Performance Growth and Opportunistic Marketing Spending

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Abstract

Marketing executives are under pressure to produce revenue and profit *growth* for their brands. In most cases that involves requesting gradually higher marketing budgets, which is expensive, especially considering the known diminishing return effects of marketing. However, in reality, brand sales tend to evolve not gradually, but rather in *spurts*, i.e. short periods of sales evolution alternating with longer periods of stability. We use the Wang-Zhang (2008) time-series test to identify such growth-spurt periods, which represent opportunity windows for the benefitting brand. We then relate these windows to exogenous events such as positive product reviews, which create a temporarily more benevolent environment for the brand. We suggest brand managers be vigilant to catch and take advantage of such opportunity windows to generate sustained growth at low cost, and derive the implications of such vigilant spending for marketing budget setting. Our empirical illustration is based on several brands in the digital single-lens reflex (DSLR) camera market. It demonstrates, among other things, that competitors in this market typically do not take advantage of windows of growth opportunity offered by positive product reviews.

Introduction

The ultimate prerogative of management is to produce sustained top-line and bottom-line growth for its brands. In many cases, this growth is fueled by increases in marketing spending, be it to acquire new customers or retain and grow existing customers. However, since most marketing actions are well known to exhibit diminishing returns to scale, a brand's growth path may become progressively more expensive, possibly leading to cuts in profitability. As such, managers continuously seek growth opportunities to allocate marketing budget to achieve sales growth with low costs.

One indicator of marketing opportunities is sales evolution. The marketing persistence literature suggests that, when sales intrinsically evolve, temporary marketing can generate persistent sales growth (Dekimpe and Hanssens 1999), thus sales growth can be achieved with lower marketing costs. In relatively new markets, for example the current market for all-electric automobiles, any successful marketing initiative can impact the growth path of a brand and thus have long-term consequences. In more mature markets, sales often evolve in *spurts*, i.e. short periods of critical sales change, followed by longer periods of sales stability (Pauwels and Hanssens 2007). Even these fleeting spurt periods can offer opportunity for brand growth.

Sales spurts may or may not be predictable. When sales spurts are predictable, managers can incorporate them in budget planning by setting budgets as a function of past or anticipated sales levels (see, e.g. the managerial survey results reported in Lilien, Kotler and Moorthy 1992). For example, in seasonal businesses such as toys, the November-December months are predictably much higher in sales volume than those of the rest of the calendar year. Knowing that, toy companies get ready for the seasonal demand surge with advertising and other marketing campaigns that grow in intensity toward year-end.

In other cases, however, sales spurts are more sudden and unpredictable, and therefore cannot easily be incorporated in marketing plans. For example, a few weeks before the launch of the 1979 motion picture *The China Syndrome*, the nuclear meltdown theme of the movie actually occurred in reality, with the Three Mile Island nuclear accident. This provided an unanticipated boost in public interest in the movie's subject, and is widely acknowledged to have lifted box office records by a large amount (Christensen and Haas 2005). Similarly, the German vodka brand Gorbatschow reportedly witnessed a 400%

increase in demand when Mikhail Gorbachev took over as leader of the Soviet Union in 1988. Interestingly, that demand shift in favor of the brand was sustained even after Gorbachev relinquished political power (Simon 1997).

What these examples have in common is that exogenous and unpredictable events can drive changes in *baseline sales* (i.e. sales without marketing inputs) and generate sustained brand growth opportunities[1]. Managers can capitalize on the opportunity through quick and swift marketing actions to generate and turn a temporary sales lift into a more sustained gain, or to prevent a temporary sales loss from becoming a sustained loss. The behavioral rationale underlying these growth opportunities is that a positive extraneous event (such as the relevance booster provided to *The China Syndrome* by the Three Mile Island accident) increases the perceived utility of the product to the consumer. When this is accompanied by aggressive marketing, many more prospects are exposed to the good news, thereby improving the market potential for the product. Insofar as product purchase and consumption leads to high customer satisfaction, for example in favor of the Gorbatschow brand, habit formation and repeat buying can extend the impact of the sudden demand increase well into the future. In this era of digital communication, when news about brands can diffuse quickly and broadly, such changes in a brand's business environment become even more frequent and influential.

Predictable growth opportunities typically apply to all market participants (e.g. in the case of seasonality) or they are known to and reacted to competitors (through past experiences). By contrast, unpredictable growth opportunities could be unique to a brand and, for a while, undetectable to competitors, and thus important for brands to capture. Being unpredictable, such events cannot be incorporated in traditional marketing planning and budgeting. As such, brands need to be *vigilant* and opportunistic in their marketing spending: by carefully monitoring key external drivers of their business environment, they can strike (with aggressive marketing) when the proverbial iron is hot.

Being vigilant and opportunistic in marketing spending significantly differs from common budgeting practice in which marketing budgets are set ahead of time and tightly

[1] Similar examples exist in the negative direction, see for example the work on managing product crises in van Heerde et al. (2007) and Cleeren et al. (2013). The focus of our paper will be on opportunities, i.e. positive events in the brand's business environment.

monitored internally. Instead, it reflects *market orientation* (Kohli and Jaworski 1990; Narver and Slater 1990) and *dynamic marketing capabilities* (Day 2011) that emphasize market-driven organizations, market intelligence, and marketing adaptability. Through vigilant marketing, firms can improve their marketing effectiveness to achieve superior performance. A similar, though broader, concept has also been explored in the strategy literature, the "sensing and seizing" framework developed by Teece (2009).

Traditional budgeting practice considers optimal budgeting under set and unchanged market conditions. For example, the marketing literature offers various optimal budgeting formulations for competitive and monopoly markets (Gatignon, Anderson and Helsen 1989; Shankar 1977), integrated marketing communications (Naik and Raman 2003) and for the purposes of offensive versus defensive marketing (Martin-Herran, McQuitty and Sigue 2012). These contributions formulate fixed optimal budgets based on existing market knowledge and outlook.

Different from these resource allocation methods, we propose vigilant marketing and opportunistic spending in recognition of changing market dynamics. Vigilant marketing requires that 1) the brand can *identify leading or concurrent indicators* of an opportunistic market development, so it knows *when* to intervene; and 2) brands are adaptive in marketing budgeting and can react quickly to market opportunities through opportunistic spending. For example, the appearance of unusually strong product reviews or a sudden celebrity product endorsement (such as a video of a celebrity dining at a certain restaurant) are observable events that can be leveraged to extend the brand's sales growth spurt. Thus the continuous monitoring of indicators that are associated with brand growth spurts may help managers to gain major market knowledge of their causes, which may differ across brands[2].

More specifically, we illustrate the need for vigilant marketing and opportunistic budgeting by examining the major brands in the digital single-lens reflex (DSLR) camera market, a high-technology sector with frequent product innovations. We show that short time windows exist in an otherwise mature and stationary market, and represent major

[2] Note that the indicator, for example product reviews, is observable in real time, but it is not known a priori when it will rise or fall. The best a brand can do is to act quickly when a rise is observed, i.e. to be vigilant.

growth opportunities where quick and swift marketing reaction can generate and *turn a temporary sales lift into a more sustained gain*, or can prevent a temporary sales loss from becoming a sustained loss. Thus brand growth can be fueled at possibly lower expense: instead of gradually increasing marketing budgets, the brand augments (temporary) windows of growth opportunity with marketing investments that *alter the growth path* of the brand. In modeling terms, we explore marketing *hysteresis*, i.e. temporary spending that induces permanent results (Dekimpe and Hanssens 2000). In more popular terms, we explore the marketing implications of Jan Carlzon's influential *Moments of Truth* (1987).

This temporary, opportunistic marketing spending is fundamentally different from *pulsing* spending tactics described in the literature (e.g. Feinberg 1992). Pulsing is desirable when the sales-marketing response function is S-shaped and/or when spending impact is subject to wearout effects. Both of these refer to the *marketing lift* parameter in a market response model. By contrast, our focus is on changes in the brand's market *environment*, i.e. the baseline or intercept in a market response model, that produce a temporary boost in brand sales. There may of course also be a concurrent increase in marketing productivity (lift), which we will test empirically, however higher lift is not a necessary condition in our framework.

The remainder of the paper is organized as follows. We first review the analytical conditions for top-line growth vs. stability and relate these to marketing spending. This results in the distinction between *intrinsic market evolution (IME)* and *marketing-induced evolution*. We argue that short IME windows exist in mature and stationary markets, driven by external factors, which enable swift marketing spending to generate sustained and less costly growth for a brand. Thus managers should adopt vigilant marketing to monitor and catch these opportunity windows. We demonstrate these principles econometrically on a longitudinal dataset of the major brands in the digital single-lens reflex (DSLR) camera market. We show that customer reviews are a major driver of the IME opportunity regimes. We also derive several principles for vigilance-based marketing budgeting and resource allocation.

Intrinsic-Evolving Versus Intrinsic-Stationary Markets

Persistence analysis (Dekimpe and Hanssens 1999) seeks to identify evolving marketing conditions as major marketing opportunity where temporary marketing can generate persistent effects. To differentiate between intrinsic and marketing-induced evolution[3], Wang and Zhang (2008) present a framework that turns univariate unit-root testing in the tradition of Dickey-Fuller into a multivariate test involving marketing spending and possibly other drivers of demand. If sales evolution intrinsically links to marketing spending, the market is *intrinsically stationary,* i.e. any observed growth is marketing-induced. For example, effective marketing exposes more new customers to the brand, which causes an increase in sales. If this marketing stops for whatever reason, there will be an adverse effect on the brand's growth trajectory.

If there is no intrinsic marketing link, the market is *intrinsically evolving* (IME), i.e. sales growth is organic and marketing spending is not essential for producing growth. For example, as more units of an eye-catching new-car model design appear on the road, consumer exposure and brand sales increase without additional marketing spending. Naturally, this second condition is more attractive to the brand stewards, as growth can be achieved without expensive marketing investments. However, a highly brand-favorable environment is needed in order to produce intrinsic growth: for example, pride of brand ownership can diffuse through a target market because of the perceived quality of the brand, without further marketing support.

Methodologically, the Wang-Zhang test proceeds as follows. Starting with a traditional sales response model

(1) $$S_t = c + \alpha S_{t-1} + \beta M_t + e_t,$$

where S_t is sales at a given time t, M_t represents marketing expenses at time t, the model assumes that sales decay over time at a decay rate $(1 - \alpha)$, c is a constant, β is the effectiveness of M_t, and e_t represents market noise. Nonlinearity in response is typically incorporated by transformation such as logarithms.

In testing the unit root of a sales series, we examine the following:

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[3] In what follows we refer to sales evolution as sustained change that can be positive or negative. The positive side is referred to as growth, the negative side as decline.

(2) $$S_t = \phi S_{t-1} + \mu + e_t.$$

The difference between Equations (1) and (2) is the marketing input, βM_t. Without marketing effects, Equations (1) and (2) are equivalent. Unit-root tests on the sales series can reflect the intrinsic market dynamics by examining the decay rate (i.e. $1 - \phi$ in Equation (2) or $1 - \alpha$ in Equation (1)).

With marketing effects, ϕ and α are different. The nature of a marketing environment is determined by α. That is, $\alpha = 1$ indicates an intrinsic-evolving market because the sales series S_t evolves *independent of marketing investments* represented by M_t. Any increase of S_t introduced by temporary marketing or any other causal driver will be sustained. In contrast, $\alpha < 1$ indicates an intrinsic-stationary market: any increase of S_t introduced by marketing or other shocks will decay and eventually disappear. Because standard unit-root tests examine ϕ and not α, they are not sufficient to identify the intrinsic market dynamics. Because both S_{t-1} and M_t (see Equation (1)) affect S_t, we need to differentiate the two causes of market evolution, namely, the intrinsic market nature and marketing investments.

To differentiate these causes of sales evolution, we consider the effect of marketing inputs on ϕ by comparing Equations (1) and (2). We re-write Equation (1) as:

(3) $$S_t = c + (\alpha + \beta\frac{M_t}{S_{t-1}})\, S_{t-1} + e_t\,.$$

Comparing Equations (2) and (3), we get:

(4) $$\phi = \alpha + \beta\frac{M_t}{S_{t-1}}\,.$$

Therefore, with marketing effects, the nature of marketing spending is essential in creating sales evolution. Indeed, a sales series can evolve from an intrinsic-evolving market or from sustained marketing spending. The two causes for sales evolution refer to different marketing environments and pose different budgeting implications. This is a unique distinction made in the Wang-Zhang test.

Specifically, the difference between intrinsic and induced evolution lies in the value of the parameter α. Intrinsic evolution exists when a unit root is present for a sales series *and* $\alpha = 1$. By contrast, when $\alpha < 1$ and a unit root exists in a sales series, sales evolution is supported by sustained marketing expenditures. This is referred to as (marketing) induced evolution. From Equations (4), we can *create such induced evolution* by satisfying a budgeting threshold, as follows:

(5) $$M_t \geq \frac{1-\alpha}{\beta} S_{t-1} \ .$$

When the budgeting threshold is met, sales evolution can be observed. Induced evolution exists when a brand must rely heavily on marketing inputs to guard its competitiveness and enable growth.

To discriminate between intrinsic evolution and induced evolution, an IME test is needed. On the basis of the classic first-order lag model (Equation (1)), we test the following hypotheses:

(6) $$H_0: \alpha = 1, \text{ and } H_1: \alpha < 1.$$

This test on Equation (1) has a similar structure to the standard unit root tests such as the Dickey-Fuller test and the Phillips-Perron test, and thus we may calculate an IME test statistic as follows:

(7) $$\mathrm{IME}_t = \frac{\hat{\alpha} - 1}{\mathrm{S.E.}(\hat{\alpha})} \ ,$$

where S.E. stands for standard error. We can then use the Dickey–Fuller critical values, c_{DF}, to determine the single-sided rejection region: $\mathrm{IME}_t < c_{DF}$. Note that other unit-root test criteria (e.g. Leybourne and McCabe 1994; Pantula, Gonzalez-Farias, and Fuller 1994) can be used as well.[4]

In summary, to evaluate a market dynamic, standard unit-root tests can first be used to assess the presence of sales evolution. If the sales series is not evolving, the underlying market is intrinsic stationary. If the sales series is evolving, the proposed IME test can be performed to diagnose intrinsic evolution versus induced evolution (i.e. the intrinsic-stationary nature of the market)[5]. The intrinsic market evolution (IME) indicates favorable market conditions where temporary marketing can generate persistent sales growth.

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[4] Note that unit root tests and our IME tests are one-sided tests for stationarity, i.e. if the test finds the process to be nonstationary, α could be greater than 1. As such these tests do not differentiate between α = 1 or α > 1 cases. In practical terms, that implies our tests are *conservative*, i.e. an opportunity window could be even better than assumed because there is a momentum effect.

[5] Note that the IME test is different from a cointegration test. The latter test examines the equilibrium relationship between evolving time series, so both sales and marketing must follow I(1) or higher

IME Applications: market evaluation and regime identification

Figure 1 shows how persistence modeling with IME tests can help marketing managers identify favorable market opportunities by: (1) market/brand evaluation, i.e. to identify an intrinsic evolving market (for example a growing brand in an emerging market) where temporary marketing can generate permanent growth as discussed by Wang and Zhang (2008); and (2) regime identification, i.e. to identify growth spurts in an overall stationary market (for example a highly competitive mature market) for vigilant and opportunistic spending, where sustained growth within the IME regimes can be generated with temporary – and thus less costly – marketing investments.

[Insert Figure 1 Here]

An application of persistence modeling with IME tests for market and brand evaluation can be seen in Figure 2, which shows the sales evolution of three major PC brands, HP, Compaq and Dell in the 1990s. While all three brands experienced growth, the IME tests in Table 1 reveal that HP's and Compaq's growth were induced by their marketing investments, whereas Dell's growth was intrinsic. Dell adopted a direct-distribution model that differentiated it from most PC brands, including HP and Compaq, who followed the standard distribution model. As a result, Dell enjoyed significant sales growth (annual growth of 49%) with only a moderate advertising-to-sales (A/S) ratio, averaging 3.4% during the 1991-2000 period. By comparison, HP achieved a lower annual growth (33%) with a higher A/S ratio (4.6%), and Compaq's growth was even lower at 14% with an A/S ratio at 2.4%. Consequently, Dell grew from a small-player status in the market (only 6% of HP sales in 1991) to a highly competitive position (65% of HP sales in 2000). The tests further imply that Compaq's modest marketing investments (relative to its sales) are a major reason for its more modest growth, and thus loss of market share, in the nineties.

[Insert Figure 2 Here]

[Insert Table 1 Here]

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processes. This condition is not required in IME testing. Furthermore, cointegration does not explore possible intrinsic evolution of the market output time series.

In addition to market and brand evaluation, we use persistence analysis with IME tests to identify growth spurts in an overall stationary market. Most brands do not have favorable markets or unique strategies to enable an overall intrinsic sales evolution, but face mature and stationary markets. Using various digital camera brands and their marketing mix in the 2000s, we illustrate that growth opportunities exist in mature and stationary markets and brands can benefit significantly by vigilant marketing.

Temporary windows of growth opportunity

Now consider the modern-day reality of rapidly changing environmental conditions. The spread of digital brand information for consumers may create temporary favorable marketing regimes, i.e. IME regimes in an otherwise mature and stationary market. As shown in Table 2, the returns on marketing, i.e. in generating sales growth and profitability, are higher for spending in an IME regime than in a stationary regime. Thus IME regimes provide a more advantageous growth opportunity. Furthermore, the longer the IME window (i.e. W) following marketing, the higher the sales returns that can be generated.

[Insert Table 2 Here]

The implications of the scenarios in Table 2 can be illustrated with a few examples. Consider a vigilant brand that monitors the market environment to identify temporary IME regimes. Figures 3(a) and 3(b) compare the sales response to one-time marketing within the IME vs. stationary regimes. As shown, sales generated by one-time marketing input M in an IME regime can be sustained at βM before the closing of the IME window, and generate returns per marketing log-dollar of

$$V_2 = W\beta + \frac{\beta}{1-\alpha} \quad .$$

The longer the IME window (i.e. W) following marketing, the higher the sales return of these marketing investments.

[Insert Figure 3 Here]

Based on careful market monitoring, i.e. vigilance, managers can detect the presence of opportunity windows (IME regimes) in time for marketing action. The length of such regimes may be affected by factors such as the driver of the opportunity window, competitive advantage and competitive behavior. Diagnosing the causes of the opportunity window is important because it will help managers predict its duration, and therefore the expected returns of additional marketing spending. Managers may also engage in efforts to manage and reinforce the opportunity window drivers in order to prolong its duration.

Importantly, the IME window enables marketing managers to generate sustained sales growth at considerably lower cost. Figure 4 compares the marketing costs required to increase sales from 5 to 20 in a stationary market ($S_t = 0.5S_{t-1} + 2M_t$) vs. a market with an IME window ($S_t = S_{t-1} + 2M_t$) from periods 6 to 10. In this example, marketing spending will need to be increased to 8.75 in a stationary market, but only to 7.5 in the IME window. Furthermore, marketing maintenance spending (to sustain the sales level of 20) will be at level 5 in a stationary market, but no such maintenance spending is needed during the opportunity window.

[Insert Figure 4 Here]

In conclusion, there is a major difference in long-term marketing impact, depending on the presence of temporary windows of opportunity. Since such opportunity windows are inherently unpredictable, market vigilance (i.e. acting when the proverbial iron is hot) is needed to take advantage of them. However, in order to enable vigilance, the brand needs to identify and focus on one or more concurrent or leading *indicators* of opportunity windows. In what follows we study the opportunity windows and their occurrence induced by *internet-based product reviews*, using a category known for its intensive consumer information search prior to purchase. Recent literature on word-of-mouth generation has emphasized the sales impacts of online product reviews, both positive and negative (Hanssens 2015). For example, Chevalier and Mayzlin (2006) demonstrated the impact of reviews on restaurant patronage and Ho-Dac, Carson and Moore (2013) examined customer review impacts in the Blu-ray and DVD player categories. The quantitative impact of product reviews on sales is significant, with average elasticities of 0.69 (review valence) and 0.35 (review volume) (Floyd et al. 2014). While we do not claim that product reviews are the sole indicator of favorable or unfavorable market environments, they are frequently updated and readily accessible online in a number of product categories. As such, they are a strong candidate for our examination of opportunity windows and their consequences for marketing.

Data

Our data source is the digital single-lens reflex (DSLR) camera market. This is a category with frequent product innovations and intensive consumer search, due to the high price point and technological sophistication of the products. We consider weekly sales and the marketing mix of the six leading brands in the US, between 2010 and 2012. Brand sales and price data are purchased from NPD, who tracks point of sales data of major retailers. Advertising data are purchased from AC Nielsen, who tracks national advertising expenditures in the cameras category across all media types. Key variables of all brands, including weekly sales, advertising spending, review quantity and valence, are plotted in Figure 5.

[Insert Figure 5 Here]

Table 3 Section A (Weekly Digital Camera Data) provides an overview of the leading brands' market shares and marketing mix in the sample period. The data covers 6 major DSLR brands with 95 models, representing an average of 98% of the DSLR market. In addition, we have access to the quantity and valence of product reviews in this category from Amazon.com. Table 3 Section B (Product Review Data) summarizes the descriptive statistics of weekly product review data, and Figures 5c and 5d illustrate weekly review quantity and valence of all brands. As shown, product review quantity and valence fluctuate considerably, i.e. the business environment for these brands is in a continued state of flux.

[Insert Table 3 Here]

Methodology

An important methodological consideration is the choice of a relevant time period. In each time period, management may aspire for future growth, but such growth is by no means guaranteed. Thus identifying windows of opportunity is a *forward*-looking task which calls for a *moving-time window approach,* where the assessment is made at time T, using only information available up to time T. By moving the assessment period forward, we obtain a series of assessments that are managerially relevant, similar to the identification of marketing regime shifts in Pauwels and Hanssens (2007). We choose 30 periods as the base window length and conduct robustness tests with longer and shorter lengths. Naturally, the shorter the window length, the more opportunistic windows will be identified, however with less statistical reliability.

Equally important is to control for events that may create opportunity windows that are readily *predictable*, at least for brand decision makers. One such time factor is *seasonality*, which increases baseline DSLR demand significantly in the last five weeks of the calendar year (coded with a value 1 in the tests, 0 otherwise). The other is *new product introductions*, which coincide with planned launch programs that are also known in advance to management. Following the recommendations of category experts, new-product introductions are identified (NPI=1, 0 otherwise) during the first eight weeks of distribution for low-end models (priced under $1,000), and the first sixteen weeks for expensive models. Finally, *competitive activity* could dampen the positive brand effects of vigilant marketing, so it needs to be included in the response models. By controlling for these factors, the IME tests identify the opportunistic, as opposed to anticipated, time windows that are the focus of our research.

We conduct the following three tests in moving windows:

(1) unit root tests on unit sales: do sales evolve?

$$Sales_t = c + \alpha Sales_{t-1} + \varepsilon_t$$

To increase the power of unit root inference, we conduct the ADF test (H_0: $\alpha = 1$, and H_1: $\alpha < 1$) as well as KPSS test (H_0: $\alpha < 1$, and H_1: $\alpha = 1$). Evolving sales are identified when the results from the two tests agree.

(2) IME tests controlling for advertising, price, competitive advertising, new-product releases and seasonality:

$$Sales_t = C + \alpha Sales_{t-1} + \beta_{adv} ln(Adv_t) + \beta_{price} ln(Price_t) + \beta_{cp} ln(CompetitiveAdv_t) + \beta_{NP} NP_t + \beta_{season} Seasonality_t + \varepsilon_t$$

We take log transformations of advertising, price, and competitive advertising in order to represent their nonlinear effects. For windows with evolving sales series, we verify the stationarity of the advertising, price and competitive advertising series; we perform the Johansen cointegration test when one or more of these series have unit roots. We perform the IME tests only when evolving variables are cointegrated.

(3) IME tests controlling for the variables in (2) plus the number and valence of customer reviews ($ReviewActivity_t$ and $ReviewValence_t$):

$$Sales_t = C + \alpha Sales_{t-1} + \beta_{adv} ln(Adv_t) + \beta_{price} ln(Price_t) + \beta_{cp} ln(CompetitiveAdv_t) + \beta_{NP} NP_t + \beta_{season} Seasonality_t + \gamma_{activity} ReviewActivity_t + \gamma_{valence} ReviewValence_t + \varepsilon_t$$

A comparison of IME test results in (2) and (3) will reveal the intrinsic evolving time windows that are created by review buzz. For example, an opportunity window identified in (2) is "created" if it is no longer an opportunity window after controlling for review activity and valence in (3), and vice versa.

Before conducting the analysis, we test for the potential endogeneity and collinearity of the covariates. A Hausman-Wu test on the possible endogeneity of advertising spending in the full sample revealed no endogeneity bias in the response estimates[6]. We also examine for the potential endogeneity of $ReviewActivity_t$ and $ReviewValence_t$. Both Granger Causality and Hausman-Wu tests showed no evidence of endogeneity bias. The maximum VIF (variance inflation factor) of the regression based on the model in (2) in the full sample is 3.12, indicating that collinearity is not an issue[7].

[6] Detailed results are available from the authors upon request.

[7] On the other hand, collinearity becomes problematic when adding a product review interaction effect to the advertising response coefficient (the VIF values exceed 10 in various experiments). Thus we cannot ascertain from these data whether or not advertising *lift* is higher during periods of highly positive product reviews. As explained earlier, this restriction does not impact our conceptualization, which focuses on fluctuations in baseline sales.

Estimation Results

For ease of exposition, we present the moving-window IME test results of two brands, Panasonic and Sony, graphically (see Figure 6[8]), where the spiking values (i.e. p>.10) denote windows of growth opportunity[9]. Overall, unit-root tests (i.e. step 1) reveal frequent sales growth periods, most of which are marketing-induced (per the IME tests of step 2), as expected. The IME growth windows occur less frequently, ranging from 3.08% of the sales-evolving periods for Canon to 31.58% for Panasonic. An interesting observation is that these opportunistic periods occur more frequently – in absolute terms, as well as relative to the number of marketing-induced evolution weeks - for smaller brands such as Panasonic (12 weeks) and Sony (9 weeks), relative to dominant brands such as Canon (2 weeks) and Nikon (7 weeks). Thus *market vigilance is an asset that can help smaller brands in particular to gain market share*. Table 4 Section A (IME Windows Identified by Rolling-Window Tests) provides a summary across brands.

[Insert Figure 6 Here]

[Insert Table 4 Here]

Importantly, we identify a number of cases where test 2 reveals evolution and test 3 indicates stationarity and summarize the results in Table 4 Section B (Sources of IME Windows). These support our hypothesis that *favorable intrinsic evolving regimes can be created by movements in customer reviews.* Among these movements, review valence is the most important (67% of cases). Sales evolution can also be generated by either review valence or quantity (22%), but rarely by review quantity alone (11%). The Pentax and Sony brands, in particular, benefit from such review-generated windows of opportunity. Several robustness tests confirm that these results are stable across different model specifications[10]. Overall, and consistent with Floyd et al. (2014), the findings support the notion that the valence of product reviews and, to a lesser extent, their quantity, contribute to brand growth and, as such, should be closely monitored by the brand stewards.

[8] Results of the remaining brands are provided in a web appendix.

[9] Note that the null hypothesis here is the presence of a unit root, so that p>0.10 represents failure to reject that unit root.

[10] We conducted tests 2 and 3 without price and competitive advertising variables and obtained similar results (i.e. there are minor differences, but major conclusions remain the same). We constructed a customer review measure by [ReviewActivity*ReviewValence] and did test 3 with this combined review measure. Similar results were obtained.

Finally, we examine the hypothesis that growth opportunity windows not only offer growth opportunity for a brand, they also increase marketing lift (β_{adv}). This is done by augmenting the advertising response parameter with a dummy-variable indicator for IME regimes. The results do not show changing advertising effectiveness for IME regimes. This is different from extant literature showing that, for example, advertising effectiveness changes with business cycles (e.g. Van Heerde et al. 2013), i.e. the advertising appeals to customers who are sensitive to these factors in their purchase decisions. By contrast, IME regimes indicate that sales changes can be sustained without advertising support, i.e. there is an inflow of customers who make decisions based on product performance, as communicated by reviews (and amplified by concurrent advertising).

Brand advertising behavior

Depending on their ability to diagnose and quickly respond to market changes, brands may or may not act on opportunistic growth opportunities. Table 5 summarizes several brand behaviors: vigilant marketing represents the case where firms takes advantage of opportunities; suboptimal behavior refers to brand's significant marketing investment when no growth opportunities are present, and wasted opportunity refers to brand's irresponsiveness to available growth opportunity.

[Insert Table 5 Here]

To what extent do existing brands recognize the opportunistic growth opportunities offered by product reviews and act on them by increasing their advertising spending? Figure 7 shows the examples of Panasonic and Sony, where the timing of advertising spending bursts are compared to windows of growth opportunity[11]. Overall, the results are mixed: while some brands took advantage of some opportunities, most brands did not exploit them fully. Conversely, most of the observed advertising spikes do *not* correspond to opportunity windows. Table 4 Section C (IME Windows and Advertising Behavior) provides a summary of the relative "vigilant spending" performance of different brands.

[Insert Figure 7 Here]

[11] The examples of remaining brands are provided in a web appendix.

These findings suggest *most growth opportunities are left untouched, which is a form of suboptimal behavior*. There are two possible reasons for this: one is a lack of awareness of the growth opportunity windows offered by movements in product reviews and, two, even with such awareness, the advertising budget setting and media buying process may cause inertia in spending behavior. Indeed, brands may follow certain pre-set budgeting rules that create a lack of flexibility to respond to market opportunities. To assess empirical support for the second explanation, we examine the relationship between brand advertising spending and several market factors known to brand managers and report the results in Table 6. We find that brands' advertising spending is reasonably well predicted (ergo, planned) by four factors: past sales, past advertising, seasonality and new-product introductions. This begs the question about the financial magnitude of the lost opportunity caused by either lack of awareness, or inertia.

[Insert Table 6 Here]

Marketing budgeting in the presence of opportunistic growth windows

The final important question for management pertains to marketing budget setting. Marketing managers are typically restricted on how much they can invest in advertising due to its diminishing returns. For example, in the model

(8) $$S_t = c + \alpha S_{t-1} + \beta \ln(A_t),$$

advertising effectiveness per one log unit of advertising is $\frac{\beta}{1-\alpha}$ (see Table 2). With a gross profit margin r, the spending $A_{optimal}$ that maximizes advertising profitability, i.e. $\frac{r\beta}{1-\alpha}\ln(A_t) - A_t$, is given by Naik and Raman (2003) as

(9) $$A_{optimal} = \frac{r\beta}{1-\alpha}.$$

Thus, the sales target is restricted to

(10) $$S_{optimal} = \frac{c+\beta ln({}^{r\beta}/_{1-\alpha})}{1-\alpha},$$

and any additional advertising to drive sales beyond $S_{optimal}$ will result in decreased profitability.

The IME regimes provide opportunity windows for marketing managers to achieve higher sales and profitability. Indeed, the effectiveness of advertising in the IME regime is

$W_t\beta + \frac{\beta}{1-\alpha}$ per one log unit of advertising, where W_t is the expected length of the remaining IME regime from time t (see Table 2). To maximize advertising profitability, i.e. $(W_t r\beta + \frac{r\beta}{1-\alpha})\ln(A_t) - A_t$, the optimal advertising increases to

(11) $$A_{IME,t} = W_t r\beta + \frac{r\beta}{1-\alpha},$$

assuming no change in advertising lift during IME periods.

The economic impact of vigilance

We illustrate the beneficial impact of vigilant marketing spending by conducting a counterfactual experiment on one of the brands, Panasonic. Following Table 4, Panasonic had an opportunity window in weeks 31 to 40, which is the time window September 18 to November 20, 2011, right before the Christmas shopping season. In actuality, Panasonic launched two noticeable advertising campaigns around this opportunity window (see Figure 7): one in the first three weeks of October, two weeks after the window opened, and its resulting sales are shown in Figure 8a; the other starting in the week of December 4, two weeks after the close of the opportunity window.

[Insert Figure 8a Here]

Suppose Panasonic fully took advantage of the IME regime and increased advertising during the entire 10-week opportunity window. Based on the advertising-sales function estimated with data of 60 weeks prior to the starting of the window,

$$Sales_t = 2779.86 + .42Sales_{t-1} + 15.65ln(Adv_t) - 441.95ln(Price_t) \\ + 9.31ln(CompetitiveAdv_t) + 43.08NP_t + 8.39Seasonality_t + \varepsilon_t$$

marketing managers could apply the optimal budgeting equation (11) and increase weekly advertising to \$167.83k (i.e. 15.65*9+15.65/(1-.42)) for the first opportunity window, \$152.18k (i.e. 15.65*8+15.65/(1-.42)) for the second window, and so on. Note the normal weekly optimal advertising in non-IME regimes is \$26.98k. The optimal advertising for the first IME-week, $167.83k, would increase total sales by $363.30k and profit by $214.73k, compared to the actual advertising of the period, $19.27k.

Figure 8b compares the optimal advertising with the actual advertising, and their sales results are shown in Figure 8a. While the total optimal advertising spending during the opportunity window is $974.05k, which is below the actual spending of $1,641.14k in the same period, it generates a higher sales result. This is possible because spending at the onset of the IME period takes the brand to a *sustained higher performance level*, unlike advertising in non-IME periods.

[Insert Figure 8b Here]

In summary, based on actual data, we are able to demonstrate the economic benefits of vigilant marketing, i.e. careful monitoring of the brand's environment and allocating resources when windows of opportunity open up, which result in either exceeding brand revenue objectives or meeting sales goals with fewer resources.

Conclusions

The central premise of this paper is that temporary windows of opportunity exist that allow brands to achieve sustained growth ("taking the brand to the next level") without proportionally increasing marketing spending. Furthermore, since such windows are driven by external events, management cannot formally plan for them. Instead, management can and should identify leading or concurrent indicators of such events, monitor them continuously and diagnose when the moment is ripe to increase marketing spending. We have referred to this management capability as *vigilance.*

We have used movements in reported product quality as a proxy for one such indicator in the digital era, characterized by instant and widespread consumer access to product review information. The behavioral rationale is that, when brands are the beneficiary of a surge in review quantity and/or quality, baseline demand increases because the brand is delivering comparatively higher consumer value. These are moments when increased marketing spending can generate more sustained, rather than temporary, growth, which is an attractive business proposition. The opposite holds as well, i.e.

temporary “bad news” windows should be kept as short as possible by management’s appropriate reaction.

Methodologically, our approach for identifying such windows of opportunity is based on the Wang-Zhang (2008) IME test, which classifies time periods as either stationary, induced-evolving or intrinsically evolving[12]. When applied in moving windows, these tests can identify growth opportunities in a forward-looking way. Furthermore, by executing the IME tests using different combinations of explanatory variables, we can identify the variables that are observable indicators of intrinsic growth. These metrics can enable management to be vigilant and know when to act.

The major implication for marketing management is the need to closely monitor the business environment and to allocate resources quickly and decisively when a window opens. Historically, that would have been difficult to implement. However, the continuous data streams available from various internet sources create opportunities for faster implementation. In so doing, management would need to, first, assess that the metric of interest acts as a leading or at least concurrent indicator of sustained brand growth. Second, management would have to put in place marketing resource allocations that can be executed quickly and, in some cases, exceed previously allocated brand budgets. Our test on the leading brands in the DSLR market reveals that, at present, most brands do not take advantage of such windows, which creates a major opportunity cost. We measure these costs econometrically and derive conditions for marketing budgeting that are partially “planned” and partially “opportunistic.” Naturally, if a brand operates in a low-innovation sector where quality perceptions and indicators are stable over time, the portion of marketing budgets that should be set aside for opportunism will approach zero.

The framework we propose can be extended in several ways. On the marketing side, we have focused on a few major categories, viz. advertising, pricing and new product launches. Future research could be more granular in examining different forms of marketing (e.g. online vs. offline advertising). Secondly, the opportunity windows could be geographically different, for example an IME growth window could exist in one regional market (e.g. a country or a DMA), but not in others. Thus marketing allocation

[12] We are grateful to the editor for pointing to an alternative metric of “degree of evolution”, measured on a sliding scale by the IME test value in each time period. Future research should explore this approach.

could have a geographical (or other segment) dimension we did not examine in the current paper. Finally, empirical replication of this work across different categories could lead to some interesting generalizations around the relative importance of “planned” vs. “opportunistic” marketing spending. We hope that future work will address these and other areas to arrive at a more complete picture of the importance of “acting in the moment” for brands.

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Figure 1. Intrinsic vs. induced sales evolution

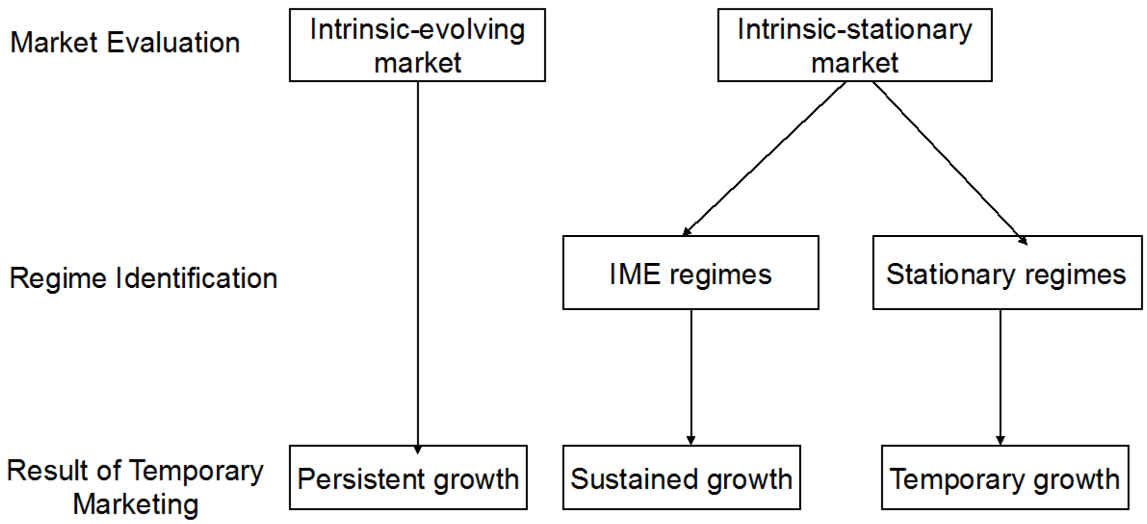


Figure 2. Sales of Compaq, Dell and HP in 1990s

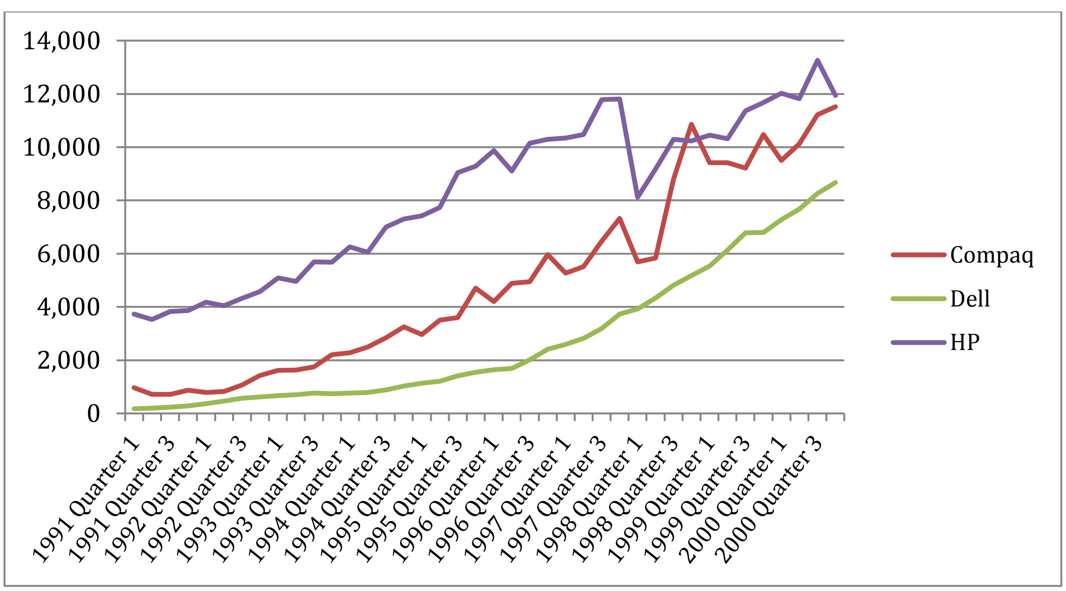
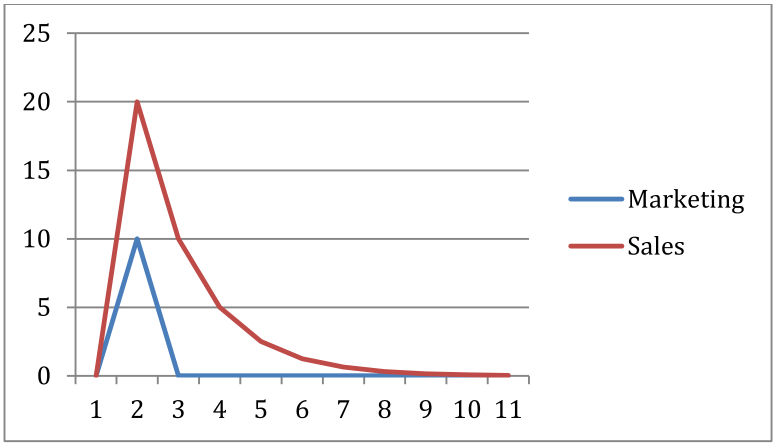


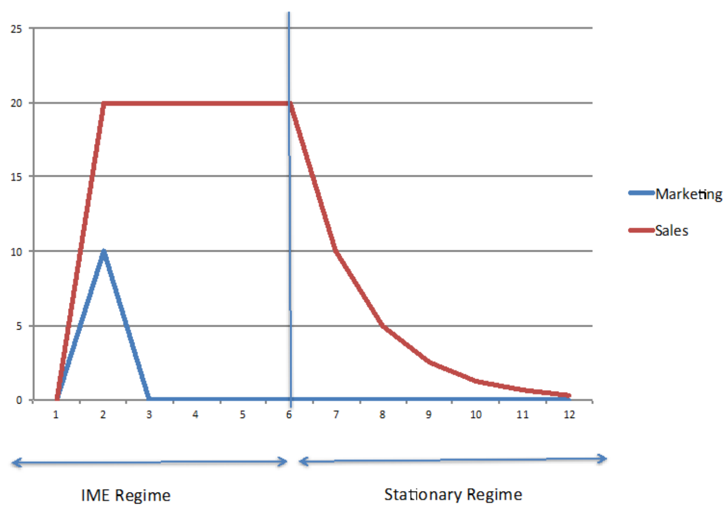
Figure 3. Marketing effects in stationary and IME regimes

(a) Sales response to a temporary marketing input in a stationary regime



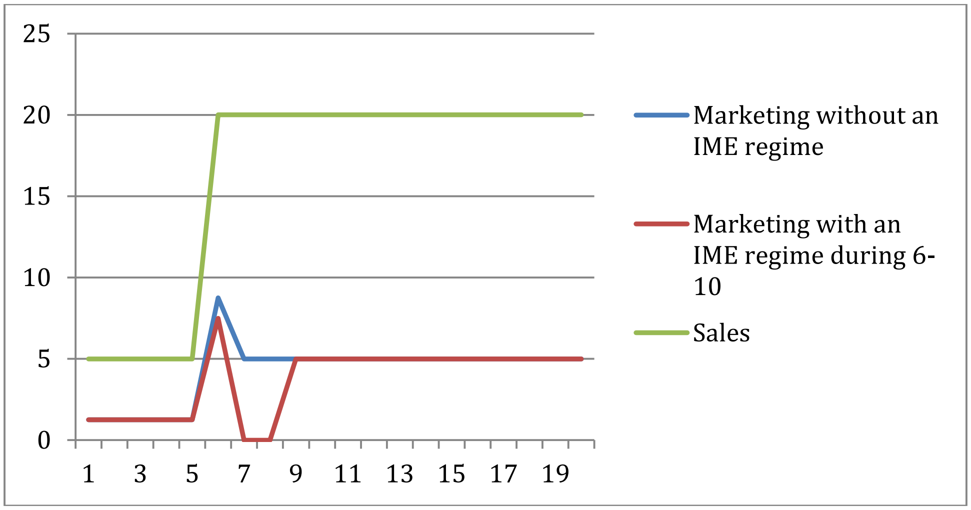
Note: a temporary marketing input M=10; a stationary regime $S_t = 0.5S_{t-1} + 2M_t$.

(b) Sales response to a temporary marketing input in an IME regime followed by a stationary regime



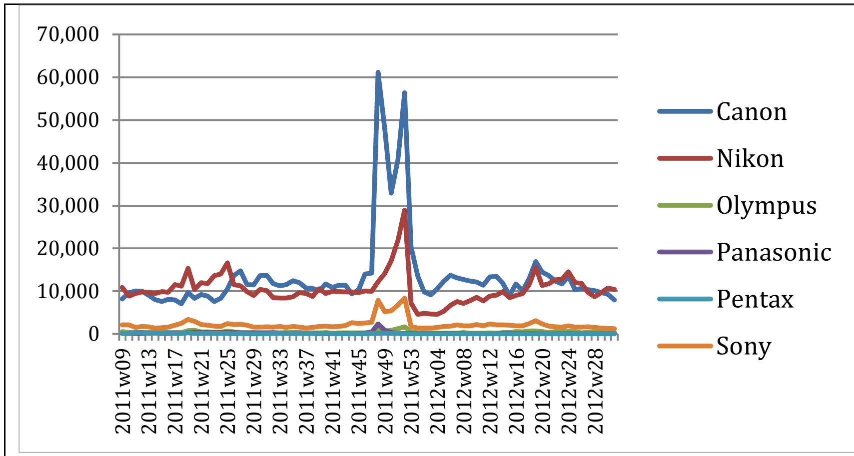
Note: a temporary marketing input (M=10); an IME regime $S_t = S_{t-1} + 2M_t$ followed by a stationary regime $S_t = 0.5S_{t-1} + 2M_t$; c=0 to isolate the marketing effects in the IME regime.

Figure 4. Marketing to achieve sales growth in a stationary vs. IME regime

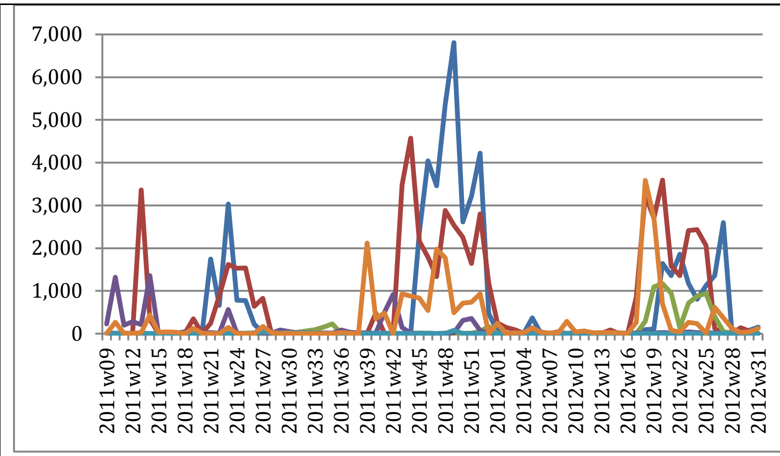


Note: a stationary regime $S_t = 0.5S_{t-1} + 2M_t$; an IME regime $S_t = S_{t-1} + 2M_t$ during the 6-8 period; c=0 to isolate marketing effects.

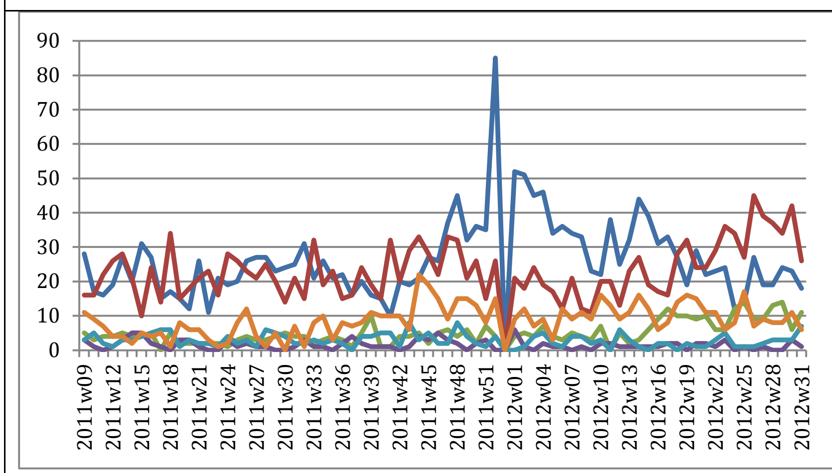
Figure 5. Key brand data



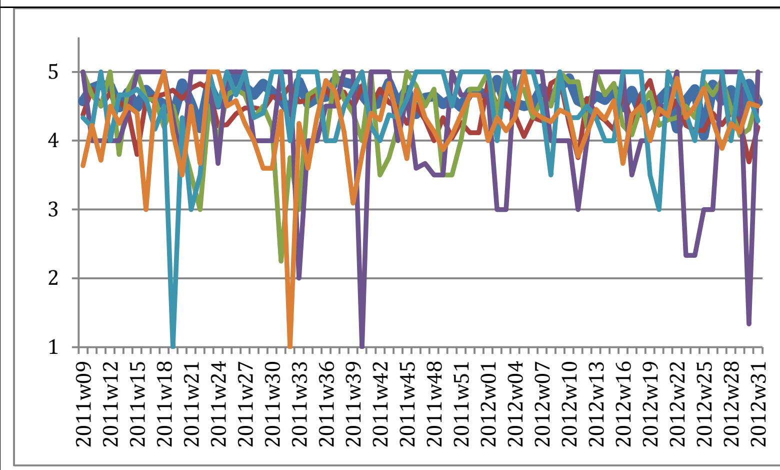
(a) Sales Units



(b) Advertising Costs (in thousands)

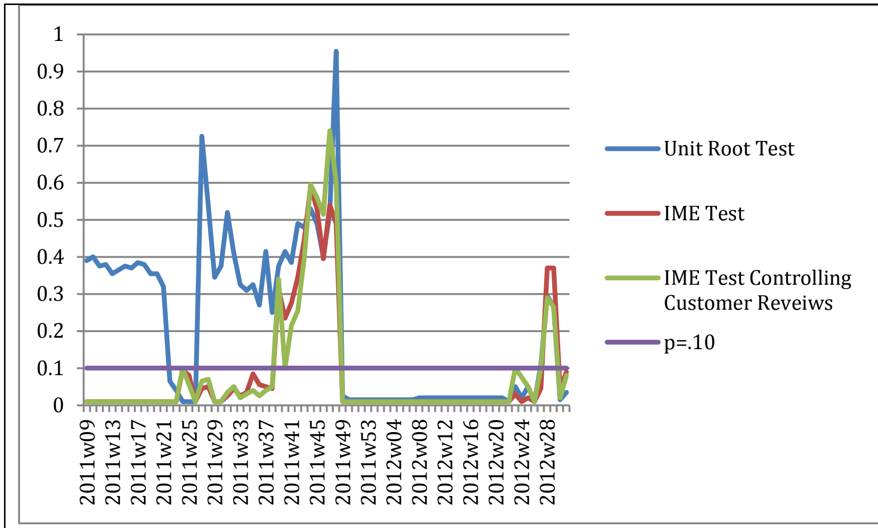


(c) Review Quantity

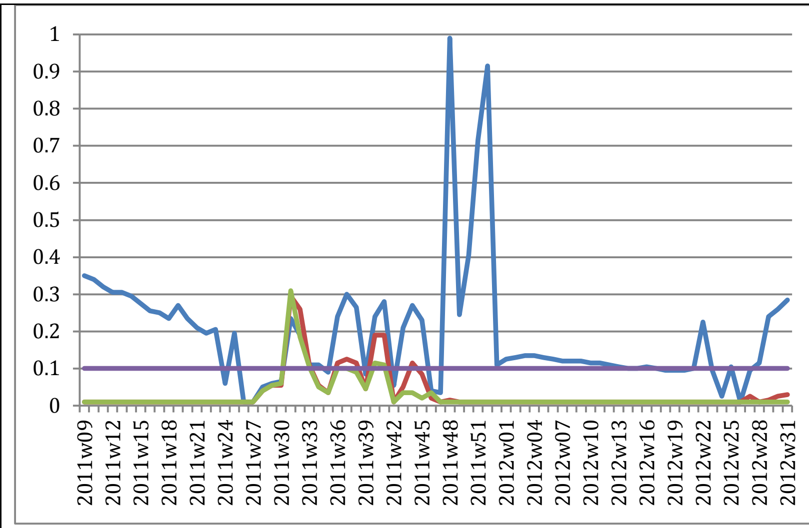


(d) Review Valence

Figure 6. Results of unit root and IME tests: p-values



Panasonic



Sony

Figure 7. Brand spending and IME windows

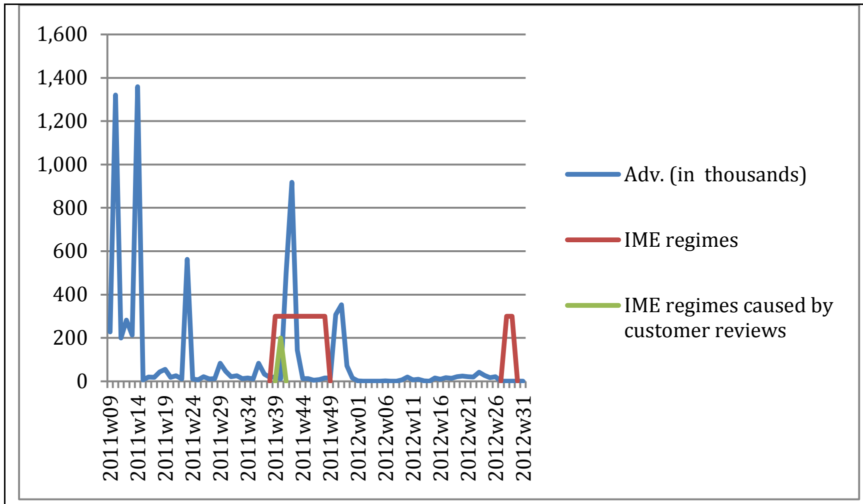
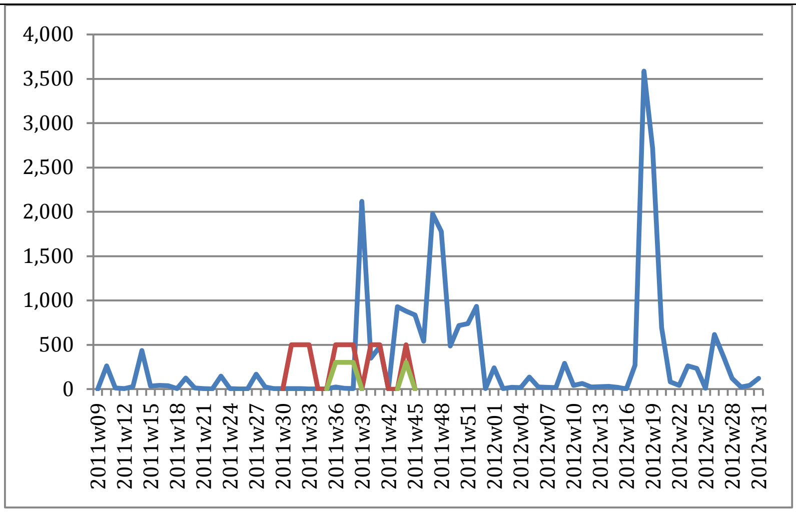
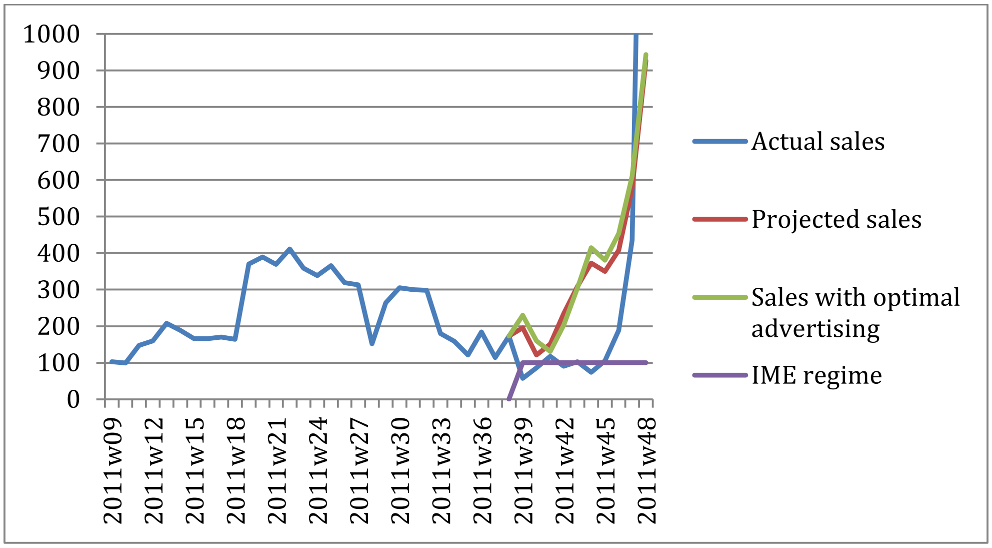
	
Panasonic	Sony

Figure 8. Illustration: the economic impact of vigilance

Figure 8a. Comparison of actual and optimal - Panasonic



Note: Sales in the IME regime are projected based on $Sales_t = 2779.86 + Sales_{t-1} + 15.65ln(Adv_t) - 441.95ln(Price_t) + 9.31ln(CompetitiveAdv_t) + 43.08NP_t + 8.39Seasonality_t + \varepsilon_t$, which is derived from data of 60 weeks prior to the IME regime (Adj. R^2 is 52.2%).

Figure 8b. Comparison of actual and optimal advertising - Panasonic

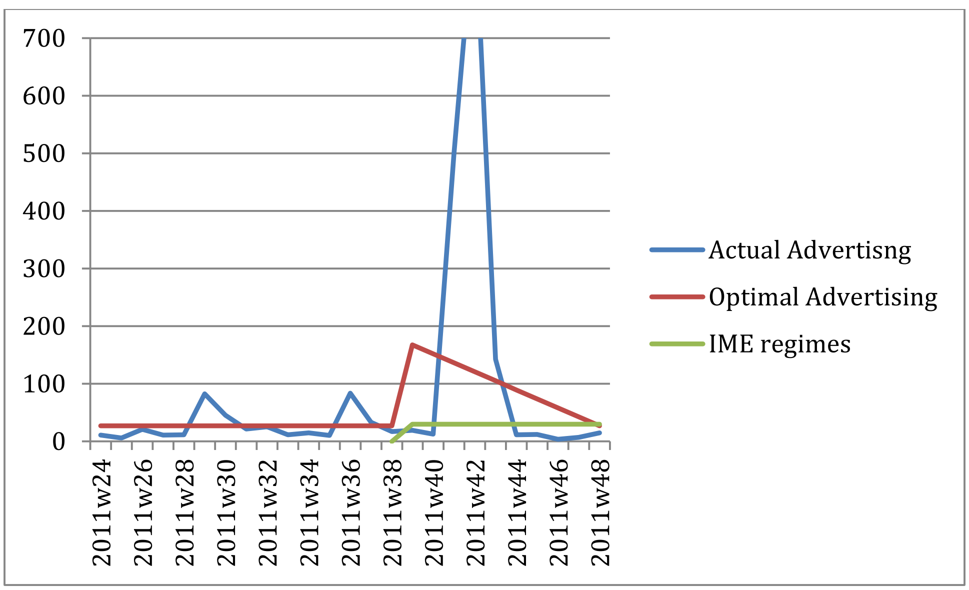


Table 1. Comparison of unit root and IME test results

Brand	N	Unit Root		IME		
		ADF test	PP test	IME test	Critical value (p=.05)	Intrinsic evolving?
HP	40	Unit root	Unit root	-5.48	-2.99	No
Dell	40	Unit root	Unit root	1.17	-2.99	Yes
Compaq	40	Unit root	Unit root	-4.78	-2.99	No

Table 2. Comparison of marketing impact in IME and stationary regimes

	Stationary regime	IME regime	Implications
Market response model	$S_t = C + \alpha S_{t-1} + \beta M_t + \varepsilon_t$, $0 \leq \alpha < 1$	$S_t = C + S_{t-1} + \beta M_t + \varepsilon_t$	
Sales growth due to one unit of incremental marketing	$\alpha^t \beta$	β	
Total sales generated by one unit of marketing (V)	$V_1 = \sum_{t=1}^{\infty} \alpha^{t-1} \beta = \frac{\beta}{1-\alpha}$	$V_2 = W\beta$ within the IME regime of W periods; $V_2 = W\beta + \frac{\beta}{1-\alpha}$, when a stationary regime follows the IME regime	Marketing return is higher for spending in an IME regime. The longer the IME regime (i.e. W), the higher the return to marketing spending and the less costly the investment.
Budget needed to generate one-time sales growth ΔS	$\frac{(1-\alpha)s_{t-1} + \Delta S - c}{\beta}$	$\frac{\Delta S - c}{\beta}$	It takes less advertising to create one time sales growth in IME than stationary regimes.
Budget needed to sustain sales growth	Recurring additional spending for each period	No additional spending needed	

Table 3. Data description

Brand	(A) Weekly Digital Camera Data*			(B) Product Review Data							
				Weekly Review Quantity				Weekly Review Valence			
	Average Market Share	Average Price	Average Weekly Advertising (in Thousands)	Average	SD	Min	Max	Average	SD	Min**	Max
Canon	.48	885.02	861.91	25.94	11.19	0	85	4.6	.19	3.78	4.96
Nikon	.40	899.50	617.17	22.01	8.24	0	45	4.47	.28	3.67	5
Olympus	.02	531.00	84.79	4.52	3.04	0	14	4.39	.56	2.25	5
Panasonic	.008	700.89	148.74	1.98	1.73	0	8	4.33	.86	1	5
Pentax	.005	780.42	4.48	3.39	2.31	0	13	4.52	.59	1	5
Sony	.08	646.59	248.21	7.93	4.41	0	22	4.30	.57	1	5
All 6 brands	.98										

*Data sources include NPD (for sales and prices) and AC Nielsen (for advertising).

** When the weekly review quantity is zero, the weekly review valence is set to that of the previous week.

Table 4. IME related test results

Brand	(A) IME Windows Identified by Rolling-Window Tests				(B) Sources of IME Windows			(C) IME Windows and Advertising Behavior	
	IME weeks	Total # of IME weeks	Total # of evolving weeks	% of IME in total sales evolution	IME weeks induced by review buzz	Total # of review induced IME weeks	% of IME induced by review buzz	% of IME in All 76 Observation Windows	Advertising % in IME
Canon	40, 76	2	65	3%		0	0%	3%	10%
Nikon	38-44	7	38	18%	41, 44	2	29%	9%	21%
Olympus	38	1	35	3%		0	0%	1%	0.1%
Panasonic	31-40, 73, 74	12	38	32%	32	1	8%	16%	22%
Pentax	36, 37, 41	3	20	15%	36, 37	2	66%	4%	25%
Sony	23-25, 28-30, 32, 33, 36	9	54	17%	28-30, 36	4	44%	12%	7%

Table 5. Brand behavior viz-a-viz opportunistic growth opportunity

		Growth Opportunity	
		Non-existent	Present
Brand Responsiveness	Additional brand investment	Suboptimal behavior	Vigilant marketing
	No additional brand investment	Business as planned / Vigilant marketing	Wasted opportunity

Table 6. Advertising spending decision rules

DV: Adv. spending	Coefficient	t-statistic	p-value
NewProductLaunch	81.33	2.49	.01
Seasonality	20.87	4.06	.00
Sales(-1)	.02	3.04	.00
Adv(-1)	.57	15.61	.00
Price	.17	.96	.34
Brand effects	Fixed effects model		
N	624		
R^2	.53		
Max VIF	3.01		