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Performance Regimes and Marketing Policy Shifts

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Even in mature markets, managers are expected to improve their brands' performance year after year. When successful, they can expect to continue executing on an established marketing strategy. However, when the results are disappointing, a change or turnaround strategy may be called for to help performance get back on track. In such cases, performance diagnostics are needed to identify turnarounds and to quantify the role of marketing policy shifts in this process. This paper proposes a framework for such a diagnosis and applies several methods to provide converging evidence for two main findings. First, contrary to prevailing beliefs, the performance of brands in mature markets is not always stable. Instead, brands systematically improve or deteriorate their performance outlook in clearly identifiable time windows that are relatively short compared to windows of stability. Second, these shifts in performance regimes are associated with the brand's marketing actions and policy shifts, as opposed to competitive marketing. Promotion-oriented marketing policy shifts are particularly potent in improving a brand's performance outlook.

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A trend is a trend, is a trend, but the question is, will it bend? Will it alter its course, through some unforeseen force, and come to a premature end?
—Sir Alec Cairncross,
Chief Economic advisor to the British government

1. Introduction

Year after year, marketing managers strive to improve the sales and profit performance of their brands. When products or markets are young, most of that sales growth comes from market expansion, which can produce positive sales trends for many years and for several competitors. As an example, *all* Japanese automobile brands gained sales and share in their emerging North American and European export markets in the 1970s and 1980s (Hanssens and Johansson 1991). However, in mature markets there are limits to expansion, e.g., consumer awareness and distribution may have reached a maximum, prices are in steady state, and competitive reaction to any new marketing initiative is fierce. Such mature product categories are typically viewed as *equilibrium markets* (Ehrenberg 1988). It is not surprising that in such markets, observed changes in market share are only temporary, and over the long run, market-share positions do not change (Dekimpe and Hanssens 1995, Nijs et al. 2001, Pauwels et al. 2002).

However, the mere fact that product markets have matured does not relieve managers of the pressure to grow their brands' performance. In particular, declining brand performance is regarded as an immediate reason for marketing intervention and even top management shake-up (Miller 1991). Moreover, management's fundamental "quest for more" (Hunt 2000) drives marketing investments, which, if effective, can create an upward trend in brand performance. On the other hand, demand saturation and competitive reaction pose limits to such performance growth (Bass et al. 1984). As a result, brand performance is subject to *two opposing influences*: mean reversion and change. Neither can last for a long time in mature markets: Prolonged periods of either flat or declining performance are incongruent with managerial objectives, and prolonged periods of growth are incongruent with market realities. Therefore, we may expect sales[1] performance in mature categories to go through successive *regimes* or *windows* of performance decline, stability, and growth.

Among these regimes, performance decline receives the most managerial and public attention because of

[1] We focus in our main application on sales performance, but find similar results for revenue performance, the best proxy for profit performance in our data.

its negative implications for investors and employees. Reversing a decline is considered more difficult than maintaining stability and often requires the use of a "turnaround strategy." For example, everyday low pricing may be gradually replaced by a strategy of high-low pricing, few advertising campaigns by many campaigns, and low levels of point-of-purchase activity by high levels of feature and display.

The empirical investigation of marketing turnaround strategies and their effects is mostly anecdotal in nature. For example, *Advertising Age* reported on the sales decline of the Budget Gourmet brand of ready-made food and attributed the turnaround to a highly effective advertising campaign (Bender 2001). However, we have no scientific evidence that the brand's performance improvement was actually due to the advertising campaign versus the pricing strategy change and increased point-of-purchase activity that occurred over this period. To the best of our knowledge, the only formal research on the impact of marketing policy changes on performance was conducted on Procter & Gamble's shift from promotion-intensive to advertising-intensive marketing support (Ailawadi et al. 2001). That research focused on a single identifiable regime shift in the data and provided no formal metrics for diagnosing gradual performance turnarounds over time.

In order to diagnose turnaround strategies, we need to first *identify* periods of poor performance in a brand's history. In particular, we must identify the beginning and the end of the decline. Secondly, we must isolate the *causes* associated with the turnaround. Such causes could be economic down- and upturns that affect the entire category, a single marketing action, or a sustained marketing policy change initiated by the brand, or competitive marketing activity.

Current market-response research does not yet offer a framework to either identify performance regime changes or to isolate their causes. Instead, recent papers have classified performance and marketing spending as evolving or stationary over the full data period (Dekimpe and Hanssens 1999). By far the most common scenario is *business as usual*, representing stationary performance and marketing in mature markets (Nijs et al. 2001, Pauwels et al. 2002). For the purpose of such classification, researchers study the full data period available, and perform their tests after allowing for seasonality and a deterministic trend (e.g., Srinivasan et al. 2004). Important changes in this full period, such as brand entry or channel addition, may be identified as structural breaks (e.g., Deleersnyder et al. 2002, Pauwels and Srinivasan 2004), with the market considered in equilibrium for the long periods in-between the breaks.

However, even in the absence of identifiable structural breaks, markets may not be stable at all times. Full-sample analysis may *mask* more subtle performance changes over time, i.e., smaller time windows in which performance is stable, improving, or declining. In other words, *what appears to be a long period of stability in market performance to the researcher may in fact be a succession of time windows in which different players face different circumstances of growing, stable, and declining performance.* Thus, the first objective of our paper is to propose a method for *identifying performance regimes* over time, along with transition points between them.

As argued earlier, some of these performance regimes (e.g., decline) are inconsistent with managerial objectives. In such cases, managers may go beyond single marketing actions and make course direction *changes* to the marketing mix to reverse an unfavorable path for the brand (Schendel et al. 1976). Therefore, the second objective of our paper is to relate *changes* in performance regimes to *changes* in marketing actions and marketing regimes. In so doing, we expand the scope of marketing-mix modeling: Whereas previous models were designed to measure the effects of single actions (such as a price change or an ad campaign) on current and sometimes future sales performance, we also analyze the regime-shifting effects of *strategic change* in marketing, such as a policy shift from low to high promotional intensity.

These two research objectives motivate us to (1) identify performance regimes and their transitions, and (2) investigate whether marketing actions may lead to improved performance regimes. We begin by classifying brand performance from a strategic perspective, and we formulate hypotheses on how different performance regimes are created over time, how these impact marketing decisions, and how these decisions, in turn, change business performance. Next we discuss three alternative methods to diagnose performance regimes and analyze marketing's power to affect them. We describe an extensive marketing database in the frozen-food category and use the three methods to provide converging evidence for our hypotheses. We conclude by highlighting managerial insights and avenues for future research.

2. Framework and Hypotheses

Reacting to a second-quarter operating loss of $1 billion, DaimlerChrysler's CEO stated "Admittedly, we have a setback in the third year [after implementing the Chrysler turnaround plan] but if you look at the trend we are moving in the right direction" (*Financial Times* 2003, p. 15). The quote illustrates how managers interpret their companies' performance in terms of trends and trend changes. Formally, brand

Table 1 Classification of Performance Regimes, Ordered by Managerial Desirability *

	Trend change	
Trend sign	Increasing	Decreasing
Positive	Accelerating growth (#1)	Saturating growth (#2)
Insignificant	Improving stability (#3)	Lessening stability (#4)
Negative	Decline turnaround (#5)*	Deteriorating decline (#6)

* Read: a negative trend sign, which is becoming less negative, indicates decline turnaround.

performance regimes can be classified by their managerial desirability, based on two dimensions: the performance trend sign (up, insignificant, or down), and the change in this trend (accelerating or decelerating).[2] Table 1 combines these dimensions in six performance regimes, with accelerating growth (#1) and deteriorating decline (#6) the best-case and worst-case scenario, respectively.

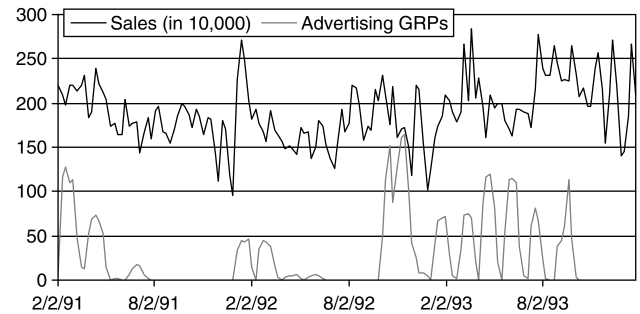
As argued earlier, we do not expect brand performance to stay in any of these regimes for long time periods. In mature markets, sustained trends over long periods are unrealistic because they imply predetermined patterns that are independent of managerial and competitive marketing interventions (Lambkin and Day 1989). Second, at least the deteriorating decline scenario (#6) is unacceptable to managers. Their marketing actions aimed at performance improvement have the potential to turn the negative trend around (scenario #5), leading up to stable or even growing performance (Salmon 1988). Likewise, accelerating growth performance (#1) is unlikely to resist the gravitational forces of competitive reaction (Bass et al. 1984) and consumer habit formation (Ehrenberg 1988) for a long time. Therefore, we expect brand performance series to go through successive regimes of trend signs and trend changes. The question now becomes how often each regime occurs and whether marketing can affect regime shifts.

In the strategic change literature, *punctuated equilibrium* is the dominant paradigm for explaining regime shifts (Mullins et al. 1995). This paradigm holds that most successful organizations evolve through long periods of relative stability that are punctuated by occasional periods of upheaval. Punctuated-equilibrium theory argues that these revolutionary change or transition periods are typically short compared to the equilibrium periods.

We propose that this punctuated-equilibrium principle holds for market performance and marketing policy as well, for two reasons. First, buying behavior typically follows a stable pattern that is adequately

[2] We thank an anonymous reviewer for suggesting that we consider insignificant trend changes as well, leading to the nine-regime classification analyzed in Appendix A.

Figure 1 Unit Sales and Advertising Gross Rating Points for Budget Gourmet



captured by a zero-order stochastic process (Bass et al. 1984, Ehrenberg 1988). In mature categories, only strong customer motivation to revisit habitual buying patterns will change buying behavior and thus brand performance. Examples of such strong motivations are reactions to dramatic price reductions or creative product extensions (Simon 1997). However, such growth periods are not likely to last for extended time periods, because of consumer saturation and competitive reaction. On the flip side, periods of deteriorating decline will be especially short-lived because managers are pressed to take action to get out of such a clearly unfavorable regime. Because of this managerial action, we should observe periods of decline less often than periods of growth, which do not raise such strong concerns.

An example of subtly changing performance regimes in the frozen food market is the Budget Gourmet brand in the early nineties (Bender 2000), as shown in Figure 1. In the summer of 1992, management argued that Budget Gourmet's sales had been deteriorating over the past year, and the survival of the brand became uncertain. At that point, a new division president dramatically changed marketing policy, particularly in pricing (30% reduction over a prolonged time period), point-of-purchase activity (a major increase in feature and display), and advertising (a new campaign). After a few months, management saw strong performance improvement, which lasted for several more months, and the marketing campaign won the *Advertising Age* "Star" award for turning the brand around. Interestingly, neither the performance turnaround nor advertising's role in it are obvious from a visual inspection of the data; they require further analysis. Therefore, we propose:

Hypothesis 1 (H1). *Regimes of trending performance are shorter than periods of stable performance.*

Hypothesis 2 (H2). *Regimes of decline in brand performance are less common than regimes of growth, which are in turn less common than regimes of stable brand performance.*

While managerially relevant, Table 1's diagnostics about performance regimes are not sufficient for marketing decision makers. They also need to know how their actions may yield more favorable performance regimes. Unfortunately, previous literature offers limited guidance on this issue. Only two marketing concepts, the product evolutionary cycle and hysteresis, provide theory and empirical evidence on the triggers of performance regime transitions. First, the *product evolutionary cycle* (PEC) proposes explicit links between market growth and marketing influences (Lambkin and Day 1989, Tellis and Crawford 1981). Empirical studies include the impact of advertising spending on cigarette markets (Holak and Tang 1990) and new products' struggles with incumbent products for retail space and market share (Bronnenberg et al. 2000, Uhlrich et al. 2001). As such, this research stream allows for more flexible market growth patterns than the traditional product life cycle. However, the above studies are focused on emerging, as opposed to mature, markets and they have analyzed only one or two marketing variables at a time.

Second, recent papers have begun to identify the circumstances under which marketing actions may induce *hysteresis*, i.e., yield long-term performance effects from a temporary marketing action (Simon 1997, Hanssens and Ouyang 2001). Anecdotal evidence leads Simon (1997) to conclude that price and product changes are important conditions for hysteresis, whereas Hanssens and Ouyang (2001) find that a company's advertising can cause hysteresis in performance during periods in which it has a clearly superior product. However, other recent research shows that such long-term marketing effects are the exception rather than the rule (Srinivasan et al. 2004, Nijs et al. 2001, Pauwels et al. 2002). Again, these inferences are based on performance analysis of the full data period, which may *mask* performance regime changes in smaller time windows. Therefore, we propose:

Hypothesis 3 (H3). *Marketing actions explain changes in performance regimes.*

3. Diagnosing Performance Regimes and Marketing Policy Shifts

3.1. Testing for Full-Sample Evolution vs. Stationarity and for Structural Breaks

Modern time-series analysis offers robust methods to diagnose the performance regimes of Table 1. First, we examine whether performance and marketing actions are stationary or evolving over the full data sample. To this end, we perform two unit-root tests: the augmented Dickey-Fuller test (ADF), which maintains evolution as the null hypothesis, and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS), test, which maintains stationarity as the null hypothesis.

The unit-root tests have two possible outcomes: Either the performance variable has a fixed mean over the full sample (mean-stationary), or it does not (evolving). Evolution in performance is often caused by *structural breaks* in the data-generating process (Perron 1990), typically due to major and relatively rare events such as the introduction of private-label brands (Pauwels and Srinivasan 2004) or the addition of Internet channels in the market (Deleersnyder et al. 2002). The statistical methods for detecting and modeling structural breaks in marketing are well understood and need not be revisited here (see Deleersnyder et al. 2002 for an excellent summary). A structural break typically marks the end of one (possibly stationary) regime and the beginning of another, and thus there is little ambiguity in identifying and explaining these regimes.

In contrast, full-sample stationary performance characterizes mature markets without such major events (Dekimpe and Hanssens 1999). Marketing impact on performance is typically found to be temporary, as in the cumulative effect of a price promotion in Pauwels et al. (2002). However, as argued above, we believe that such full-period stationarity *masks* successive performance regimes of growth and decline, and that marketing actions have the power to affect these regimes in ways that have not been identified to date. Therefore, we focus on this more intricate case of detecting *gradually changing* performance regimes in markets that are diagnosed as stationary in the full sample.

3.2. Diagnosing Performance Regimes and Assessing Marketing Effects

Assessing performance regimes can be achieved in three ways, through direct trend assessment, filtering, and time-varying parameters. *Direct trend assessment* specifies a relevant time window (e.g., the most recent 52 weeks), and measures the sign and significance of a trend in this window in order to classify the performance regime according to Table 1. *Filtering* the performance data separates the high-frequency from the low-frequency movements that represent the underlying performance "baseline." Finally, a performance trend may also be measured as a *time-varying parameter* over the full sample. Below we discuss these models and their (dis)advantages in detail.

Having established these performance regimes, we need to assess the impact of marketing on them. With the direct assessment and performance filter approaches, this is done by a second-stage regression of the performance regime (a transformed performance variable) on marketing. In contrast, a time-varying trend model allows us to directly assess marketing effects in a single stage.

Under either approach, an important decision needs to be made on the definition of the time window over which a performance regime is measured. Although statisticians generally prefer larger samples and thus gradually longer time windows as new data arrive, managers are interested in their brand's performance during prespecified shorter periods—for example, annual or quarterly. As an illustration, we posted the following question on www.marketingprofs.com, a popular website for marketing professionals: "In your company, how long does performance have to be in decline before the company rethinks its strategy and executes on a turnaround strategy?" We received the following responses:

- "In my company, a well-known global brand and a key contributor to strategy know-how, there is a quarterly review of all major performances in terms of fresh orders, revenues, margin, collected cash, past dues. All of these financial performance measures are projected for one year in advance through a rolling strategic planning process."
- "Being from the information technology sector, in my organization, the 'rolling window' is semiannual, that is, six months is targeted for reviews and assessment, and for fine-tuning the strategies. But to completely set new targets and develop new strategies, a year's timeline is what we look at."
- "Performance is evaluated year-over-year and versus the plan."

These illustrative answers support the notion that managers evaluate performance trends based on *prespecified* windows. The choice of window length may differ across industries; For example, a consumer goods firm with weekly data may use a year (which also allows accounting for seasonal fluctuations), whereas an Internet service provider with hourly data may prefer weekly windows (which account for day-of-week seasonality observed in, e.g., Pauwels and Dans 2001).

Fixed-length time periods for performance evaluation match the econometric concept of "*rolling* windows," which prune out old data that are no longer deemed relevant. However, such rolling-windows models have an inherent statistical disadvantage of limited sample size. Therefore, an alternative in econometrics is to use a *recursive* window, typically starting at the first available data point, whose sample size increases as time moves on. Thus, in choosing relevant time windows for performance assessment, we will have to balance the managerial need for fixed evaluation windows with the statistical superiority of larger samples.

3.3. Direct Trend Assessment

3.3.1. Identifying Performance Regimes. The most direct approach to assessing performance regimes in a given time period is to estimate a trend in rolling windows. To this end, we specify a simple performance time trend model that controls for seasonal fluctuations[3] if applicable:

$$y_t = \alpha + \delta t + \sum \lambda_j SD_{j,t} + \varepsilon_t, \qquad (1a)$$

with *SD* representing seasonal dummy variables for weeks with exceptionally high and low demand (Franses 1998, Miron 1996). Least-squares estimation of Equation (1a) yields the coefficient and t-statistic on δ that reveal the sign and significance of the time trend.

Model (1a) is the classical decomposition of time-series movements into trend, seasonal, and irregular components (e.g., Enders 2003). However, if the irregular terms ε_t are not white noise, the least-squares trend estimate may not be efficient. In that case, the trend test model (1a) could be extended to include a lagged error term,[4] for example:

$$y_t = \alpha + \delta t + \sum \lambda_j SD_{j,t} + \varepsilon_t + \theta \varepsilon_{t-1}. \qquad (1b)$$

In order to test for the trend *change*, we estimate Equation (1) in rolling windows of 52 weekly observations. This *rolling-window* analysis uses a data sample of fixed size and estimates the model in every window before moving on to the next (Leeflang et al. 2000, Swanson and White 1997, Tashman 2000). Appendix A elaborates on the use of rolling-windows analysis and its close alternative, recursive-windows analysis.

3.3.2. Assessing Marketing Effects on Performance Trends: The Performance Barometer. We propose to base the interpretation of performance trends on the estimated trend t-statistics.[5] These reveal both

[3] Because we want to compare equation results from one window to the next, the model specification selection is consistently based on the full-sample analysis. We also verify that our results are robust to (not) controlling for seasonal effects; results are available upon request.

[4] This MA(1) term is the equivalent of an AR(∞) process, and is thus quite flexible. Nevertheless, additional ARMA terms may be added as needed, without loss of generality.

[5] In contrast to the t-statistic, the trend coefficient itself is not comparable across settings (e.g., different brands and categories) and thus does not lend itself to the classification in Table 1. Thanks to the suggestion of the associate editor, we also note that the t-statistic is directly related to the partial correlation coefficient (the standardized parameter): $t \sim pc/\sqrt{1+pc^2}$. In essence, the t-statistic transforms the bounded $[-1, -1]$ partial correlation coefficient into a continuous variable, which is desirable for the second-stage regression. As such, the performance barometer relates to the broad class of varying-parameter models in marketing. In our empirical analysis, we both report on the high correlation between the trend coefficient and its t-statistic and estimate a varying-trend model directly to investigate the convergence of our results across methods.

Figure 2 Performance Barometer (t-Statistic Trend) for Budget Gourmet and Healthy Choice

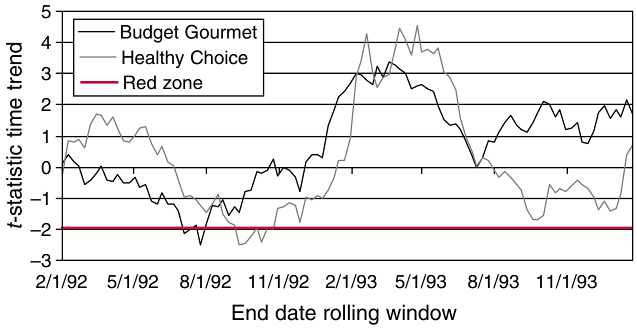
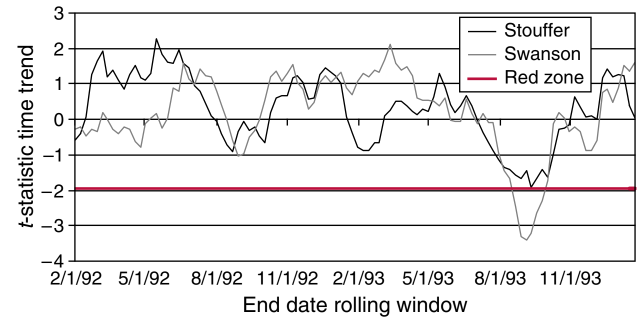


Figure 4 Performance Barometer (t-Statistic Trend) for Stouffer and Swanson



the sign and the significance of the trend coefficient, so we may classify performance into the growth, stability, or decline rows in Table 1. For example, if $t < -1.96$ for a given time window, we classify performance as systematically deteriorating over that period (identified as the "red zone" in Figures 2–5). The *change in this t-statistic* from one window to the next indicates whether this trend is increasing or decreasing (the columns of Table 1). Therefore, we operationalize the performance regimes by combining information on the trend t-statistic with the change of this t-statistic from one rolling window to the next. The best-case scenario combines a significant positive trend (t-stat > 1.96) with a positive trend change, and produces the "accelerating growth" performance regime. The worst-case scenario combines a significant negative trend (t-stat < -1.96) with a negative trend change, thus producing the "deteriorating decline" performance regime. We label the graph of the trend's t-statistic the *performance barometer*, as it visualizes how performance is trending and whether this trend is increasing or decreasing.

As a summary of trend information in past performance, the performance barometer is *forward looking*, as it communicates what managers may expect for the future if the regime were to continue. In addition, we may use the barometer to test H3 as follows:

$$\Delta PB_{i,t} = \alpha_i + \rho_i(L)\Delta PB_{i,t-1} + \sum \beta_{ki}(L)x_{ki,t} + \varepsilon_{i,t}, \quad (2)$$

where, for each brand i, PB represents the performance barometer, expressed in changes to obtain a stationary series and thus avoid spurious regression problems (Granger and Newbold 1974). Furthermore, x_k is the value of marketing-mix effort k, expressed in levels when its time series is stationary (ibid). The response parameters $\rho_i(L)$ and $\beta_{ki}(L)$ are polynomials in the lag operator L, whose maximum lag length is established empirically using the Schwartz Information Criterion (SIC). Note that these rolling-window estimates are different from time-varying models of performance and marketing. They are new metrics for establishing the performance outlook of a brand at any point in time and for assessing marketing's power to change that outlook (see our comparison with benchmark models below).

Equation (2) explains changes in the performance trend (barometer) by changes in marketing *levels*. However, when temporary marketing actions fail, sustained marketing policy changes may be needed to improve performance regimes. In the context of

Figure 3 Performance Barometer (t-Statistic Trend) for Lean Cuisine and Weight Watchers

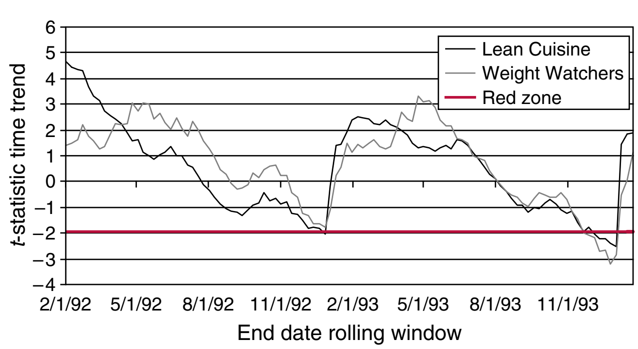
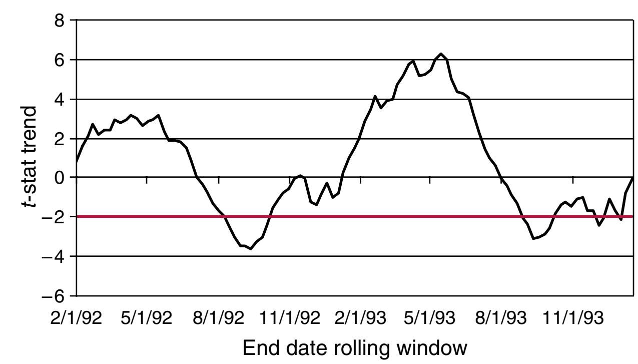


Figure 5 Performance Barometer (t-Statistic Trend) for the Frozen Dinner Category



our model, we may test for this phenomenon by first constructing *marketing policy* barometers similar to the performance barometer.[6] Changes to these marketing barometers identify policy shifts, such as sustained increases in advertising spending, deeper promotional discounts, or product-line expansions. Next, we regress changes in the performance barometer against changes in these marketing policy barometers (xB) using the model:

$$\Delta PB_{i,t} = c_i + \lambda_i(L)\Delta PB_{i,t-1} + \sum \gamma_{ki}(L)\Delta xB_{ki,t} + \eta_{i,t}. \quad (3)$$

Finally, we extend Equations (2) and (3) to investigate the effect of competitive marketing on the brand performance barometer. Specifically, we regress each brand's performance barometer on respectively (1) the marketing levels of all analyzed brands, and (2) the marketing barometers of these brands. Similarly, we investigate category expansion effects by regressing the category performance barometer on respectively (1) the marketing actions of all brands, and (2) the marketing barometers of all brands.[7]

3.4. Performance Filtering

Instead of rolling-window analysis, recursive-windows analysis can also be performed using Equation (1) to identify the performance regimes and calculate the performance barometer. Alternatively, we may use recursive-window methods that smoothen the performance series and thus separate the higher versus lower-frequency fluctuations. One such smoothing technique, the *Hodrick-Prescott* (H-P) filter, is widely used in macroeconomics, and was originally designed for the analysis of postwar U.S. business cycles (Hodrick and Prescott 1997). It was recently applied in marketing by Deleersnyder et al. (2004) to study the impact of the business cycle on the sales evolution of consumer durables.

The H-P filter is a two-sided linear filter that computes the smoothed series S of y by minimizing the variance of y around S, subject to a penalty that constrains the second difference of S. That is, for each brand I, the H-P filter chooses S to minimize:

$$\sum_{t=1}^{T}(y_{i,t} - S_{i,t})^2 + \lambda \sum_{t=2}^{T-1}[(S_{i,t+1} - S_{i,t}) - (S_{i,t+1} - S_{i,t})]^2. \quad (4)$$

The penalty parameter λ controls the smoothness of the series and is typically set at 270,400 for weekly series[8] (Hodrick and Prescott 1997). The H-P filtered series $S_{i,t}$ becomes the dependent variable in a second stage that examines the impact of marketing. Specifically, we adapt the model of Equation (3) as:

$$\Delta S_{i,t} = c_i + \lambda_i(L)\Delta S_{i,t-1} + \sum \gamma_{ki}(L)\Delta xB_{ki,t} + \eta_{i,t}, \quad (5)$$

3.5. Time-Varying Parameters

Performance barometers and H-P filters require two stages to assess the impact of marketing on performance trends. As a result, the second-stage estimates (Equations (3) and (5)) are subject to error-in-variables and thus are biased towards zero.[9] An alternative is to formulate a one-stage model that allows marketing actions to impact both performance levels and performance trends. Specifically, we may use Kalman-filter equations to estimate a model adapted from Harvey (1989) for each brand i:[10]

$$Performance_{i,t} = \mu_{i,t} + \delta_{i,t} * t + \sum \lambda_j SD_{j,t} + \varepsilon_{i,t} \quad (6)$$

$$\mu_{i,t} = \mu_{i,t-1} + \sum \beta_{ki}(L)x_{ki,t} + \eta_{i,t} \quad (7)$$

$$\delta_{i,t} = \delta_{i,t-1} + \sum \gamma_{ki}(L)x_{ki,t} + \varepsilon_{i,t}. \quad (8)$$

In this model, performance follows the classical time-series decomposition in intercept, trend, and seasonality (Box and Jenkins 1971). Equation (7) relates the varying coefficient for the intercept to marketing actions, which yields the direct impact of marketing on performance. Equation (8) relates the varying coefficient for performance trend to marketing, which yields a test of marketing's power to affect performance trends.

Our empirical application will focus on the direct trend assessment method and cross-validate the approach with an H-P-filter and time-varying trend model.

[6] In our analysis, marketing barometers are constructed based on the same rolling-window length (52 weeks) as the performance barometers. Other window lengths are possible for the marketing barometer, and we considered lengths of 4, 8, and 13 weeks so that the marketing barometers quickly reflect a change in marketing strategy (we thank an anonymous reviewer for this suggestion). However, technical issues prohibit these short-period marketing barometers from generating insights. First and foremost, many marketing actions variables do not vary in a four-week period: Product assortment growth and advertising are typically zero for several weeks, as is the price promotion variable for several brands. Moreover, any period of less than 52 weeks does not allow inclusion of all the seasonal dummies in the barometer equation. Therefore, the marketing barometer would be based on a different equation from one window to the next. To address this problem, we could work with deseasonalized data—a less than ideal solution in econometric literature because it may easily distort relationships among variables of interest (e.g., Ghysels et al. 1994).

[7] Modeling the combined effects of marketing actions and their barometers results in a lower SIC value and has some collinearity problems.

[8] The rule is to divide the number of periods in a year by four, square this number, and multiply it by 1,600.

[9] This error-in-variables problem may be relaxed through Monte Carlo simulations drawing from the estimated distribution of both the performance and the marketing policy barometers. A regression of the performance barometer draws on the marketing policy barometer draws would then account for parameter uncertainty. We thank the associate editor for this suggestion, which we leave as an area for future research.

[10] We are grateful to an anynomous reviewer for suggesting this alternative method.

Table 2 Descriptive Statistics of Sales and Marketing Variables for Category and Brands*

	Category	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Unit sales	15,746,007	1,897,238	1,338,506	1,496,902	2,091,549	1,685,501	1,132,408
Product additions	0.20	0.21	0.22	0.20	0.18	0.16	0.26
Regular price ($)	2.28	1.99	2.88	2.41	2.55	2.21	2.46
Temp. price reduction ($)	−0.49	−0.32	−0.45	−0.41	−0.52	−0.46	−0.43
Display (%)	5	5	4	4	6	5	3
Feature (%)	12	23	20	11	15	17	13
Advertising	289.77	28.88	34.76	40.09	58.29	38.88	21.61

*Advertising (gross rating points) is only available till 12/18/1993, which therefore serves as the ending date for empirical analyses involving this variable.

4. Empirical Analysis

4.1. Data

A comprehensive marketing data set is available for frozen dinners, which is the largest category within the frozen-food market, with more than $5.9 billion in annual sales (*American Frozen Food* 2003). The category experienced major changes in the 1980s, both in the form of technological innovations such as newly designed cryogenic railcars for transporting frozen foods and in the form of product improvements such as the introduction of single-serve packages and low-calorie entrees. In the late 1990s, renewed growth was fueled by the product innovation of rising-crust pizzas (Holcomb 2000, van Heerde et al. 2004). By contrast, in the early nineties, category sales and marketing expenditures were fairly stable. Our sample combines 156 weeks of ACNielsen Sales and Causal data with advertising exposure data for the period from February 1991 to January 1994. For the total U.S. market,[11] we obtain category and brand[12] sales (our performance measure), regular price (per serving) and temporary price reductions, display (percentage of All Commodity Volume displayed), feature (percentage of All Commodity Volume featured), and advertising (gross rating points). Moreover, we compute product-line additions as the number of SKUs that are added to the brand's assortment in a given week. As the advertising data are collected for Monday-to-Sunday periods, we align them with the ACNielsen Saturday-to-Friday periods assuming equal distribution of advertising over the days of the week. The aligned data set covers the period 2/2/1991–12/18/1993 for all variables. Six national brands compete for the bulk of the market: Stouffer (15% market share), Swanson (11%), Healthy Choice (11%), Budget Gourmet (10%), Lean Cuisine (10%), and Weight Watchers (8%). Table 2 summarizes their descriptive statistics. Based on the deterministic seasonality in category sales (Miron 1996), eight weeks are identified with exceptionally high or low demand. According to the data provider, demand peaks in mid-January and March reflect consumers' New Year and spring resolutions for low-calorie entrees, whereas family get-togethers around Thanksgiving, Christmas, and New Year greatly reduce the demand for frozen food (Bender 2000).

4.2. Full-Sample Analysis

4.2.1. Assessing Full-Sample Evolution. For the full data period, we find that category sales are mean stationary, i.e., fluctuating around a stable mean. Similarly, all but one of the top six brands exhibit mean-stationary sales performance in the full sample (see the unit-root test results in Table 3).

The one exception, Lean Cuisine, is trend stationary (trending upwards), and its gradual gain is realized at the expense of smaller brands not formally analyzed here. Moreover, unit-root tests in rolling windows (of 52 weeks) find no evidence for evolution in any window for any brand. In sum, a full-period analysis would conclude that the frozen-foods market is mature, with no structural breaks, and with one growing and five stable major brands.

4.2.2. Full-Sample Marketing-Mix Analysis. As comparison benchmarks from the extant marketing literature, we estimate marketing elasticities using a log-log model of brand sales on product-line additions, price changes,[13] display, feature, and advertising. We also include past sales, a constant, and a time trend. As shown in Table 4, the estimated elasticities have the expected signs and magnitudes. Price, display, and feature significantly impact sales for virtually all brands. In contrast, product-line additions are

[11] We focus on the total U.S. market as the relevant level of analysis for diagnosing brand turnarounds. Our hypotheses were also verified successfully at the regional-market level.

[12] Because advertising data are only available at the brand level, we aggregate the ACNielsen data from the SKU level to the brand level by using the first-quarter SKU market shares as constant weights.

[13] Replacing price by regular price and temporary price reductions results in inferior SIC values, as does including lags of the marketing actions. Hausman specification tests on the possible endogeneity of advertising did not reveal any endogeneity bias.

Table 3 Unit-Root Test Results for Sales and Marketing Variables over the Full Period

	Category	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Unit sales	A*: −4.68 K**: 0.175	A: −6.89 K: 0.425	A: −5.12 K: 0.128	A: −6.98 K: *0.041*	A: −8.26 K: 0.062	A: −5.40 K: 0.128	A: −4.07 K: 0.275
Product additions	A: −5.89 K: 0.187	A: −6.47 K: 0.226	A: −5.17 K: 0.240	A: −7.82 K: 0.075	A: −12.91 K: 0.183	A: −4.06 K: 0.165	A: −4.51 K: 0.184
Regular price	A: −3.78 K: *0.071*	A: −4.72 K: *0.105*	A: −5.39 K: *0.101*	A: −4.75 K: 0.351	A: −5.61 K: 0.304	A: −5.02 K: 0.366	A: −4.58 K: *0.097*
Temp. price reduction	A: −6.03 K: *0.051*	A: −3.85 K: 0.426	A: −5.68 K: 0.242	A: −4.43 K: 0.402	A: −4.20 K: *0.042*	A: −6.40 K: 0.113	A: −4.28 K: 0.295
Display	A: −3.72 K: 0.068	A: −5.72 K: *0.113*	A: −5.83 K: *0.049*	A: −4.34 K: 0.308	A: −4.71 K: 0.134	A: −4.40 K: 0.202	A: −5.39 K: *0.112*
Feature	A: −4.12 K: 0.260	A: −10.14 K: 0.121	A: −6.26 K: 0.121	A: −6.78 K: 0.029	A: −6.22 K: 0.294	A: −6.91 K: 0.109	A: −6.89 K: 0.147
Advertising	A: −5.82 K: 0.210	A: −6.57 K: 0.153	A: −4.43 K: 0.195	A: −4.94 K: 0.041	A: −3.63 K: 0.403	A: −5.12 K: 0.259	A: −4.62 K: 0.251

* Augmented Dickey-Fuller test rejects H_0 of unit root at 5% significance level below critical value of −3.44.
** KPSS test rejects H_0 of stationarity at 5% significance level above 0.463 without, *0.146* with linear trend.

not significantly related to sales performance for any brand. Finally, advertising effects are significant only for the growing brand Lean Cuisine and the market leader Stouffer. Although informative, these results represent short-term elasticities, which do not necessarily address marketing's power to change the long-run performance outlook of a brand.

Next, we compare our results to those of a full-sample VAR model that accounts for long-term marketing effects. Following Dekimpe and Hanssens (1999), we estimate the VAR model in logarithms, using the Schwarz criterion to establish maximum lag length. Based on these model estimates, we obtain long-term elasticities by generalized impulse response functions to a 1-unit error shock in the marketing variable (ibid).

Compared to the short-term marketing-mix effects, the VAR results only add Stouffer's product introductions as significant contributors to brand sales. All effects are temporary; i.e., sales return to their baseline after the marketing effect has died out. In sum, even a full-period VAR-analysis does not reveal that marketing actions have the power to change the sales trajectory of a brand such as Budget Gourmet, despite management's claims to the contrary.

4.3. Identifying Performance Regimes

4.3.1. Direct Trend Assessment. Following the approach outlined in the direct assessment section, we obtain the results summarized in Table 5.

Table 4 Sales Elasticity to Own Marketing Actions Based on Log-Log Response Model*

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Product additions (t-value)	−0.008	0.012	−0.017	−0.031	0.021	−0.001
	(−0.38)	(0.56)	(−0.70)	(−1.25)	(1.02)	(−0.03)
Price	**−1.841**	**−2.770**	**−3.085**	**−3.708**	**−1.868**	**−3.197**
	(−7.65)	(−7.75)	(−12.51)	(−14.48)	(−8.09)	(−11.36)
Display	**0.155**	**0.100**	**0.151**	**0.099**	**0.034**	**0.075**
	(6.11)	(4.41)	(5.90)	(3.00)	(1.94)	(3.56)
Feature	**0.163**	**0.076**	**0.040**	−0.024	**0.058**	**0.021**
	(8.23)	(3.20)	(1.96)	(−1.03)	(4.18)	(2.95)
Advertising	0.001	−0.001	**0.004**	**0.003**	0.002	0.001
	(0.94)	(−0.70)	(2.83)	(1.95)	(1.47)	(0.76)
R^2	0.851	0.837	0.864	0.787	0.829	0.890
Adjusted R^2	0.844	0.829	0.857	0.776	0.820	0.885

* Each model also includes a constant, the lagged dependent variable, and a trend (insignificant for all brands except Lean Cuisine). Bold coefficients are significant at $p < 0.10$.

Table 5 Relative Frequency of Performance Regimes for Category and Brand Sales

	Accelerating growth (#1) (%)	Saturating growth (#2) (%)	Improving stability (%)	Lessening stability (%)	Decline turnaround (%)	Deteriorating decline (%)
Budget Gourmet	20	22	32	21	2	3
Healthy Choice	11	12	29	31	9	10
Lean Cuisine	10	18	18	44	3	7
Stouffer	5	7	38	47	1	3
Swanson	12	5	36	39	5	4
Weight Watchers	24	25	14	24	4	9
Brand average	**14**	**15**	**28**	**34**	**4**	**6**
Category sales	22	14	24	22	7	11

In contrast to the full-sample analysis, the direct assessment of trends in rolling windows reveals *successive performance regimes* for the category and for each brand.[14] Table 5 presents the relative frequency of these performance regimes, based on the 104 weeks for which the regimes can be computed. Consistent with our first hypothesis, stable regimes are the most common by far: brand performance is stable 62% of the time, growing 29% of the time, and declining 10% of the time (with about the same occurrence of accelerating and decelerating trends). Likewise, the category performance barometer is classified at least once in each of the six performance regimes, among which stability is the most common scenario.

Second, the performance barometers presented in Figures 2–4 for the six brands show that these regimes alternate for *all* brands. In particular, brand performance barometers dip in the decline zone for only a few weeks, after which they improve towards stability. Interestingly, the timing of these performance regimes differs for the brands, suggesting brand-specific instead of category-wide drivers. Indeed, no brand performance barometer completely overlaps with the category performance barometer in Figure 5. Sensitivity analysis reveals that the support for our hypotheses is robust to window sizes of 40, 60, and 80 weekly observations.[15] Barometers based on windows of 100 and more observations show less variation and start to resemble the full-period results. Moreover, the higher data requirements of these longer window sizes reduce the ability to pick up transition points near the start and the end of the data (Banerjee et al. 1992).

In summary, these findings support our conjecture that category and brand performance go through successive regimes of trend signs and change.[16] Consistent with Hypotheses 1–2, windows of trending performance (38%) are shorter than those of stable performance (62%), and windows of decline (10%) are less common than those of growth (28%).[17]

A detailed brand-by-brand comparison is beyond the scope of this paper. Instead, we focus on our introductory example. The deteriorating-decline regime for Budget Gourmet corresponds to the time when the company changed its division president (early summer of 1992), citing an urgent need for a performance turnaround (Bender 2000). Budget Gourmet's performance subsequently transitioned to a decline turnaround and a stability regime. Subsequently, both the company and external observers recognized that the brand had made a turnaround, which led to the advertising award being bestowed on the new management (Bender 2000).

4.3.2. Hodrick-Prescott Performance Filter. Our identification of performance regimes is corroborated by a performance filter analysis, based on visual data inspection. Figures 6–8 display the results of the H-P filter based on recursive windows for the same periods and brands as in Figures 2–4.

In Figure 6, observe that the Hodrick-Prescott filter reveals dips and improvement in brand sales at the same time as the performance barometer. For Budget Gourmet, note the low point in July–August 1992 and the fast turnaround compared to Healthy Choice. However, the H-P filter does not clearly reflect the mixed fortunes in 1993 (shown as dips in the performance barometer): because it is computed in recursive

[14] These estimates, based on the trend t-values in the parsimonious model (1a), have a 0.989 correlation with those of model (1b). Similarly, the t-values have a 0.997 correlation with the trend coefficient estimates.

[15] In contrast, smaller window sizes (e.g., 20 and 30 weeks) show increased occurrence of significant growth and decline, because (1) the estimated time trends are based on smaller samples and (2) the model has a harder time controlling for seasonality. Detailed results are available upon request.

[16] To verify that these barometer patterns are not idiosyncratic to the category or time period under study, we estimate and present in Appendix B the results of the rolling-windows analysis in a different setting, the automotive industry between 1996 and 2002. We find similar patterns of successive performance regimes: stable performance regimes (65%) are more common than growth regimes (20%) and decline regimes (15% decline).

[17] These results are robust to using $p < 0.10$ and $p < 0.20$ (instead of $p < 0.05$) to establish trend significance.

Figure 6 **Hodrick-Prescott Filter for Budget Gourmet and Healthy Choice**

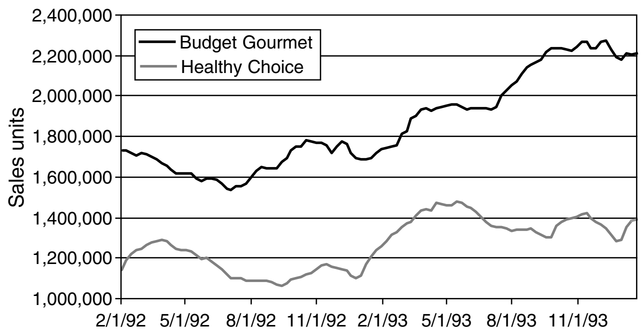


Figure 7 **Hodrick-Prescott Filter for Lean Cuisine and Weight Watchers**

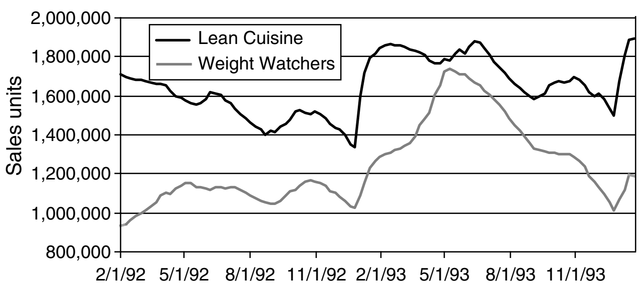
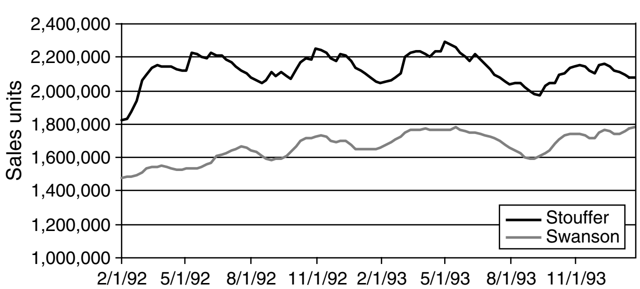


Figure 8 **Hodrick-Prescott Filter for Stouffer and Swanson**



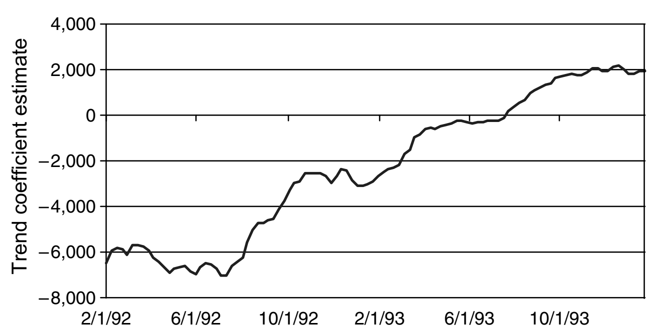
windows,[18] the H-P filter becomes less diagnostic on the current situation the more we drag the past along. Figure 7 shows that, for Lean Cuisine, the H-P and the *PB* patterns are very similar: sales slide until the annual promotion period in January, which bumps them up to a higher level each year. The H-P filter misses the *PB*-observation that Lean Cuisine's sales trend exactly hits the red zone each year before the promotions occur. Detailed comparisons are available from the authors upon request. Overall, a comparison of the performance barometer and the H-P filter reveals that:

- they identify the same dips and improvements in sales at the same times for the earlier period; the H-P filter tends to "miss" changes in the latter data period.
- the H-P filter is better at spotting longer-lasting trends (e.g., for Weight Watchers and Swanson). With the performance barometer we have to examine the relative frequency of positive versus negative trends over an extended period (e.g., a year) to diagnose such phenomena;
- the performance barometer is better at spotting the cyclical behavior in sales trends (e.g., for Weight Watchers and Swanson), especially in later periods, which shows the advantage of rolling windows over recursive windows. Moreover, only the performance barometer offers natural benchmarks to classify the sales changes in Table 1, including the important "red zone" of significant negative trend.

4.3.3. Time-Varying Trend Models. Likewise, graphs of the time-varying trend of performance in Equation (6) show similar patterns for the analyzed brands. Figure 9 displays this trend for Budget Gourmet.

Observe that the time-varying sales trend is initially negative and deteriorates till mid 1992, consistent with the other two approaches. As with the H-P filter, the time-varying trend does not clearly reflect the brand's mixed fortunes in 1993 (shown as dips in the performance barometer), because it is computed in recursive windows. Likewise, we have no "red zone" benchmark for comparison. Instead, the true value of this third approach for our research objectives is its ability to estimate this time-varying trend and in the same stage relate it to marketing actions. We next turn to this issue.

Figure 9 **Budget Gourmet Sales Trend in Time-Varying Trend Model**



[18] An important caveat in this comparison is that the ability of each method to "pick up peaks and troughs" also depends on the specific choices regarding the window length (direct trend assessment for the performance barometer), the smoothing parameter (Hodrick-Prescott filter), and the path of the time-varying parameters (Kalman Filter). For instance, the longer the window length for the performance barometer, the higher the amount of "smoothing" and thus the lower the ability to pick up peaks and troughs. We thank the associate editor for this insight.

4.4. The Impact of Marketing on Performance Regimes

4.4.1. Marketing Effects on the Performance Barometer. Following the testing frameworks set up in (2) and (3), we test the hypothesis that marketing levels have an impact on performance barometer changes using the equation

$$\Delta PB_{i,t} = c_i + \rho_i \Delta PB_{i,t-1} + \beta_1 PA_{i,t} + \beta_2 RP_{i,t} + \beta_3 TPR_{i,t} + \beta_4 Disp_{i,t} + \beta_5 Feat_{i,t} + \beta_6 Adv_{i,t} + \varepsilon_{i,t} \qquad (9)$$

where PB is the performance barometer, PA represents SKU additions to the product line, RP the regular price, TPR temporary price reductions, $Disp$ display activity, $Feat$ feature activity, and Adv advertising gross rating points. Note that the response effects are contemporaneous, as a result of our lag specification tests. Similarly, we test the relation between marketing regime changes and performance barometer changes using the model

$$\Delta PB_{i,t} = \alpha_i + \lambda_i \Delta PB_{i,t-1} + \gamma_1 \Delta PaB_{i,t} + \gamma_2 \Delta RpB_{i,t} + \gamma_3 \Delta TprB_{i,t} + \gamma_4 \Delta Disp\,B_{i,t} + \gamma_5 \Delta Feat\,B_{i,t} + \gamma_6 \Delta Adv\,B_{i,t} + \eta_{i,t} \qquad (10)$$

where ΔPaB is the barometer change in SKU additions Pa, and similarly for the other marketing mix variables in this category. Here again, lag specification tests resulted in the contemporaneous-response model represented in (5). The parameter estimates are summarized in Tables 6 and 7.[19]

Three general findings emerge. First, in support of H3, marketing actions in the form of marketing levels as well as marketing policy shifts explain changes in the performance barometer. In each brand equation, the F-test is significant at $p < 0.05$ and at least one marketing variable has a significant impact on the performance barometer. Second, we observe that, for each brand, the models with marketing policy shifts (Table 7) have a higher explanatory power and better AIC and BIC values than the model with marketing levels (Table 6). Logically, the model with marketing policy shifts isolates the lower frequency movements in the marketing data, and thus provides a better explanation for the performance barometer, which likewise isolates lower frequency movements in the sales data. Among these marketing policy shifts, *promotional* policies (temporary price reductions, display, and feature) are the most potent in changing the performance barometer across our analyzed brands.[20] In contrast, policy shifts in product additions and advertising only improve the performance barometer for one out of six brands.

Our analysis also reveals an interesting insight about the one brand that experienced an upward performance trend in the full sample, Lean Cuisine. As shown in Figure 3, the rolling window analysis demonstrates that this brand does not grow steadily over the full data period. Instead, its performance barometer, which starts out with a clear positive trend, decreases over a full year's cycle, until it enters the "deteriorating decline" regime. At that

Table 6 Effects of Brand Marketing Actions on Brand Performance Barometer Changes*

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Product additions	0.060	0.003	0.023	−0.108	−0.008	−0.047
(t-value)	(0.52)	(0.03)	(0.41)	(−1.17)	(−0.07)	(−0.64)
Regular price	−1.06	−1.304	2.079	0.421	1.254	−0.172
	(−1.61)	(−1.08)	(0.68)	(0.86)	(0.93)	(−0.12)
Price promotion	**−0.941**	**−1.338**	**−0.468**	−0.122	0.007	−0.397
	(−1.71)	(−2.46)	(−1.28)	(−0.41)	(0.02)	(−0.63)
Display	3.754	3.130	**5.632**	−2.407	**4.236**	4.652
	(1.55)	(0.88)	(2.65)	(−1.01)	(2.05)	(1.46)
Feature	**2.207**	**2.027**	**2.266**	**3.064**	**3.115**	**2.294**
	(4.92)	(3.98)	(3.89)	(5.15)	(5.15)	(3.54)
Advertising	0.000	−0.001	**0.002**	**0.002**	0.001	0.000
	(0.07)	(−0.46)	(2.57)	(3.13)	(0.43)	(0.18)
R^2	0.415	0.584	0.689	0.480	0.665	0.600
Adjusted R^2	0.369	0.550	0.663	0.438	0.638	0.567
AIC	0.490	0.961	0.090	0.619	0.456	0.782
Schwartz criterion	0.703	1.178	0.311	0.834	0.668	0.997

*Each model also contains a constant and the lagged dependent variable. The analysis period starts on 2/8/1992. Boldface coefficients are significant at $p < 0.10$.

[19] White and Jarque-Bera tests on the equation residuals fail to detect heteroskedasticity and significant deviations from normality.

[20] We also analyzed whether brand marketing actions have the power to impact the category's performance barometer. Indeed, the category performance barometer improves due to SKU additions (Swanson), regular-price cuts (Budget Gourmet, Stouffer, Weight Watchers), feature activity (Budget Gourmet, Lean Cuisine), and advertising (Stouffer). Compared to our brand-level findings, we thus find similar marketing power in improving category performance, a result which is of key interest to the retailer. Among all marketing actions, regular price changes are effective the most often (for half of all brands). However, while changes in the category performance barometer are reasonably well explained by marketing actions ($F = 3.20$; $R^2 = 0.70$, $AIC = 1.14$, $BIC = 2.21$), the adjusted R^2 is only 0.48, and only 5 out of 36 actions have a significant impact at $p < 0.10$. In contrast, regression on changes in the marketing barometers results in lower values of the Akaike (0.62) and Schwartz Information (1.60) criteria, an F-statistic of 7.94, R^2 of 0.82, and adjusted R^2 of 0.72. The category performance barometer increases with marketing policy shifts due to price promotional activity (Healthy Choice), display activity (Weight Watchers), feature activity (Budget Gourmet, Healthy Choice, Lean Cuisine, and Stouffer), and advertising (Budget Gourmet and Stouffer). Overall, feature and advertising policy shifts are the most often effective. Intuitively, the increased use of both marketing instruments attracts more consumers to the store and to the category.

Table 7 Effects of Marketing Policy Changes on Brand Performance Barometer Changes*

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Product additions	−0.015	0.025	0.034	**0.118**	0.019	0.090
(t-value)	(−0.26)	(0.33)	(0.39)	(1.94)	(0.33)	(1.18)
Regular price	−0.073	0.032	0.008	0.085	−0.028	−0.034
	(−0.97)	(0.38)	(0.18)	(1.26)	(−0.43)	(−0.53)
Price promotion	**−0.211**	**−0.265**	**−0.097**	0.005	0.001	**−0.301**
	(−2.92)	(−2.92)	(−1.70)	(0.06)	(0.02)	(−3.37)
Display	**0.243**	**0.173**	**0.284**	0.090	**0.198**	**0.455**
	(3.41)	(1.92)	(3.47)	(1.12)	(2.11)	(4.59)
Feature	**0.492**	**0.540**	**0.683**	**0.571**	**0.694**	**0.328**
	(8.26)	(6.20)	(8.76)	(7.14)	(8.46)	(3.32)
Advertising	0.087	−0.054	**0.119**	0.054	0.072	0.008
	(1.13)	(−0.75)	(2.48)	(0.73)	(1.25)	(0.07)
R^2	0.644	0.698	0.872	0.650	0.788	0.750
Adjusted R^2	0.618	0.675	0.863	0.624	0.773	0.731
AIC	0.039	0.652	−0.286	0.232	−0.044	0.524
Schwartz criterion	0.245	0.858	−0.081	0.438	0.162	0.729

*Each model also contains a constant and the lagged dependent variable. The analysis period starts on 2/8/1992. Boldface coefficients are significant at $p < 0.10$.

point, Lean Cuisine manages to turn performance around quickly and even attains a growth regime, after which the barometer starts to decline again. Closer examination of this turnaround reveals policy shifts in temporary price reductions, display, feature, and advertising. As shown in Tables 6 and 7, these marketing interventions succeed in increasing the performance barometer for Lean Cuisine as well as for several other brands.

4.4.2. Marketing Effects Using the Hodrick-Prescott Filter in Recursive Windows. Similar to our second-stage analysis for the performance barometer, we relate the H-P filters of unit sales to the H-P filters of marketing actions. The models are specified in changes, as the H-P filtered series are evolving, similar to the performance barometer procedure. Table 8 displays the results, which can be compared to those in Table 7.

We observe first that, as with the performance barometer, marketing explains performance for each of the 6 brands (significant F-statistic, satisfactory R^2, and adjusted R^2). Moreover, marketing for Lean Cuisine explains more variance of sales than it did for the other brands, consistent with Table 7. In terms of specific marketing instruments, we again observe that temporary price reductions, display, and feature are the most potent. Compared to Table 7, regular price reductions are effective for two additional brands, and advertising for one additional brand.

In sum, the second-stage results obtained from the Hodrick-Prescott filter, based on a recursive analysis in the first stage, are consistent with the findings from the performance barometer, based on a rolling-window analysis in the first stage.

4.4.3. Marketing Effects Using a Time-Varying Trend Model. Table 9 displays the relevant findings of the one-stage Kalman filter model on the effect of marketing actions on the time-varying trend in sales[21] (Equation (7)). The results show that, even after controlling for marketing effects on sales levels, marketing actions have a significant impact on sales trends for all brands. This occurs for the same marketing instruments identified by the performance barometer (Table 7), and also for product additions (Weight Watchers), regular price (Healthy Choice and Swanson), temporary price reduction (Stouffer and Swanson), display (Stouffer), and advertising (Swanson).

In conclusion, the performance barometer results are corroborated by the one-stage Kalman filter model. Compared to the performance barometer and the H-P filter, the Kalman filter model identifies a few more marketing actions as having a significant impact on sales trend, consistent with the notion that its estimates are not biased towards zero. Overall, the marketing diagnostics are robust across methods: temporary price reductions, feature, and display matter for most brands (all brands according to the Kalman filter), while product and advertising matter for a minority of brands (two each with the Kalman filter). Table 10 summarizes the evidence of marketing's power to affect sales trends across the three methods.

4.5. Competition and the Management of Performance Turnarounds

Compared to the full-sample benchmark models, several new managerial insights may be obtained by our proposed rolling-window approach. Among these, we focus on two questions:

- Do competitive marketing actions impact a brand's performance regimes?
- Does marketing induce performance turnarounds?

4.5.1. Competitive Effects. We investigate competitive effects[22] by modeling the brand performance barometers in function of the marketing levels and policy shifts of all brands. Table 11 shows the frequency distributions of the effects of competitive marketing levels and policy shifts.[23] In both cases, the predominant effect is barometer-neutral. Furthermore, in the minority cases where competition has

[21] Detailed results are available on the first author's website.

[22] We focus on competitive effects as the most likely candidates, besides own marketing actions, of explaining performance regimes for this 1991–1994 data set. Of course, other factors could apply in a more general setting, including economic indicators such as business cycles and a change in the unemployment rate.

[23] Due to the sheer number of estimates, detailed results are available upon request.

Table 8 Effects of Marketing H-P-Filter Changes on Sales H-P-Filter Changes*

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Product additions (t-value)	−20,502	23,587	21,970	**285,145**	15,045	6,144
	(−0.29)	(0.53)	(0.39)	(2.28)	(0.30)	(0.15)
Regular price	−1,100,914	176,446	−**2,388,146**	1,037,292	−238,752	−**2,364,730**
	(−1.40)	(0.38)	(−2.28)	(1.11)	(−0.43)	(2.25)
Price promotion	−**94,948**	−**614,354**	−**1,300,886**	−609,147	−61,376	−117,346
	(−3.21)	(−1.83)	(−2.66)	(−0.95)	(0.23)	(−0.22)
Display	**78,009**	**53,233**	**146,177**	35,662	**32,549**	**66,265**
	(5.57)	(3.30)	(7.36)	(1.58)	(3.46)	(3.36)
Feature	**20,908**	**13,724**	**44,075**	**42,750**	**15,824**	**16,639**
	(7.83)	(6.19)	(7.10)	(6.76)	(4.57)	(3.62)
Advertising	201	−162	**3,244**	**1,667**	−211	310
	(0.31)	(−0.24)	(5.27)	(2.57)	(−0.33)	(0.44)
R^2	0.710	0.728	0.807	0.623	0.743	0.770
Adjusted R^2	0.688	0.706	0.792	0.594	0.723	0.751
AIC	21.54	21.27	22.39	22.80	20.88	21.95
Schwartz criterion	21.75	21.48	22.60	23.02	21.09	22.16

*Each model also contains a constant and the lagged dependent variable. The analysis period starts on 2/8/1992, Bold coefficients are significant at $p < 0.10$.

an impact, the direction is as likely to be beneficial as harmful to the brand. In particular, competitive price reductions hurt the brand's long-run performance outlook, while increased competitive advertising activity often increases the brand's performance barometer. As for own marketing effects, the Akaike and Schwartz's Information criteria indicate that competitive marketing *policy shifts* explain performance barometer changes better than single competitive marketing levels do. The R^2 of the competitive marketing level models ranges from 0.68 to 0.85, while that of competitive marketing policy shifts ranges from 0.83 to 0.92.

In summary, our analysis of category expansion and competitive effects shows that (1) the category performance barometer is affected by marketing levels and policy shifts, (2) own and competitive marketing policy shifts are more powerful than single marketing levels in changing the category and brand performance barometers, and (3) competitive marketing is predominantly neutral to the brand's long-run performance outlook. The latter conclusion is consistent with recent findings by Horváth et al. (2005), Pauwels (2004, 2007), and Steenkamp et al. (2005). Likewise, several authors have noted that competitive advertising can both harm and help brand sales (e.g., Keller 1993, Steenkamp et al. 2005). In the context of the category under study, Bender (2000) argues that competitive advertising has a "confusion" as well as a "share of voice" effect and urges researchers to allow for both positive and negative cross-effects of advertising.

Table 9 Effects of Marketing on the Varying Trend Coefficient (One-Stage Kalman Filter)*

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Product additions	8.35	0.04	0.56	**2.01**	11.82	**13.63**
(z-statistic)	(1.03)	(0.69)	(1.16)	(3.85)	(0.82)	(2.00)
Regular price	−56.78	−**0.44**	−0.31	1.06	−**15.86**	4.66
	(−1.46)	(−3.70)	(−0.57)	(1.25)	(−3.87)	(0.42)
Price promotion	−**70.32**	−**0.24**	−**2.20**	−**5.75**	−**138.54**	−**65.85**
	(−2.70)	(−6.39)	(−6.52)	(−2.20)	(−3.86)	(−9.01)
Display	**111.63**	**3.11**	**43.04**	−7.07	**698.59**	**164.31**
	(5.58)	(3.33)	(3.32)	(−0.65)	(2.68)	(7.08)
Feature	**81.55**	**0.86**	**10.83**	**0.07**	**7.82**	**70.89**
	(2.24)	(1.95)	(3.33)	(2.81)	(7.73)	(2.58)
Advertising	−0.01	0.00	**0.02**	0.01	**0.04**	0.02
	(−0.19)	(0.76)	(4.20)	(0.25)	(3.86)	(0.70)

*Each model also contains a constant and the lagged dependent variable. The analysis period starts on 2/8/1992. Boldface coefficients are significant at $p < 0.10$.

4.5.2. Performance Turnarounds. As a special case of managerial relevance, we focus on marketing policy shifts during periods of decline turnaround in the brand performance barometer. As illustrated in Figures 2–4, four brands experienced one window of decline turnaround, while Lean Cuisine and Weight

Table 10 Summary of Marketing's Power to Affect Performance Trends Across 3 Methods*

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
Product				PB, H-P, K		K
Regular price		H-P, K			K	H-P
TPR	PB, H-P, K	PB, H-P, K	PB, H-P, K	PB, K	K	K
Display	PB, H-P, K	PB, H-P, K	PB, H-P, K	K	PB, H-P, K	PB, H-P, K
Feature	PB, H-P, K	PB, H-P, K	PB, H-P, K	PB, H-P, K	PB, H-P, K	PB, H-P, K
Advertising			PB, H-P, K	H-P	K	

**PB* = according to the Performance Barometer analysis; H-P = according to the Hodrick-Prescott filter Analysis; K = according to the one-stage Kalman filter analysis.

Table 11 **Frequency of Competitive Effects on Brand Performance Barometer Changes**

Competitive activity	Effect on barometer (%)	Budget Gourmet (%)	Healthy Choice (%)	Lean Cuisine (%)	Stouffer (%)	Swanson (%)	Weight Watchers (%)
Single actions	Neutral	80	93	90	77	67	97
	Negative	13	0	7	13	23	3
	Positive	7	7	3	10	10	0
Policy shifts	Neutral	63	90	90	56	77	80
	Negative	20	3	7	27	13	13
	Positive	17	7	3	17	10	17

Watchers experienced two such windows. As shown in Table 12, *each incidence of decline turnaround is associated with at least one marketing policy shift*. Second, brand policy typically changes on two or more marketing variables during turnaround times. In particular, promotional activity is the most common driver of performance decline turnaround, as feature, display, and temporary price reductions play a role in at least half of all cases. Advertising policy shifts only help one brand, Lean Cuisine, out of the red zone.

Returning to our opening example, the results for Budget Gourmet show that its performance barometer was *not* improved by advertising, but instead by increased promotional activity in the form of temporary price reductions, feature, and display. Figures 10 and 11 illustrate this effect by showing the barometers for sales and marketing policies.

From Figure 10, note that the turnaround of the sales barometer around August 1, 1992, coincides with a similar turnaround in display policy, increases in feature activity and with the time the temporary price reductions enter the "red zone" (i.e. the brand is offering deeper discounts than before). Because all three policy shifts need to be negotiated with retailers, Budget Gourmet likely offered trade support to achieve this turnaround. In contrast, Figure 11 shows that the brand's regular price was higher during the sales turnaround, and that advertising and product assortment increase about two months later, when the performance barometer already shows stability. Visual inspection of the barometers thus suggests that advertising and product assortment policy shifts cannot be credited for the sales decline turnaround. This conclusion is confirmed by our model estimates in Table 7, as neither marketing policy significantly affects changes in the brand performance barometer.

5. Conclusions and Recommendations for Future Research

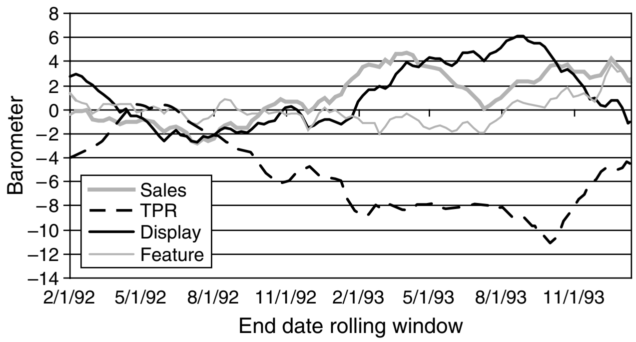
The first major contribution of this research is the demonstration that, even in mature markets, performance stability is not the only observed business scenario. While over extended time periods, brand performance often appears to be mean reverting, there are clearly identifiable sub-periods or windows when brands systematically improve or deteriorate their performance. These performance regimes may be diagnosed using rolling-window time-series tests. Similar to the punctuated equilibrium paradigm in the strategic change literature, windows of significant growth and decline in market performance are short compared to windows of stability. We have proposed the use of the performance barometer (i.e. a plot of the estimated trend's t-statistic in rolling windows) to summarize this important diagnostic information for different brands and for the category as a whole.

Our second major contribution is the demonstration that marketing plays an important role in turning around declining performance, i.e. changing the performance regime from deteriorating to improving. Indeed, *all* of the observed decline turnarounds in our database were associated with managerial action. Thus marketing actions not only explain variations in sales, as in the traditional market response model, they also explain most of the variance in a brand's performance barometer. We note, though, that such performance turnarounds may take time, as customers do not always respond immediately to improvements (e.g., Mitra and Golder 2006). Our results also indicate that improving-trend regimes are more likely to end because of consumer saturation than because of competitive actions, which is in line with previous findings on different data (e.g., Pauwels

Table 12 **Significant Contributors to Decline Turnaround in the Performance Barometer**

	Budget Gourmet	Healthy Choice	Lean Cuisine	Stouffer	Swanson	Weight Watchers
First decline turnaround	TPR, display, feature	TPR	TPR, display, feature, advertising	Product, feature	Display, feature	TPR, display
Second decline turnaround			TPR, feature, advertising			Display, feature

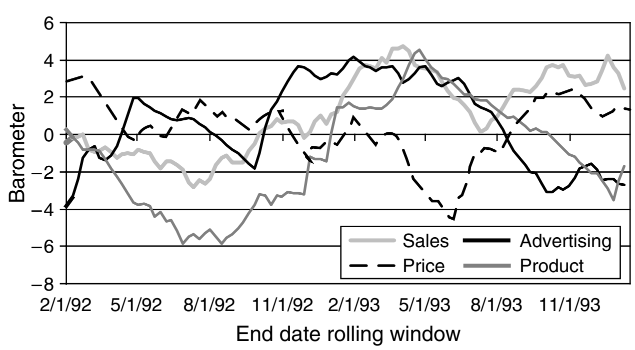
Figure 10 Budget Gourmet Barometers for Sales, TPR, Display, and Feature



2004, Steenkamp et al. 2005). Converging evidence for these conclusions was obtained by the two-stage performance filter (Hodrick-Prescott analysis based on recursive windows) and the one-stage time-varying time trend (Kalman filter) model, which estimated marketing's impact on both sales levels and sales trends. While the performance barometer procedure is easy to understand and estimate by researchers and managers alike, the one-stage Kalman Filter model resolves several issues with the two-stage analysis and thus provides more direct evidence for marketing' power to affect performance trends.

Among the marketing-mix variables in our study, we find that promotion-oriented actions such as temporary price reductions, feature, and display are the most potent in improving a brand's performance barometer. Moreover, the integrated use of several promotional variables appears especially effective in turning brand performance around. For instance, our rolling-window analysis shows that Lean Cuisine sales do not rise steadily, as suggested by its full-period trend, but instead grow in bursts during January campaigns of promotional and advertising activity. Possibly, these annual campaigns enable Lean Cuisine to enlarge its consumer trial base, which in turn increased repeat purchases throughout the year (Ehrenberg et al. 1990). Lean Cuisine subsequently discontinued its marketing blitz for a full year, allowing its performance barometer to steadily

Figure 11 Budget Gourmet Barometers for Sales, Product, Regular Price, and Advertising



decrease. Future research may address the rationale behind such a seasonal marketing campaign approach (e.g., is it motivated by marketing effectiveness or by marketing cost savings?), and whether an annual campaign cycle is preferable over a semi-annual or quarterly cycle.

These insights set up an agenda for important future research. First, while our empirical work on the frozen food market was extensive, it needs to be replicated and extended across different product categories and marketing variables. Second, while we find that product-line additions have little impact on brand performance in this mature market, substantial product innovation may well be able to refuel growth in the category (van Heerde et al. 2004). Third, the combination of the performance barometer and VAR-models may provide a richer picture as to how marketing affect the long-term outlook for a brand. In particular, such a model may investigate whether the performance barometer in turn affects marketing actions over time ("performance feedback" in Dekimpe and Hanssens 1999). Fourth, the performance barometer response model may be extended to include marketing interaction effects, covariation among errors for the different brands, and distinction between the impact of controllable (marketing) and uncontrollable factors (e.g., economic conditions) on performance trends. A separate modeling of brand market share and category sales would be particularly useful in this regard, and may extend this paper's substantive findings. For instance, we may hypothesize that promotion-oriented marketing changes can turn around brand market share in recessions (such as the early 1990s time period in this paper), but that new products and advertising do so during economic expansions. Fifth, our framework focuses on mature markets; performance turnarounds in younger and turbulent markets remain a rich avenue for future research. Finally, since our central finding is consistent with punctuated equilibrium in the organizational change literature, research is needed on the characteristics of marketing organizations that enable quick and effective marketing turnaround strategies for the long-term health of the brand.

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Appendix A
The appendix examines two methodological issues in more detail: (1) analysis in rolling versus recursive windows, and (2) the expanded analysis of our conceptual framework by the varying trend model approach.

Table A.1 Expanded Conceptual Framework: 9 Performance Regimes

	Trend change		
Trend sign	Increasing	Insignificant	Decreasing
Positive	Accelerating growth (#1)	Growth (#7)	Saturating growth (#2)
Insignificant	Improving stability (#3)	Stability (#8)	Lessening stability (#4)
Negative	Decline turnaround (#5)	Decline (#9)	Deteriorating decline (#6)

A1. Rolling Windows and Recursive Windows Analysis

In the econometric literature, analysis in rolling (moving) and recursive windows has shown its use in different applications. First, moving window regression (Leeflang et al. 2000, p. 474) allows parameters to change slowly with each additional datapoint. Second, recursive and rolling-window estimation of unit-root tests have been proposed to analyze the stability of the test result and to endogenously uncover structural breaks (Perron and Vogelsang 1992, Zivot and Andrews 1992). Our approach, while methodologically similar, differs in focus: while moving-window regression models capture the *time path* of a regression parameter, and rolling-window unit root tests assess inference stability, we are interested in capturing *regime shifts* in performance and marketing actions.

Methodologically, Banerjee et al. (1992) showed that recursive and rolling estimation of the parameters does not affect the asymptotic distribution of the estimates. Compared to full-period analysis (on which our benchmark models are based), rolling and recursive procedures are also appealing from a diagnostic and prescriptive perspective: if we base our performance regime classification on information that managers possessed at a certain time, it is possible to evaluate their actions using that information set. This argument is eloquently expressed by Swanson and White (1997): "Using only data which were available prior to period t allows us to guard against future information creeping in to our econometric specifications, and thus, our forecasts" (p. 441).

In contrast to the fixed-sample length of rolling or moving windows, recursive-window analysis, keeps the window origin fixed at the first time period in the sample and successively adds observations. As an application in marketing, Bronnenberg et al. (2000) used recursive windows to detect at what point in time the emerging market for flavored ice tea in the U.S. was beginning to show signs of maturity.

The advantages of rolling windows over recursive windows are twofold. First, the fixed sample size allows direct comparisons between the test estimates in different windows. Because a fixed fraction of the sample is used, the sampling variability of rolling coefficients stays constant in expectation throughout the sample, unlike recursive estimators. Second, the rolling window prunes out old data, i.e. it drops observations in a distant past that may no longer represent the data generating process. In contrast, full-sample and recursive-window analyses imply that the distant data remain relevant. Therefore, conclusions from full-period and recursive-window analysis depend on the initial conditions of the empirical data set. These starting dates are typically not under the researcher's control, nor do they include the initial zero value of the series (Franses 1998). As a result, any empirical "full sample period" is itself only a window of observations, and its window size may not fit the preferences of researchers or practitioners. In contrast, the rolling-window analysis makes the choice of a window size explicit and allows (a) an analysis of how performance and marketing regimes change over time and (b) a sensitivity analysis on the window size.

A potential drawback of rolling windows compared to recursive windows and full sample analysis is that its sample size is restricted, which may lead to inefficient estimates (Van Heerde et al. 2004, p. 167). However, this restricted sample size corresponds more closely to management information at the time of decision, and appears more appropriate to study gradually changing regimes in the data, using relatively simple models that do not consume too many degrees of freedom.

A2. Expanded Analysis of Conceptual Framework by Varying Trend Model

Our conceptual framework in Table 1 can be expanded to a 9-cell matrix in which, similar to the trend itself, trend changes are classified as significantly negative, significantly positive, or insignificant. Table A.1 shows this expanded conceptual framework, where we termed the 3 new regimes

Table A.2 Relative Frequency of 9 Performance Regimes from the Varying Trend Model

	Budget Gourmet (%)	Healthy Choice (%)	Lean Cuisine (%)	Stouffer (%)	Swanson (%)	Weight Watchers (%)	Brand average (%)	Category sales (%)
Accelerating								
Growth (#1)	8	7	2	2	1	10	**5**	14
Growth (#7)	12	5	13	0	0	6	**6**	13
Saturating growth (#2)	3	7	6	0	0	11	**4**	8
Improving								
Stability (#3)	25	21	10	26	28	13	**21**	13
Stability (#8)	27	29	36	36	38	29	**32**	22
Lessening stability (#4)	23	26	29	37	27	25	**28**	20
Decline (#5) turnaround	0	2	0	0	3	1	**1**	2
Decline (#9)	1	2	4	0	1	3	**2**	4
Deteriorating decline (#6)	2	2	2	0	2	3	**2**	3

Table B.1 Relative Frequency of Performance Regimes for Car Manufacturers

	Accelerating growth (#1) (%)	Saturating growth (#2) (%)	Improving stability (%)	Lessening stability (%)	Decline turnaround (%)	Deteriorating decline (%)
Chrysler	11	13	27	32	6	11
Ford	7	4	37	43	4	5
General Motors	9	7	30	37	6	11
Honda	12	14	26	35	5	8
Toyota	17	14	24	28	7	10
Nissan	9	6	33	38	5	9
Average	**11**	**10**	**29**	**36**	**6**	**9**

"growth" (#7), "stability" (#8), and "decline" (#9) and numbered them to allow easy comparison with Table 1. The idea behind the expanded classification is that, for example, a trend change from $t = 2$ to $t = 2.01$ ("accelerating growth" in Table 1) is likely to be insignificant and thus does not represent the same good news as a significant trend change, e.g., from $t = 2$ to $t = 3$. We can assess the significance of both trend and trend changes with the varying trend model, and display the results in Table A.2 (compare with Table 5). We conclude, first, that the support for Hypotheses 1–2 remains: brands go through different performance regimes, and decline regimes are less common than growth regimes, which are in turn less common than stability regimes. Second, we observe that regimes with insignificant trend change are quite common (40% of all cases). This can be expected given our analysis at the weekly level. While any single weekly increase in the performance trend may be insignificant, several consecutive increases (as indicated by Figures 2–5) may be very good news for the company. As a result, we believe the additional complexity of an expanded classification does not generate better substantive insights.

Appendix B

Performance Regimes in the Automobile Market

We present a cross-validation of our results in another mature industry, that of automobiles in the United States. We analyze weekly revenues between 1996 and 2002 for Chrysler, Ford, General Motors, Honda, Nissan, and Toyota, representing about 86% of the U.S. car market. We thank J. D. Power & Associates for making the data available.

Using the identical moving-windows regression approach, we find that the inflation-adjusted weekly revenues for the six major auto makers are stable in 65% of the cases,

Figure B.1 Performance Barometer (t-Statistic Trend) for the Main 3 US Car Manufacturers

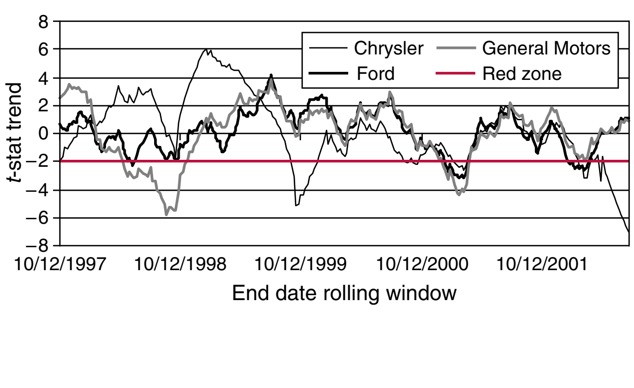
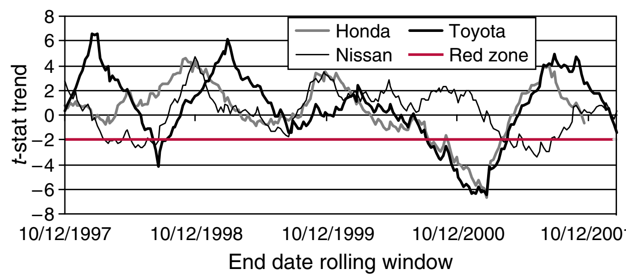


Figure B.2 Performance Regimes (t-Statistic Trend) for the Main 3 Japanese Manufacturers



improving in 21% of the cases and declining in the remaining 14% (Table B.1). While differences in these frequencies across brands exist, all of the brands are predominantly in a stable performance regime, consistent with Hypotheses 1–2. Figures B.1–B.2 show the performance barometers for the three major U.S. and Japanese firms. Detailed results are available from the first author.

In sum, we find support for Hypotheses 1–2 for two mature industries involving rather different product and company characteristics.

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