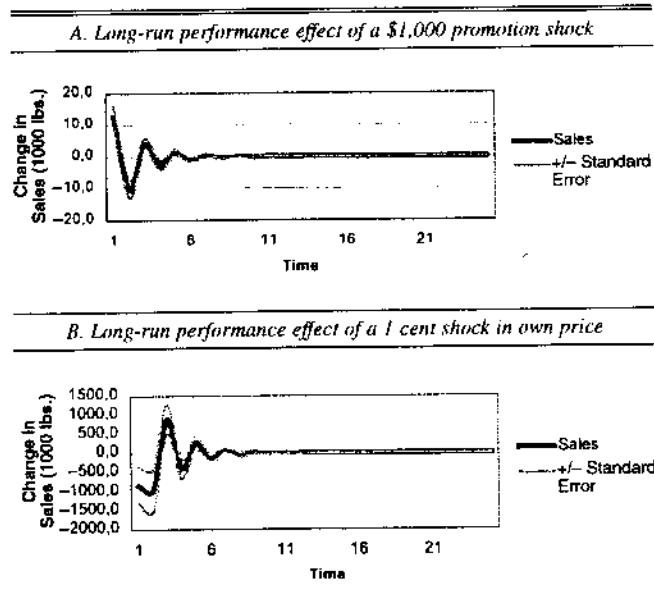|	m	t-value	Unit root?
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Competitor price (CP$_t$)	0	-1.110	Yes
Price differential (PD$_t$)	0	-2.040	Yes
Advertising (A$_t$)	0	-7.146	No
Promotion (PR$_t$)	0	-8.726	No
Sales (S$_t$)	0	-9.657	No

Notes: m = number of lagged difference terms, selected on the basis of the Schwarz criterion. t-value = t-statistic for the parameter estimate associated with the lagged level in the augmented Dickey-Fuller equation, to be compared with the 5% critical value of -2.93.

Figure 6
PERSISTENCE LEVELS IN THE CONSUMER-PRODUCT EXAMPLE

A. Long-run performance effect of a $1,000 promotion shock

B. Long-run performance effect of a 1 cent shock in own price

Table 6
VAR PARAMETER ESTIMATES FOR THE FREQUENTLY PURCHASED CONSUMER PRODUCT

	Equation				
	ΔOP_t	ΔCP_t	A_t	PR_t	S_t
ΔOP_{t-1}	-.007 (.127)	—	-45.529 (13.556)	-111.976 (22.171)	-1745.203 (369.958)
ΔCP_{t-1}	—	—	24.885 (8.043)	33.395 (13.164)	1006.643 (235.647)
A_{t-1}	—	—	—	—	—
PR_{t-1}	—	—	—	-.262 (.132)	-11.185 (1.669)
S_{t-1}	—	—	-.011 (.004)	-.015 (.006)	—

Notes: Standard errors are in parentheses. All values with |t-statistic| ≤ 1 are restricted to zero. Deterministic components (e.g., seasonal dummies, intercept, strike dummy) are not presented because of space limitations. OP = own price, CP = competitor price, A = advertising, PR = promotion, and S = sales.

incremental profit that accrues every period (i.e., as a flow rather than a stock variable) to the company.

Long-run cross-effects are only possible on the competitive prices, because advertising and promotional support are mean-reverting. We find an immediate cross-price effect of .439 cents per pound, which is sustained fully in the long run (s.e. = .196). Price shocks initiated by the competing brand, in contrast, result in a long-run cross-effect of .298 (s.e. = .131) on the price level of the target brand (Table 7).

Similar results were found when estimating a four-equation system in which the two prices are replaced by (the first difference of) the price differential. A substantial fraction (approximately 70%) of changes in this differential is sustained over time.

In conclusion, our reanalysis of the BRANDAID data reveals that observed differences in effectiveness between advertising and promotion, as reported by Little (1975), did not have long-term sales or profit consequences. Conversely, gradual price increases offered a sizeable long-run profit opportunity for the target brand in this mature category.

STRATEGIC RECOMMENDATIONS

In this article, we have argued conceptually and empirically that marketing resources should be allocated for their long-run impact on response and that it is now possible to trace such impact when high-quality time-series (tracking) data are available. These new empirical methods have enabled us to estimate the short- and long-run economic impact of pricing and marketing spending scenarios and to make cost–benefit comparisons. To the best of our knowledge, our approach is the first to have quantified the long-run profit implications of marketing allocations from readily observable data.

The results also lend themselves to the formulation of broad guidelines for marketing strategy and resource allocation. The first task, we argue, is to determine if the brand's sales and marketing support follow a business as usual or a continuously changing (evolving) pattern. If it is business as usual, managers can fit traditional market response models on levels and use cost–benefit analysis to determine the profitability of their pricing and marketing spending strategies. Even though there may be some lagged response effects, the results do not have long-run profit implications because brand spending and performance return to their mean after a finite number of periods. A company that generates a short-run surplus in such conditions may be able to repeat its profitable marketing tactics and accumulate substantial wealth in the long run.

If the sales pattern is evolving, the strategic picture changes dramatically. Short-run marketing decisions can,

but need not, influence the long-run position and profitability of the company, so managers should pay particular attention to the long-run consequences of their actions. By calculating spending sustenance and response persistence, we can quantify these consequences and draw important inferences, such as the following:

- If response persistence is low, creating long-run marketing effects will require repeated efforts, which may or may not be profitable;
- If response persistence is high, it is possible to obtain long-run benefits from one-time or infrequent short-term actions; and
- In general, marketing managers should ensure that response persistence is sufficiently higher than spending sustenance. If the reverse is true, the company, and indeed the entire industry, may evolve into an unprofitable spending escalation.

CONCLUSIONS

Most marketing managers and academics alike agree that scarce marketing resources should be allocated to create long-term as opposed to short-term impact and profitability. However, what constitutes the long term and how it should be measured is an entirely different story, one that lacks definitions and analytical rigor.

In this article, we proposed that the analytical rigor should come from classifying marketing spending, market performance, and their interrelation as either stationary (mean-reverting, temporary) or evolving (sustained, persistent). Building on previous work that described and illustrated empirical time-series measures of stationarity, evolution, and persistence, we defined four possible strategic scenarios in which managers and their products may find themselves: business as usual, evolving business practice, hysteresis, and escalation. We reviewed reasons why changes in marketing spending and market response are either short-lived or persistent. Finally, we proposed measures of long-term marketing effectiveness and related them to the four scenarios.

Our discussion revealed that real markets are a mixture of the scenarios we described. Sometimes companies can reap long-term rewards from short-term marketing investments (hysteresis). Other times, it takes sustained spending to steer products or brands in a certain strategic direction (evolving business practice). Yet other times, market response is onl y temporary, yet managers spend their products into an unprofitable escalation scenario. Finally, some markets are in a comfortable spending/response equilibrium in which nothing changes in the long run.

By offering the tools for distinguishing among these scenarios and measuring their financial consequences, we hope to have contributed a rigorous yet implementable method for diagnosing product markets. This diagnosis leads, in turn, to specific strategic recommendations for marketing resource allocation. For example, our framework can be used to diagnose the difference between "do or die" and unnecessary price wars.

All the diagnosing we propose is based on routinely available time series of market performance (e.g., sales volumes) and marketing spending (e.g., sales force and promotion data). This focus makes our approach practical but also imposes some restrictions. First, we are dependent on relatively abundant, equally spaced data for all the important variables. From a managerial perspective, that means the company must have access to a good marketing data ware-

Table 7
PRICE SUSTENANCE ESTIMATES FOR THE FREQUENTLY PURCHASED CONSUMER PRODUCT

	Long-Run Impact on	
Shock to	Own Price	Competitor Price
Own price (cents/pound)	.993	.439
	(.160)	(.196)
Competitor price (cents/pound)	.298	1.000
	(.131)	(.110)

house. Second, we have offered little guidance for the treatment of purely qualitative aspects of marketing strategy, such as positioning and communications message choice. Therefore, the methods we advocate will be less useful in really new product categories with little or no historical data or established attribute structures. Third, we have not investigated the scenario in which an evolutionary strategic scenario gradually turns into a stationary scenario (or vice versa), for example, because of the natural progression of the product life cycle.

Such limitations lead us to recommend significant new research efforts in the development of empirical generalizations about long-term marketing effectiveness and spending patterns. Because time-series statistical software is becoming more accessible, we should be able to replicate the four strategic scenarios and learn about the determinants of spending sustenance and response persistence. In particular, we should investigate segment differences among these determinants (Mela, Gupta, and Lehmann 1997). For example, we should allow for the possibility that market response effects are persistent for one group of customers but not for another (for a recent discussion on the application of long-run time-series techniques to heterogeneous panels, see Pesaran and Smith 1995). In this process, various theories and frameworks from other disciplines, including psychology, economics, and management strategy, can help us offer intuitively appealing explanations for the patterns we find. We hope that such research will advance our understanding of long-term marketing resource allocation and its effectiveness.

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