Performance Growth and Vigilant Marketing Spending

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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 and relate them to exogenous events such as positive product reviews, which create a temporarily more benevolent environment for the brand. We then explore how vigilant marketing can take advantage of such periods to generate and turn temporary sales growth into more sustained growth, at considerably lower cost to the brand relative to traditional percent-of-sales decision rules. We also 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.
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.

Despite the desire for sustained growth, many if not most growth patterns for brands exhibit a different behavior: they tend to evolve in spurts, i.e. short periods of critical sales change, followed by longer periods of sales stability (e.g. Pauwels and Hanssens 2007). These spurts may be related to extraneous events that may or may not be predictable. 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 from experience, 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, base demand expansion is more sudden and unpredictable. Absent the ability to anticipate, brands need to be vigilant and opportunistic in their marketing spending, so they can strike when the proverbial iron is hot.

Analytically, the relationship between baseline sales (defined as sales with zero, or minimal marketing support) and optimal marketing spending is well known to be of the form

\[
\text{Optimal Spending} = f(\text{baseline sales, marketing lift, profit margin})
\]

For example, in the Cobb-Douglas response model for sales (S) with one overall marketing input (M)

\[
S_t = \text{base} \times M^\beta
\]

the relationship would be

\[
\text{Optimal Spending } M^* = \left[ \text{base} \times \text{profit margin} \times \beta \right]^{1/(1-\beta)}
\]
where marketing lift $\beta$ is measured as a response elasticity.

Thus, ceteris paribus, as baseline increases, higher marketing support is called for, and vice versa. This relationship between marketing investments and firm revenue/profitability serves as a basis for marketing planning, where budgets are typically set in function of past or anticipated sales levels (see, e.g. the managerial survey results reported in Lilien, Kotler and Moorthy 1992).

However, as alluded above, the case is different when such baseline movements are unanticipated and therefore cannot easily be incorporated in marketing plans. For example, 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 (Simon 1997).

What these examples have in common is that baseline sales can be sensitive to exogenous and unpredictable events\(^1\). 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.

What are the marketing implications of such developments? Being unpredictable, such events cannot be incorporated in traditional marketing planning and budgeting. Yet quick and swift marketing reaction can capitalize on the opportunity 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. If that is the case, then brand growth can be fueled at possibly lower expense: instead of gradually increasing sustained spending, 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*,

\(^{1}\) 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.
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 “Moments of Truth” (1987).

Vigilant marketing implies that the brand can identify leading or concurrent indicators of an opportunistic market development, so it knows when to intervene. 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 examples of 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.

What is the behavioral rationale underlying these growth opportunities? 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.

We note that 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 (1). By contrast, our focus is on changes in the brand’s market environment, i.e. the baseline in (1), 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 the 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

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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 the brand can do is to act quickly when a rise is observed, i.e. to be vigilant.
results in the distinction between *intrinsic market evolution (IME)* and *marketing-induced evolution*. We argue that, when a market is in intrinsic-evolution stage, immediate marketing spending can generate sustained and less costly growth, thus managers should monitor and catch the intrinsic-evolving opportunity windows. We demonstrate these principles econometrically on a longitudinal dataset of the major brands in the digital single-lens reflect (DSLR) market. We also derive several principles for vigilance-based marketing budgeting and resource allocation.

**Intrinsic-Evolving Versus Intrinsic-Stationary Markets**

A framework for testing intrinsic vs. marketing-induced evolution was introduced in Wang and Zhang (2008). Their approach turns univariate unit-root testing in the tradition of Dickey-Fuller into a multivariate test involving marketing spending and possibly other drivers of demand. So, if sales are found to evolve, is this evolution intrinsically linked to marketing spending or not? If yes, 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 no intrinsic marketing link, the market is said to be *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

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

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

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

(4) \[ S_t = \phi S_{t-1} + \mu + e_t. \]

The difference between Equations 3 and 4 is the marketing input, \( \beta M_t \). Without marketing effects, Equations 3 and 4 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 4 or \( 1 - \alpha \) in Equation 3). The nature of a marketing environment is determined by \( \alpha \). That is, \( \alpha = 1 \) indicates an intrinsic-evolving market because the sales series \( S_t \) evolves \textit{independent of marketing investments}. 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.

With marketing effects, \( \phi \) and \( \alpha \) are different. Because standard unit-root tests examine \( \phi \) and not \( \alpha \), they are not sufficient to identify the intrinsic market dynamics. Because both \( S_{t-1} \) and \( M_t \) (see Equation 3) 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 need to consider patterns of marketing budgets in relation to sales. The simple percent-of-sales budgeting equation

(5) \[ M_t = \gamma S_{t-1} \]

would create the following market-response dynamic:

(6) \[ S_t = c + (\alpha + \beta \gamma) S_{t-1} + e_t. \]

Therefore, the autoregressive parameter in (4) may be expressed as:
\[
\phi = \alpha + \beta \gamma.
\]

Because standard unit-root tests examine \(\phi\), we derive from Equation 7 that 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 \(\alpha\). 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 Equation 7, we can create such induced evolution by satisfying a spending rule, as follows:

\[
\gamma \geq \gamma_{th} = \frac{1-\alpha}{\beta},
\]

where \(\gamma_{th}\) is a threshold percentage and, thus, \(\gamma_{th} S_{t-1}\) is a budgeting threshold. 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.

As Figure 1 shows, an intrinsic-evolving market generates sales evolution independent of marketing, whereas sales evolution appears in an intrinsic-stationary market only when there is adequate, sustained marketing spending. When marketing spending is inadequate in an intrinsic-stationary market, sales performance will cease to evolve and, instead, will be stationary.

[Insert Figure 1 Here]
An IME test is needed to discriminate between intrinsic evolution and induced evolution on the basis of the Dickey–Fuller test. Other available unit-root tests, such as the Phillips and Perron test, may also be used to test the nature of market evolution.

On the basis of the classic first-order lag model (Equation 3), we test the following hypotheses:

\[ H_0: \alpha = 1, \text{ and } H_1: \alpha < 1. \]  

This test on Equation 3 has a similar structure as the standard Dickey-Fuller unit root test, and thus we may calculate an IME test statistic as follows:

\[ \text{IME}_t = \frac{\hat{\alpha} - 1}{\text{S.E.}(\hat{\alpha})}, \]

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

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)\(^4\). As shown in Figure 1, this capability has two important implications in our current context: (1) 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) to identify growth spurts in an overall stationary market (for example a highly competitive mature market), where sustained growth can be generated with temporary — and thus less costly — marketing investments. We illustrate the first scenario using the revenue evolution of three major personal computer brands in the 1990s. We examine the second scenario using various digital camera brands and their marketing mix in the 2000s.

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\(^4\) 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 processes. This condition is not required in IME testing. Furthermore, cointegration does not explore possible intrinsic evolution of the market output time series.
Illustration
We illustrate the difference between intrinsic and marketing-induced growth using data from the PC market in the 1990s. Most PC brands, including HP and Compaq, were traditional in that they followed the majority business model of Windows operating systems and general distribution. A few brands, such as Dell, followed a differentiated strategy, in this case a direct-distribution channel. All brands experienced growth, as shown in Figure 2.

[Insert Figure 2 Here]

Using data on sales and marketing spending, the IME tests reveal that HP’s and Compaq’s growth were induced by their marketing investments, whereas Dell’s growth was intrinsic. As a result, Dell enjoyed significant sales growth (annual growth of 49%) with 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 lower growth, and thus loss of market share, in the nineties.

The case of temporary windows of growth opportunity
Now consider the modern-day reality of rapidly changing environmental conditions, due largely to the spread of digital brand information for consumers. In Wang-Zhang terms, the market is changing over time, with IME regimes alternating with stationary market regimes. The alternating two regimes are illustrated in Figure 3(a) where sales show a sudden growth spurt, without changes in marketing spending. The characteristics of the two regimes are summarized and compared in Table 1. As shown, the returns of marketing, i.e., in generating sales growth and profitability, are different in the two evolutionary regimes. Overall, 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 Figure 3 Here]
[Insert Table 1 Here]

The implications of the scenarios in Table 1 can be illustrated with a few examples. Consider a vigilant brand that closely monitors the market environment for the purpose of identifying temporary IME regimes to generate opportunistic sales growth. Figures 4(a) and 4(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 $\beta M$ before the closing of the IME window, and generate returns per marketing log-dollar of

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

The longer the IME window (i.e. W) following marketing, the higher the sales return of these marketing investments. The difference of marketing in an IME vs. stationary regime can also be observed in Figure 3(b), where sales growth generated by temporary marketing lasts for four periods in the IME regime but only one in the stationary regime.

[Insert Figure 4 Here]

Based on careful market monitoring, i.e. vigilance, managers can detect the presence of IME regimes in time for marketing action. However, it is difficult to predict the length of such IME regimes, which may be affected by factors such as drivers of IME, strength of competitive advantage and competitive behavior. For example, if the IME is driven by a superior product feature in a high-technology sector, how long it will take for competitors to catch up is generally not known in advance. Diagnosing the IME causes is important because it will help managers predict the IME duration, and therefore the expected returns of additional marketing spending. Managers may also engage in efforts to manage and reinforce the IME drivers in order to prolong the IME regimes.
Importantly, the IME window enables marketing managers to generate sales growth and turn temporary sales growth to sustained growth at considerably lower cost. Figure 5 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 in the IME window.

[Insert Figure 5 Here]

In conclusion, there is a major difference in long-term marketing impact, depending on the presence of temporary IME regimes. 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 focus on one or more concurrent or leading indicators of IME windows. In what follows we study the opportunity offered by monitoring internet-based product reviews as indicators of IME opportunities, 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. 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. 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 IME windows and their consequences for marketing.
Data

Our data source is the digital single-reflex lens (DSLR) market. This is a fast-moving consumer electronics category, with frequent product innovations and intensive consumer search, due to the high price point and technological sophistication of the category. We consider weekly sales and the marketing mix of the six leading brands in the US, between 2010 and 2012. Table 2 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 summarizes the descriptive statistics of weekly product review data, and Figure 6 illustrates weekly review quantity and valence of Nikon. 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 2 Here]
[Insert Table 3 Here]
[Insert Figure 6 Here]

Methodology

An important methodological consideration is the choice of a relevant time sample. 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 that should not benefit from hindsight. This 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 $1000), 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?

\[ Sales_t = c + a Sales_{t-1} + \varepsilon_t \]

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

\[ Sales_t = C + a Sales_{t-1} + \beta_{adv} \ln(Adv_t) + \beta_{price} \ln(Price_t) + \beta_{cp} \ln(CompetitiveAdv_t) + \beta_{NPI} NPI_t + \beta_{season} Seasonality_t + \varepsilon_t \]

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 and ReviewValence):

\[ Sales_t = C + a Sales_{t-1} + \beta_{adv} \ln(Adv_t) + \beta_{price} \ln(Price_t) + \beta_{cp} \ln(CompetitiveAdv_t) + \beta_{NPI} NPI_t + \beta_{season} Seasonality_t + \gamma_{activity} \text{ReviewActivity}_t + \gamma_{valence} \text{ReviewValence}_t + \varepsilon_t \]
A comparison of IME test results in (2) and (3) will reveal the intrinsic evolving time windows that are created by reviewer buzz. For example, an IME window identified in (2) is “created” if it is no longer an IME window after controlling for review activity and valence in (3), and vice versa. A Hausman-Wu test on the possible endogeneity of advertising spending in the full sample revealed no endogeneity bias in the response estimates.

**Estimation Results**

For ease of exposition, we present the moving-window IME test results graphically (see Figure 7), where the spiking values (i.e., p>.10) denote windows of growth opportunity. 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. These are periods that vigilant brands can and should take advantage of, as increased marketing spending could generate long-lasting trends in brand sales. 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 dominating 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 provides a summary across brands.

![Insert Figure 7 Here](image-url)

![Insert Table 4 Here](table-url)

Importantly, we identify a number of cases where test 2 reveals evolution and test 3 indicates stationarity and summarize the results in Table 5. These are the most relevant periods in our context, as they 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

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5 Detailed results are available from the authors upon request.
6 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.
generated by either review valence or quantity (22%), but rarely so 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. Overall, the findings support the notion that the valence of product reviews and, to a lesser extent, its quantity, contribute to brand growth and as such should be closely monitored by the brand stewards.

[Insert Table 5 Here]

Finally, we examine the hypothesis that favorable-review windows not only offer growth opportunity for a brand, they also increase marketing lift ($\beta_{adv}$). 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**

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 8 shows several examples, where the timing of advertising spending bursts are compared to windows of growth opportunity. 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

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7 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 $\text{[ReviewActivity} \times \text{ReviewValence]}$ and did test 3 with this combined review measure. Similar results were obtained.
windows. Table 6 provides a summary of the relative “vigilant spending” performance of different brands.

[Insert Table 6 Here]

[Insert Figure 8 Here]

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 possible lack of awareness that movements in product reviews impact baseline sales and, two, even with such awareness, the advertising budget setting and media buying process may cause inertia in spending behavior. The second explanation has empirical support in that brands’ advertising spending is reasonably well predictable (ergo, planned) from four factors: past sales, past advertising, seasonality and new-product introductions (See Table 7 for a summary of estimation results). This begs the question about the financial magnitude of the lost opportunity caused by either lack of awareness, or inertia.

[Insert Table 7 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

\[
S_t = c + aS_{t-1} + \beta \ln(A_t),
\]

(11)

advertising effectiveness per one log unit of advertising is \( \frac{\beta}{1-\alpha} \) (see Table 1). With a gross profit margin r, the spending \( A_{t,optimal} \) that maximizes advertising profitability, i.e.

\[
\frac{r\beta}{1-\alpha} \ln(A_t) - A_t ,
\]

(12)

\( A_{t,optimal} = \frac{r\beta}{1-\alpha} \).

Thus, the sales target is restricted to

\[
S_{t,optimal} = \frac{c + \beta \ln(r\beta/1-\alpha)}{1-\alpha},
\]

(13)
and any additional advertising to drive sales beyond $S_{t,\text{optimal}}$ 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 1). To maximize advertising profitability, i.e. $(W_tr\beta + \frac{r\beta}{1-\alpha})\ln(A_t) - A_t$, the optimal advertising increases to

$$A_{\text{IME},t} = W_tr\beta + \frac{r\beta}{1-\alpha},$$

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 IME opportunity 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 IME regime (see Figure 8d): one in the first three weeks of October, two weeks after the IME regime started, and its resulting sales are shown in Figure 9a; the other starting in the week of December 4, two weeks after the close of the IME regime.

[Insert Figure 9a Here]

Suppose Panasonic could fully take advantage of the IME regime and increase advertising during the entire 10-week IME window. Based on the advertising-sales function estimated with data of 60 weeks prior to the starting of the IME regime,
\[ Sales_t = 2779.86 + .42Sales_{t-1} + 15.65\ln(Adv_t) - 441.95\ln(Price_t) \\
+ 9.31\ln(CompetitiveAdv_t) + 43.08NP_t + 8.39\beta_{season} + \varepsilon_t \]

marketing managers could apply the optimal budgeting equation (14) and increase weekly advertising to $167.83k (i.e. 15.65*9+15.65/(1-.42)) for the first IME-regime period, $152.18k (i.e. 15.65*8+15.65/(1-.42)) for the second IME period, and so on. Note the normal weekly optimal advertising in non-IME regimes is $26.98k.

Figure 9b compares the optimal advertising with the actual advertising, and their sales results are shown in Figure 9a. While the total optimal advertising spending in the IME regime is $974.05k, which is below the actual spending of $1641.14k 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 9b 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 growth 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 inherently unpredictable, vigilance in spending is called for. In particular, brands should monitor and act on indicators that allow management to diagnose when the moment is ripe to increase marketing spending.

We have used movements in perceived 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 turn temporary growth into more sustained 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. 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 are the metrics that will 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 internet 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, may even exceed previously allocated
brand budgets. Our test on the leading brands in the DSLR market reveals that, at present, most brands are unable to 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.”

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 the marketing allocation 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.
References


Christensen, Terry and Peter J. Haas (2005), *Projecting Politics: Political Messages in American Films*, M.E. Sharpe.


Figure 1. Intrinsic vs. induced sales evolution

Figure 2. Sales of Compaq, Dell and HP in 1990s
Figure 3. Illustration of intrinsic evolving and stationary regimes

(a) Stationary regimes alternating with IME regimes with constant marketing inputs

Note: stationary regimes $S_t = 1 + 0.5S_{t-1} + 0.75M_t$; IME regimes $S_t = 1 + S_{t-1} + 0.75M_t$ during 8-11 and 37-40 periods; constant marketing inputs ($M_t = 10$).

(b) Comparison of returns of marketing expenses occurred in an IME vs. stationary regime

Note: marketing inputs increase from 4.5 to 18 at $t=8$ in an IME regime ($S_t = 1 + S_{t-1} + 2M_t$) and at $t=33$ in a stationary regime ($S_t = 1 + 0.5S_{t-1} + 2M_t$).
Figure 4. 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 $S_t = 0.5S_{t-1} + 2M_t$.

(a) 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 5. 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 6-10 period; $c=0$ to isolate marketing effects.
Figure 6. Weekly product reviews of Nikon
Figure 7. Results of unit root and IME tests: p-values

(a) Canon

(b) Nikon

(c) Olympus

(d) Panasonic
(e) Pentax

(f) Sony
Figure 8. Brand spending and IME windows

(a) Canon

(b) Nikon

(c) Olympus

(d) Panasonic
Figure 9. Illustration: the economic impact of vigilance

Figure 9a. Comparison of actual and optimal - Panasonic

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

Figure 9b. Comparison of actual and optimal advertising - Panasonic
Table 1. Comparison of marketing impact in IME and stationary regimes

<table>
<thead>
<tr>
<th></th>
<th>Stationary regime</th>
<th>IME regime</th>
<th>Implications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market response model</td>
<td>$S_t = C + \alpha S_{t-1} + \beta M_t + \varepsilon_t$, $0 \leq \alpha &lt; 1$</td>
<td>$S_t = C + S_{t-1} + \beta M_t + \varepsilon_t$,</td>
<td></td>
</tr>
<tr>
<td>Sales growth due to one unit of incremental marketing</td>
<td>$\alpha^t \beta$</td>
<td>$\beta$</td>
<td></td>
</tr>
<tr>
<td>Total sales generated by one unit of marketing (V)</td>
<td>$V_1 = \sum_{t=1}^{\infty} \alpha^{t-1} \beta = \frac{\beta}{1-\alpha}$</td>
<td>$V_2 = W \beta$ within the IME regime of W periods; $V_2 = W \beta + \frac{\beta}{1-\alpha}$, when a stationary regime follows the IME regime</td>
<td>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.</td>
</tr>
<tr>
<td>Budget needed to generate one-time sales growth $\Delta S$</td>
<td>$\frac{(1-\alpha)S_{t-1} + \Delta S - c}{\beta}$</td>
<td>$\frac{\Delta S - c}{\beta}$</td>
<td>It takes less advertising to create one time sales growth in IME than stationary regimes.</td>
</tr>
<tr>
<td>Budget needed to sustain sales growth within the IME regime</td>
<td>Recurring additional budgeting for each period</td>
<td>No additional budget needed</td>
<td></td>
</tr>
</tbody>
</table>
Table 2. Weekly digital camera data*

<table>
<thead>
<tr>
<th>Brand</th>
<th>Models</th>
<th>Average Market Share</th>
<th>Average Price</th>
<th>Average Weekly Advertising (in Thousands)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon</td>
<td>19</td>
<td>.48</td>
<td>885.02</td>
<td>861.91</td>
</tr>
<tr>
<td>Nikon</td>
<td>21</td>
<td>.40</td>
<td>899.50</td>
<td>617.17</td>
</tr>
<tr>
<td>Olympus</td>
<td>16</td>
<td>.02</td>
<td>531.00</td>
<td>84.79</td>
</tr>
<tr>
<td>Panasonic</td>
<td>5</td>
<td>.008</td>
<td>700.89</td>
<td>148.74</td>
</tr>
<tr>
<td>Pentax</td>
<td>9</td>
<td>.005</td>
<td>780.42</td>
<td>4.48</td>
</tr>
<tr>
<td>Sony</td>
<td>25</td>
<td>.08</td>
<td>646.59</td>
<td>248.21</td>
</tr>
<tr>
<td>All 6 brands</td>
<td>95 models</td>
<td>.98</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Data sources include NPD (for sales and prices) and AC Nielsen (for advertising). We exclude small brands such as Fujifilm (1 model), Leica (2 models) and Samsung (3 models) due to missing data.

Table 3. Product review data

<table>
<thead>
<tr>
<th>Brand</th>
<th>Weekly Review Quantity</th>
<th>Weekly Review Valence</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>SD</td>
</tr>
<tr>
<td>Canon</td>
<td>25.94</td>
<td>11.19</td>
</tr>
<tr>
<td>Nikon</td>
<td>22.01</td>
<td>8.24</td>
</tr>
<tr>
<td>Olympus</td>
<td>4.52</td>
<td>3.04</td>
</tr>
<tr>
<td>Panasonic</td>
<td>1.98</td>
<td>1.73</td>
</tr>
<tr>
<td>Pentax</td>
<td>3.39</td>
<td>2.31</td>
</tr>
<tr>
<td>Sony</td>
<td>7.93</td>
<td>4.41</td>
</tr>
</tbody>
</table>

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

Table 4. IME windows identified by rolling-window tests

<table>
<thead>
<tr>
<th>Brand</th>
<th>IME weeks</th>
<th>Total # of IME weeks</th>
<th>Total # of evolving weeks</th>
<th>% of IME in total sales evolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon</td>
<td>40, 76</td>
<td>2</td>
<td>65</td>
<td>3%</td>
</tr>
<tr>
<td>Nikon</td>
<td>38-44</td>
<td>7</td>
<td>38</td>
<td>18%</td>
</tr>
<tr>
<td>Olympus</td>
<td>38</td>
<td>1</td>
<td>35</td>
<td>3%</td>
</tr>
<tr>
<td>Panasonic</td>
<td>31-40, 73, 74</td>
<td>12</td>
<td>38</td>
<td>32%</td>
</tr>
<tr>
<td>Pentax</td>
<td>36, 37, 41</td>
<td>3</td>
<td>20</td>
<td>15%</td>
</tr>
<tr>
<td>Sony</td>
<td>23-25, 28-30, 32, 33, 36</td>
<td>9</td>
<td>54</td>
<td>17%</td>
</tr>
</tbody>
</table>
### Table 5. Sources of IME windows

<table>
<thead>
<tr>
<th>Brand</th>
<th>IME weeks induced by review buzz</th>
<th>Total # of review induced IME weeks</th>
<th>% of IME induced by review buzz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon</td>
<td>0</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Nikon</td>
<td>41, 44</td>
<td>2</td>
<td>29%</td>
</tr>
<tr>
<td>Olympus</td>
<td>0</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Panasonic</td>
<td>32</td>
<td>1</td>
<td>8%</td>
</tr>
<tr>
<td>Pentax</td>
<td>36, 37</td>
<td>2</td>
<td>66%</td>
</tr>
<tr>
<td>Sony</td>
<td>28-30, 36</td>
<td>4</td>
<td>44%</td>
</tr>
</tbody>
</table>

### Table 6. IME windows and advertising behavior

<table>
<thead>
<tr>
<th>Brand</th>
<th>#/ratio of IME</th>
<th>Advertising % in IME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon</td>
<td>2/3%</td>
<td>10%</td>
</tr>
<tr>
<td>Nikon</td>
<td>7/9%</td>
<td>21%</td>
</tr>
<tr>
<td>Olympus</td>
<td>1/1%</td>
<td>0.1%</td>
</tr>
<tr>
<td>Panasonic</td>
<td>12/16%</td>
<td>22%</td>
</tr>
<tr>
<td>Pentax</td>
<td>3/4%</td>
<td>25%</td>
</tr>
<tr>
<td>Sony</td>
<td>9/12%</td>
<td>7%</td>
</tr>
</tbody>
</table>

Notes: total 76 observation windows

### Table 7. Advertising spending decision rules

<table>
<thead>
<tr>
<th>DV: Adv. spending</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>NewProductLaunch</td>
<td>81.33</td>
<td>2.49</td>
<td>.01</td>
</tr>
<tr>
<td>Seasonality</td>
<td>20.87</td>
<td>4.06</td>
<td>.00</td>
</tr>
<tr>
<td>Sales(-1)</td>
<td>.02</td>
<td>3.04</td>
<td>.00</td>
</tr>
<tr>
<td>Adv(-1)</td>
<td>.57</td>
<td>15.61</td>
<td>.00</td>
</tr>
<tr>
<td>Price</td>
<td>.17</td>
<td>.96</td>
<td>.34</td>
</tr>
</tbody>
</table>

Brand effects: Fixed effects model

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>624</td>
</tr>
<tr>
<td>R²</td>
<td>.53</td>
</tr>
<tr>
<td>Max VIF</td>
<td>3.01</td>
</tr>
</tbody>
</table>