

Marketing Spending and the Volatility of Revenues and Cash Flows

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Abstract

While effective marketing spending is known to improve a brand's financial performance, it can also increase the volatility of performance, which is not a desirable outcome. This paper analyzes how revenue and cash-flow volatility are influenced by own and competitive marketing spending volatility, by the level of marketing spending, by the effectiveness of own and competitive marketing spending, and by competitive reactivity. We develop hypotheses about the influence of these variables on revenue and cash-flow volatility that are rooted in market response theory. Based on a broad sample of 99 pharmaceutical brands in four clinical categories and four European countries, we test these hypotheses and assess the magnitude of the different sources of marketing-induced performance volatility.

The results show that marketing spending policies have an impact on the level as well as the volatility of revenues and cash flows. Such performance volatility may incur negative financial side effects such as greater financing costs or higher opportunity costs of cash holdings. Our results offer new and surprising insights, as we demonstrate that common volatility-increasing marketing practices such as advertising pulsing are effective at the top-line, but may turn out to be ineffective at the bottom-line.

Keywords: Cash-Flow Volatility, Econometric Models, Market Response Models, Marketing Metrics, Marketing Volatility

Introduction

Marketing managers are commonly interested in improving the effectiveness of their expenditures. As marketing moves away from a sole focus on customer-demand impact to a focus on firm-value impact (Rust et al. 2004; Srivastava, Shervani, and Fahey 1998), it adopts an investor perspective and additional financial measures such as cash flows and shareholder value become relevant.

Marketing expenditures are usually considered to be more effective if they generate higher cash flows or accelerate cash flows (Srivastava, Shervani, and Fahey 1998). There are many reasons why the effectiveness of marketing expenditures varies. For example, higher product quality or brand equity may make marketing actions more successful (e.g., Keller 1993). The type of product, its stage in the life cycle and regional-market characteristics represent other important moderators of marketing effectiveness (e.g., Sethuraman and Tellis 1991; Shankar, Carpenter, and Krishnamurthi 1999). It may also depend on the order of entry (Bowman and Gatignon 1996; Shankar, Carpenter, and Krishnamurthi 1998), and the degree of competitive reaction (Steenkamp et al. 2005).

While all these factors can make a difference in long-term marketing investment decisions, they are largely exogenous to a brand manager in any given year. At the beginning of a fiscal year, a brand manager typically obtains approval for a fixed marketing communications budget to be spent during the next four quarters. He still has a number of opportunities to influence the impact of these expenditures in the fiscal year. For example, he can choose among different media, creatives and times that have been shown to influence the success of a marketing campaign (Tellis, Chandy, and Thaivanich 2000). In addition, many marketers believe in the effectiveness of a *pulsing* strategy, which implies an uneven distribution of expenditures over

time.¹ A survey among media-planners in the U.S. reports that almost 70% use pulsing to increase the effectiveness of their spending (Leckenby and Kim 1994). Indeed, theoretical as well as empirical research have shown that pulsing may be a superior strategy under various conditions. Sasieni (1971) and Mahajan and Muller (1986) prove that pulsing is optimal in the case of an S-shaped response function. Dubé, Hitsch and Manchanda (2005) generalize this result by considering competition and a response function with an advertising threshold. Empirical studies have shown that market response is subject to both decreasing returns to scale and advertising wearout effects (e.g., Hanssens and Levien 1983; Simon 1982). Advertising wearout implies that the response to an increase in expenditures is immediate but levels off even if the higher expenditure level is maintained. Thus one should distinguish between a *level stimulus* and a *differential stimulus*, generated by the *change* between current and previous periods' expenditures. For a given budget, Simon (1982) shows that higher cash flows can be obtained with a pulsing strategy compared to an even-spending strategy. However, pulsing creates *volatility* in spending, which may create additional financing costs to the firm. Indeed, from a shareholders' perspective, not only the *level* of cash flows but also their *distribution* is relevant because it determines how much capital must be mobilized over time to finance a specific expenditure strategy. The example in Table 1 illustrates the financial side effect that may arise from a pulsing strategy.

Consider a brand manager with a budget of \$400,000 to be spent over the fiscal year. Under even spending he invests \$100,000 in marketing activities every quarter. Under the alternative pulsing strategy, \$200,000 is spent in the first and third quarters, and zero is spent in the remaining two. Following the market response literature, we incorporate a carryover effect of

¹ We define any strategy that varies expenditures over time as a pulsing strategy. Some researchers have used a more restrictive definition of pulsing where expenditures are only allowed to vary between zero and a certain level (e.g., Dubé, Hitch, and Manchanda 2005).

marketing, i.e. sales do not drop immediately to their base level when expenditures are reduced to zero.

The upper panel shows the statement of cash flows associated with the two spending strategies. Column 3 and 4 present the incremental revenues, net of costs of goods sold, that accrue from marketing expenditures.² Consistent with the idea of the differential stimulus effect, incremental revenues are higher under pulsing. The last two columns show the incremental cash flows (net revenues minus marketing expenditures). We assume pulsing generates cash flows that are 5% higher than those from even spending.³

== Table 1 about here ==

Normally, the comparison of the two alternative spending schedules would stop at this point. However, the alternatives involve quite different levels of volatility of incremental revenues and cash flows, as shown in the last two rows of the upper panel. Volatility can be expressed as the range of monetary quantities or their standard deviation. By definition, it is zero for even spending but reaches a remarkable level under pulsing. The financial side effect associated with pulsing is demonstrated in the lower panel of Table 1. Columns 1 and 2 show how cash flows accumulate over time until they reach their year-end total of \$80,000 and \$84,000, respectively. The accrual of cash flows is booked at the end of a quarter, for example, \$20,000 is booked under even spending at the end of the first quarter. In order to realize these cash flows, however, capital must be provided at the beginning of the quarter. Columns 3 and 4 list the required level of cash holdings. It equals the size of marketing expenditures in the first quarter but decreases in subsequent quarters since incremental cash flows generated by

² The figures are generated by a typical market response function that accounts for carryover and differential stimulus effects. Marketing spending elasticity under even spending is assumed to be .30.

³ Dubé, Hitsch, and Manchanda (2005) and Mahajan and Muller (1986) report gains in cash profits due to pulsing between 1% and 5%.

marketing in previous periods can be used. These required cash holdings are not costless, as shareholders expect their invested capital to generate at least a certain rate of return. Since pulsing creates a more volatile spending pattern with negative cash flows in some quarters, more capital is locked up over time. Compared with even spending, these higher capital needs incur additional financing costs as shown in the last two columns. Assuming annual capital cost of 15% or 3.8% per quarter, these financing costs *reverse the policy recommendation*. Cash flows net of financing cost now amount to \$70,000 for even spending, but only \$68,000 for the pulsing strategy. Hence, despite its higher impact on customer demand, pulsing would not be the optimal strategy if the aim is to maximize shareholder value.

The example illustrates the importance of considering the level *and* volatility effects of marketing on cash flows. Finance executives and senior managers are used to pay attention to cash-flow volatility, since they know that it is inherently linked with the firm's stock-market risk or *beta*, which in turn impacts the company's terms of financing. Yet the marketing discipline has only recently begun to investigate the impact of marketing on volatility and risk (Srivastava, Shervani, and Fahey 1998; Gruca and Rego 2005; McAlister, Srinivasan, and Kim 2007).

This paper will focus on three important, yet unanswered questions in this emerging research area:

- What are the factors that create a relationship between marketing spending and the volatility of revenues and cash flows at the brand level?
- Are these effects empirically meaningful?
- Can managerial decisions be improved by considering the financial side effect of volatile marketing spending?

We will approach these questions as follows. First, we use market response theory to develop propositions about the volatility effects of marketing spending. Specifically, we consider

the *level*, the *volatility* and the *sales effectiveness* of marketing spending as important drivers of revenue and cash-flow volatility. In addition, we develop hypotheses about the impact of competitor behavior on volatility. Second, we use a database of 99 pharmaceutical brands from four categories and four European countries to test our hypotheses and measure the magnitude of the impact of the various volatility drivers. We also examine how spending volatility can enhance the effectiveness of marketing expenditures. Third, we use the empirical results to evaluate the marketing spending policies used by the brand managers in our sample, and to offer recommendations for improvement.

The remainder of the article is organized as follows. In the next section, we provide a brief overview of the related literature on volatility and risk drivers. We continue with the development of a theoretical framework around the effects of marketing spending on revenue and cash-flow volatility. The subsequent section describes our methodology to measure the hypothesized effects. We then present an empirical study and discuss the theoretical and managerial implications of our findings. The article concludes with a synthesis of the findings, limitations and suggestions for future research.

Literature Review

The volatility of cash flows or earnings is closely linked to the risk an investor faces when making an investment decision. A seminal accounting paper by Beaver, Kettler, and Scholes (1970) related several accounting measures such as dividend payout, leverage or liquidity to the beta, the equilibrium risk measure of capital markets. More importantly for our study, they also identified a *strong empirical relationship between the variability of earnings and risk*. Volatility of earnings alone could explain as much as 80% of the variation in beta. Subsequent studies identified additional variables such as financial structure, cash flow

measures, and operating leverage that influence risk (Hill and Stone 1980; Ismail and Kim 1989; Mandelker and Rhee 1984).

A recent finance study (Opler et al. 1999) examined the determinants of corporate cash holdings. Holding liquid assets is costly because such assets have a lower rate of return due to a liquidity premium and because of potential tax disadvantages. An important finding of this study is that *cash flow volatility is a principal determinant of corporate cash holdings*. Firms therefore can lower their cash holding cost by reducing cash-flow volatility that may be induced by marketing policies such as pulsing.

Marketing scholars have only recently begun to explore the effects of marketing activities on value relevant measures such as cash flows, firm value and risk. Much of this recent work fits into the conceptual framework on market-based assets and marketing process capabilities by Srivastava, Shervani, and Fahey (1998). Two research streams have emerged. The first focuses on developing new marketing metrics that relate marketing expenditures to value-relevant measures such as customer equity (e.g., Reinartz, Thomas, and Kumar 2005; Rust, Lemon, and Zeithaml 2004). The second stream of research focuses on the drivers of firm value and related measures. For example, Pauwels et al. (2004) find that product innovations increase firm value in the long run, whereas sales promotions hurt firm value. Gupta, Lehmann, and Stuart (2004) propose an alternative corporate valuation approach based on the concept of customer equity. They demonstrate that the retention rate is one of the most important drivers of firm value. Anderson, Fornell, and Mazvancheryl (2004) find a positive link between customer satisfaction and shareholder value. More recently, Fornell et al. (2006) demonstrate that publicly known increases in customer satisfaction can lead to excess returns in the capital markets, which points to a market inefficiency.

Only a few marketing studies have addressed the risk or volatility component of valuation to date. Gruca and Rego (2005) analyze the impact of satisfaction on cash flow volatility, and conclude that satisfied customers are an important asset because they lower the volatility of cash flows. This argument has also been supported by Anderson, Fornell, and Mazvancheryl (2004) and Fornell et al. (2006). An event study by Devinney (1992) investigates the importance of new-product introductions on the change of betas around new-product announcements. He finds that the frequency of new-product introductions affects risk in both directions. Finally, McAlister, Srinivasan, and Kim (2007) show that the level of marketing expenditures plays an important role in reducing risk above and beyond established accounting based risk drivers such as dividend payout, earnings variability, and liquidity. Their findings show that firms that spend more on marketing enjoy lower earnings volatility.

We conclude from this review that, first, cash-flow volatility and risk are closely related to each other and represent important performance metrics that finance executives and senior managers care about. Second, these metrics are not only driven by financial operations, but also by marketing phenomena such as customer satisfaction, marketing spending and new-product introductions. As a consequence, *marketers should care about cash-flow volatility as well*. Third, in addition to the increased financing costs that arise from higher volatility (as in the example in Table 1), there are two other financial side effects: volatility influences the stock market beta, which helps determine a company's weighted average cost of capital, and volatility induces firms to reserve more cash, which increases their opportunity cost.

The few marketing studies on volatility to date focused on volatility and risk at an aggregated firm level. In contrast, we will provide results at the brand level, and we will decompose the volatility impact coming from spending *level*, spending *variation* and spending

effectiveness. Such a focus is more actionable for marketing managers, but still offers a close link to the company's financial performance.

Theory

The main focus of our analysis is on marketing spending behavior. We start the theoretical development with the impact of marketing spending behavior on the volatility of revenues, followed by its effects on the volatility of cash flows. We use the range of revenues and cash flows (i.e. the difference between maximum and minimum values) as a measure of volatility.⁴ It is closely linked to other volatility measures such as the variance or standard deviation. The discussion starts with a single-firm marketing scenario. We then relax this restriction and discuss the effects of competitive actions. Our general argument is that the volatility, the average level and the effectiveness of marketing expenditures altogether affect the volatility of revenues and cash flows.

Single-firm Scenario

Effects on Revenue Volatility. Marketing theory and empirical evidence suggest that higher marketing expenditures generally lead to higher sales but at a decreasing rate (e.g., Hanssens, Parsons, and Schultz 2001; Leeflang et al. 2000). Figure 1 shows this type of market response, where X denotes the level of marketing spending and REV is the level of revenues resulting from a concave response function. Consider first the case of higher spending *volatility* while keeping the mean spending level constant at X_1 . In Figure 1, $R_{1A}(X)$ and $R_{1B}(X)$ denote the ranges of expenditures where $R_{1A}(X)$ is twice as large as $R_{1B}(X)$. On the ordinate, $R_{1A}(REV)$ and $R_{1B}(REV)$ reflect the ranges of revenues associated with these two conditions. Our first hypothesis follows directly from Figure 1:

⁴ In the following, we use volatility and range interchangeably if not indicated otherwise.

Hypothesis 1: Given a constant mean level of marketing expenditures, a larger range of spending translates into a larger range of revenues.

== Figure 1 about here ==

Next, consider the effects of a higher *mean* spending level while holding the range constant. Such a situation can be analyzed in Figure 1 by comparing the revenue realizations associated with expenditure levels around X_1 and X_2 . $R_{1A}(\text{REV})$ and $R_2(\text{REV})$ are the corresponding ranges of revenues, and we conclude:

Hypothesis 2: Given a constant range of marketing expenditures, the range of revenues decreases with a higher level of marketing expenditures.

Finally, we consider the effect of higher marketing *effectiveness* on revenue volatility, illustrated in Figure 2. We keep the average level of spending as well as the volatility of spending constant but vary the shape of the response function $f(\text{REV})$. Figure 2 shows that, the more effective the marketing spending (e.g. f_1 denotes higher responsiveness than f_2) the wider the range of revenue realizations. Hence,

Hypothesis 3: Given a constant range of marketing expenditures, higher marketing effectiveness turns into a larger range of revenues.

== Figure 2 about here ==

Effects on Cash-Flow Volatility. The results on revenue volatility cannot be automatically transferred to cash-flow volatility since an increase (decrease) in revenues is also associated with an increase (decrease) in costs. Figure 3 illustrates the cash-flow curve that derives from the market response function of Figure 1. Cash flows are defined as the difference between gross margin (i.e., revenues multiplied by a profit margin) and marketing costs. Operating and other non-marketing-related expenditures are covered by the profit margin. Note that this curve is concave, left skewed and has a unique maximum reflecting the optimal spend

level, as a result of combining a concave response function with a linear cost function. These properties lead to different results compared to those of the revenue volatility effects. We focus first on the consequences of a higher volatility of marketing expenditures. Since cash flows are a direct function of marketing expenditures, greater spending volatility causes greater cash-flow volatility. We therefore do not demonstrate this straightforward effect in Figure 3. The corresponding hypothesis is:

Hypothesis 4: Given a constant mean level of marketing expenditures, a larger range of marketing spending translates into a larger range of cash flows.

== Figure 3 about here ==

By contrast, the impact of a higher spending level is different from the revenue volatility result. Figure 3 compares three different levels of spending, X_1 , X_2 and X_3 , while keeping the range of spending constant [i.e. $R_1(X_1)=R_2(X_2)=R_3(X_3)$]. Obviously, the range of cash flows, Π , decreases with a rise in the spending level when comparing the results for X_1 and X_2 [$R_2(\Pi)<R_1(\Pi)$], consistent with the result for revenues. However, the relation turns into the opposite for sufficiently high level of spending, X_3 in Figure 3. The volatility of cash flows is higher compared to X_2 [$R_3(\Pi)>R_2(\Pi)$], suggesting a U-shaped effect. The exact inflection point of the U-shaped curve lies behind the optimal level of spending.⁵ Given the well-known flat maximum principle (e.g., Tull et al. 1986) and an asymmetric cash-flow function as depicted in Figure 3, we expect the inflection point to be rather far behind the optimal spending level for many brands. The following hypothesis reflects our argumentation:

⁵ The inflection point is approached faster the smaller the volatility of spending and the steeper the curve around the profit maximum are. This property is due to the asymmetry of the curve since the slope is less steep behind the optimal spending level. If we had a symmetric cash-flow curve the point of minimum cash-flow volatility would coincide with the profit-maximizing spending level, provided the spending volatility does not change.

Hypothesis 5: Given a constant range of marketing expenditures, the range of cash flows decreases with higher levels of marketing expenditures up to a certain point, then increases for higher levels behind this point.

Finally, consistent with the result for revenues, higher marketing responsiveness should also lead to a higher volatility of cash flows. Indeed, since only the revenue side is affected by a change in marketing effectiveness, the difference in cash-flow volatility can only be due to a change in revenue volatility. Since we already know that higher marketing effectiveness increases the volatility of revenues, it also makes the cash-flow function steeper:

Hypothesis 6: Given a constant range of marketing expenditures, higher marketing effectiveness turns into a larger range of cash flows.

Summary. We have established, first, that higher marketing spending volatility leads to a higher volatility of revenues as well as cash flows. Thus managers who decide on the timing of media plans, promotion plans, etc. can influence the volatility of both the top-line and bottom-line performance of their brands. Since marketing costs grow linearly while revenues grow at a decreasing rate, we anticipate that their impact on cash-flow volatility is *larger* than on revenue volatility

Second, higher market response parameters also translate into higher volatility of revenues and cash flows. Thus, on the one hand, larger response parameters are good news for the marketing manager because his expenditures produce higher returns. On the other hand, higher effectiveness has a dark side since it makes revenues and cash flows more volatile, even if spending volatility itself does not change.

Third, we predict that a higher level of marketing expenditures reduces revenue volatility, holding spending volatility constant. Higher spending also decreases the cash-flow volatility for

typical left-skewed cash-flow distributions, up to a certain level which is greater than the optimal spending level.

Our results so far are derived from a scenario without competitors (or at least without competitive reactions) and holding constant the other marketing-mix elements, e.g., price. We now extend these volatility results to account for the impact of competitive actions and other factors.

Impact of Competition

In analogy to the preceding section, we discuss the effects of volatility and effectiveness of competitors' marketing expenditures on the volatility of own revenues and cash flows. We do not consider the mean level of competitive spending as a driver of volatility in lack of a clear understanding how this relates to the volatility of market response for the focal firm.

The influence of competitive marketing expenditures on own sales (cross-effect) is negative or positive depending on whether the primary demand effect or the substitution effect dominates. Since the cross-effect of competitive spending is structurally equivalent to the effect of own spending, we expect the same effects on volatility of revenues and cash flows as discussed above. This holds true for both directions of the cross-effect, since volatility has no directional meaning. It is therefore straightforward to transfer the results from own spending:

Hypothesis 7: A larger range of competitive marketing expenditures leads to a larger range of own revenues and cash flows.

Hypothesis 8: Given a constant range of competitive marketing expenditures, higher competitive marketing effectiveness turns into a larger range of own revenues and cash flows.

As a result, competitors' actions may hurt, not only through their impact on the level of own sales and own cash flows, but also via the volatility effect. How strong this effect is remains an empirical issue.

Knowing that competitive actions may impact the level and volatility of their performance, managers are interested in appropriate reactions. We discuss a number of retaliatory actions they may consider to neutralize the adverse effects of competitive actions. We consider only reaction decisions with respect to own marketing expenditures, which include (1) increase own expenditures, (2) decrease own expenditures, or (3) no reaction (e.g., Leeflang and Wittink 1996; Steenkamp et al. 2005). In the first case, the manager tries to synchronize his spending behavior with that of his competitors, which induces a positive correlation between the expenditures. The effectiveness of this counteraction depends on the relation between the own effect and assumed negative cross-effect, as well as on the magnitude of both expenditures. Provided that the retaliatory action reduces the negative impact of the change in competitive spending, we would expect a higher correlation between own and competitive marketing expenditures to reduce the revenue and cash-flow volatilities due to competitive marketing activity. However, if competitive marketing exerts a positive influence on own revenues, the volatility caused by competitive activity will be amplified. As a result, the direction of the effect of a retaliatory measure depends on the sign of the cross-effect.

Hypothesis 9a: Given a negative cross-effect of competitive marketing expenditures, a higher correlation between own and competitive marketing expenditures reduces the range of own revenues and cash flows.

Hypothesis 9b: Given a positive cross-effect of competitive marketing expenditures, a higher correlation between own and competitive marketing expenditures increases the range of own revenues and cash flows.

In the second case, a negative correlation between own and competitive expenditures results from counter-cyclical spending relative to competition. This does not alter hypotheses 9a and 9b. Finally, the third case (no reaction) introduces zero correlation between the expenditures, and thus no effect on the volatility of revenues and cash flows will occur.

Table 2 summarizes our hypotheses that we subsequently test with a large dataset from the pharmaceutical industry.

== Table 2 about here ==

Methodology

The empirical testing of the hypothesized effects on the volatility of revenues and cash flows proceeds in two steps. The first step estimates a *market response model* that relates brand unit sales to relevant variables, among them own and competitive marketing expenditures. This market response model provides us with brand-specific estimates of marketing effectiveness that are used in two different ways in the second step. First, we treat them as a dependent variable in a model that explains differences in marketing effectiveness across brands (*marketing effectiveness model*). Second, the effectiveness estimates are used as predictor variables in a model that explains differences in volatility of revenues and cash flows (*volatility models*). In addition, we use the results of the market response model to remove the effects of exogenous factors such as seasonality and trend from the brand sales time series. Such factors are outside the control of management and are therefore not relevant for the study of marketing spending impact on volatility.

Market Response Model

We apply the multiplicative interaction model, a standard response model, to explain brand unit sales (e.g., Hanssens, Parsons, and Schultz 2001). Our data cover several European

pharmaceutical markets in the period 1987-1996. We include variables that are relevant to those markets and that time period. The market response model is specified as follows:

$$q_{ikst} = \alpha_{0i} MKT_{ikst}^{\alpha_{1i}} MKT_{ikst-1}^{\alpha_{2i}} CMKT_{ikst}^{\alpha_{3ks}} CMKT_{ikst-1}^{\alpha_{4ks}} GDP_{st}^{\alpha_{5ks}} \left(\prod_{l=6}^8 \alpha_{l,ks}^{SD_{l,t}} \right) \text{Exp}(\alpha_{9ks} ET_{ikst} + \varepsilon_{ikst}), \quad (1)$$

$$\text{with } \varepsilon_{ikst} = \rho_1 \varepsilon_{ikst-1} + \rho_2 \varepsilon_{ikst-2} + \mu_{ikst}, \mu_{ikst} \sim N(0, \kappa)$$

where,

q_{ikst}	=	Unit sales (daily dosages) of brand i in therapeutic area k , country s and period t
MKT_{ikst}	=	Marketing expenditures of brand i in therapeutic area k , country s and period t
$CMKT_{ikst}$	=	Marketing expenditures of brand i 's competitors in therapeutic area k , country s and period t
GDP_{st}	=	Gross domestic product in country s and period t
SD_t	=	Quarterly seasonal dummy variable in period t
ET_{ikst}	=	Elapsed time since the launch of brand i in therapeutic area k , country s and period t
α	=	Parameter vector to be estimated
ε, μ, κ	=	Error terms and variance
ρ_1, ρ_2	=	First and second order autocorrelation coefficients
i	=	$1, \dots, I$ (number of brands)
k	=	$1, \dots, K$ (number of therapeutic areas) ⁶
s	=	$1, \dots, S$ (number of countries)
t	=	$1, \dots, T_i$ (number of observation periods for brand i).

The response model includes own and competitive marketing expenditures that cover expenditures on detailing, professional journal advertising, and direct marketing. Time is measured in quarters. The coefficients associated with previous quarter's own and competitive marketing expenditures capture lagged effects. Specification tests indicated that this order sufficiently represents the expenditure dynamics. We account for brand heterogeneity in demand (e.g., quality, brand equity) via brand-specific intercepts, i.e. fixed effect terms. The model further includes three types of covariates, i.e., seasonal dummies, a trend variable (elapsed time),

⁶ A therapeutic area typically includes several product categories that treat the same diseases but represent different technological approaches. To account for substitution effects across categories in a therapeutic area we treat brands from other categories as competitors.

and a country's gross domestic product (GDP). The seasonal dummies and the trend variable are to accommodate exogenous influences on sales that are due to seasonal variation in demand and the brand life cycle. We use the GDP as a surrogate measure of the overall economic strength of a country.

Distribution and *price* are not relevant variables in our context. In Europe, pharmacies are required to list every approved drug, resulting in 100% distribution for the drugs in our sample. Prices were highly regulated in European countries during our observation period and were not used as a tactical marketing instrument. Hence, while there is cross-sectional price variation (which is absorbed in the brand-specific constant), there is virtually no time variation.

We transform equation (1) into a log-log specification, construct deviations from the group mean to remove the fixed effects, and estimate the model with generalized least squares.

Marketing Effectiveness Model

The marketing effectiveness model is a cross-sectional model that relates marketing effectiveness to a number of variables. The sum of the estimated current and lagged effects of own marketing expenditures measures the total marketing effectiveness and serves as a dependent variable:

$$\begin{aligned} \widehat{EFF}_{im} &= \beta_{0m} + \beta_1 \overline{MR(MKT)}_{im} + \beta_2 \overline{PRC}_{im} + \beta_3 \overline{CMKT}_{im} + \beta_4 \overline{QUAL}_{im} + \beta_5 \overline{OE}_{im} + \\ &\quad \beta_6 \overline{ET}_{im} + \eta_{im}, \end{aligned} \quad (2)$$

with $\beta_{0m} = \bar{\beta}_0 + \omega_m$, $\omega_m \sim N(0, \zeta)$, $\eta_{im} \sim N(0, \tau_i)$, $Cov(\omega_m, \eta_{im}) = 0$,

where,

$$\begin{aligned} \widehat{EFF}_{im} &= \text{Estimated total marketing effectiveness for brand } i \text{ in product market } \\ &\quad \text{m: } \hat{\alpha}_{1i} + \hat{\alpha}_{2i} \text{ (estimated from eq. 1)} \\ \overline{MR(MKT)}_{im} &= \text{Average moving range of marketing expenditures of brand } i \text{ in product} \\ &\quad \text{market m} \\ \overline{PRC}_{im} &= \text{Average price of brand } i \text{ in product market m} \end{aligned}$$

\overline{CMKT}_{im}	=	Average level of marketing expenditures of brand i 's competitors in product market m
$QUAL_{im}$	=	Quality level of brand i in product market m
OE_{im}	=	Order of entry of brand i in product market m
\overline{ET}_{im}	=	Average elapsed time of brand i in product market m
β	=	Parameter vector to be estimated
$\eta, \omega, \zeta, \tau$	=	Error terms and variances
m	=	1, ..., M (number of product markets). ⁷

The average moving range of marketing expenditures measures the volatility of these expenditures. Consistent with the differential stimulus hypothesis, we expect its influence on marketing effectiveness to be positive. Based on previous research, we anticipate that the impacts of order of entry (Bowman and Gatignon 1996) and the stage of the life cycle (Sethuraman and Tellis 1991; Shankar, Carpenter, and Krishnamurthi 1999) on marketing effectiveness are negative. Marketing activities for higher-quality brands are expected to be more effective (e.g., Keller 1993; Shankar, Carpenter, and Krishnamurthi 1998) whereas a higher level of competition should reduce effectiveness (Stenkamp et al. 2005). Price volatility is not considered a predictor in this study since it is not used as a tactical instrument by the firms in our sample. We do not make a prediction about the influence of price level on marketing effectiveness. Finally, we expect differences in marketing effectiveness due to the type of product and market (e.g., Sethuraman and Tellis 1991). Random intercepts which vary across country-level product markets capture such effects.

We estimate the model using simulated maximum likelihood technique (Greene 2004) to account for the random intercepts. Our dependent variable is subject to measurement error,

⁷ A product market is defined by category \times country. It is a subcategory of a therapeutic area. Such a narrow definition is meaningful because marketing effectiveness may depend on the type of a product that is only fully captured at the product market level.

which creates a heteroskedastic error term structure.⁸ We therefore use the estimated standard errors as weights to control for heteroskedasticity.

Volatility Models

Structural Equations. Let $R(REV)$ denote the volatility of revenues measured as a range, $R(MKT)$ represent the range of own marketing expenditures, $A(MKT)$ be the average level of own marketing expenditures, $R(CMKT)$ denote the range of competitive marketing expenditures, $CORR$ represent the correlation between own and competitive marketing expenditures, EFF denote own marketing effectiveness, $CEFF$ denote competitive marketing effectiveness, $\boldsymbol{\gamma}$ be a parameter vector to be estimated, and ν be an error term with variance ξ . Omitting brand and time subscripts for the moment, we specify the revenue volatility model as follows:

$$R(REV) = \gamma_0 R(MKT)^{\gamma_1} A(MKT)^{\gamma_2} R(CMKT)^{\gamma_3} \text{Exp}(\gamma_4 CORR + \gamma_5 EFF + \gamma_6 CEFF + \nu), \quad (3)$$

with $\nu \sim N(0, \xi)$.

We assume the relationship between revenue volatility and its drivers to be multiplicative. Thus the variables interact with each other, consistent with the results from the theory discussion. The correlation between own and competitive marketing expenditures and the estimated own and competitive marketing effectiveness parameters appear as part of an exponential function because they may become negative.⁹ The parameters γ_{1-3} can be directly interpreted as elasticities and facilitate the comparison of volatility drivers.

Since cash flows are constructed from revenues and costs, revenue volatility enters the cash-flow volatility equation:

⁸ We assume the errors of α_{1i} and α_{2i} to be normally distributed. Therefore, its sum will also be normally distributed justifying our distributional assumptions with respect to the error term of (2).

⁹ Conceptually, own marketing effectiveness should be bounded by zero. But we may find cases with negative values due to estimation error.

$$R(CF) = \delta_0 R(REV)^{\delta_1} R(MKT)^{\delta_2} A(MKT)^{\delta_3} \text{Exp}[\delta_4 A(MKT) + v], \quad (4)$$

with $v \sim N(0, \psi)$,

where $R(CF)$ denotes the range of cash flows, δ is a parameter vector to be estimated, and v represents an error term with variance ψ . The effects of competitive marketing and marketing effectiveness on cash-flow volatility are mediated through revenue volatility. In addition, revenue volatility mediates the impact of own expenditures. Since own expenditures also enter the cash-flow equation as cost we expect an additional direct effect on cash-flow volatility. Finally, note that specification (4) allows for a U-shaped influence of the level of marketing expenditures on cash-flow volatility, consistent with hypothesis 5. This situation occurs if $\delta_3 < 0$ and $\delta_4 > 0$. We further allow the error terms to be correlated across the two equations.

Data Transformation. By using the estimates of the brand sales model, we remove the effects of exogenous market factors such as season, trend, and overall economic condition (measured by the GDP), and derive an adjusted unit-sales time-series for each brand. We multiply the unit sales with the brand's unit price and arrive at adjusted brand revenues. We then multiply the adjusted revenues by a cash contribution margin of 65% as given in Myers and Howe (1997). From these gross cash flows we subtract the marketing expenditures and arrive at the final variable of adjusted brand cash flows.¹⁰

The volatility of the adjusted revenues and cash flows is measured by the range of these quantities over a time period of 8 quarters. Consequently, we use the first two available years of sales for each brand as an initialization period. We compute the range of the subsequent period by dropping the first period and including the information of the following period. We continue until the end of the brand-specific time series and thus obtain a time series of moving ranges of

¹⁰ We note that brands may differ slightly in their contribution margins due to differences in inventory policies etc. However, we do not need this information since we are not interested in explaining volatility of cash flows that accrues from accounting practices.

adjusted revenues and cash flows (moving-window analysis). This procedure is also applied to compute moving ranges for own and competitive marketing expenditures and the moving average of own marketing expenditures. We denote moving ranges with MR and moving averages with MA.

The application of moving-window analysis is well established in the accounting literature (e.g., Kothari 2001) and justified for two reasons. First, it increases sample size and therefore improves the power of statistical tests. Note that observations are inevitably lost due to the calculation of the volatility measures. Second, it accounts for possible dynamic effects. Capital markets research has shown that it often takes some time until economic effects have fully materialized in earnings volatility (e.g., Kothari et al. 2002).

Estimation Equations. The use of moving windows is helpful to increase the power of the hypothesis tests due to the increase in degrees of freedom, but it is also likely to generate autocorrelated error terms in the time series of adjusted revenues and cash flows. We therefore transform expressions (3) and (4) into a series of relative differences. By taking the total differentials of the log-transformed equations (3) and (4), we obtain (see the appendix):

$$\frac{\Delta MR(AREV)_{ikst}}{MR(AREV)_{ikst-1}} = \gamma_1 \frac{\Delta MR(MKT)_{ikst}}{MR(MKT)_{ikst-1}} + \gamma_2 \frac{\Delta MA(MKT)_{ikst}}{MA(MKT)_{ikst-1}} + \gamma_3 \frac{\Delta MR(CMKT)_{ikst}}{MR(CMKT)_{ikst-1}} + \gamma_4 \Delta MA(CORR)_{ikst} + \Delta v_{ikst}, \quad (5)$$

$$\frac{\Delta MR(ACF)_{ikst}}{MR(ACF)_{ikst-1}} = \delta_1 \frac{\Delta MR(AREV)_{ikst}}{MR(AREV)_{ikst-1}} + \delta_2 \frac{\Delta MR(MKT)_{ikst}}{MR(MKT)_{ikst-1}} + \delta_3 \frac{\Delta MA(MKT)_{ikst}}{MA(MKT)_{ikst-1}} + \delta_4 \Delta MA(MKT)_{ikst} + \Delta v_{ikst}, \quad (6)$$

where,

$MR(AREV)_{ikst}$ = Moving range of adjusted revenues of brand i in therapeutic area k , country s and period t

- $MR(MKT)_{ikst}$ = Moving range of marketing expenditures of brand i in therapeutic area k , country s and period t
 $MA(MKT)_{ikst}$ = Moving average of marketing expenditures of brand i in therapeutic area k , country s and period t
 $MR(CMKT)_{ikst}$ = Moving range of marketing expenditures of brand i 's competitors in therapeutic area k , country s and period t
 $MA(CORR)_{ikst}$ = Moving average correlation between own and competitive marketing expenditures of brand i in therapeutic area k , country s and period t .

Δ = first-difference operator.

Equations (5) and (6) represent the original equations in terms of relative differences. Unlike absolute differences, this representation not only removes autocorrelation, but also controls for brand-size effects. For example, bigger brands are expected to have larger absolute changes in revenues, cash flows and marketing spending.

We estimate equations (5) and (6) with three-stage least squares to account for the endogeneity of revenue volatility and the error-term correlation (Greene 2004). All variables except for the relative differences of adjusted revenues and cash flows are exogenous to the two-equation system. In addition to these variables, we use the range and variance of competitive marketing expenditures measured in absolute terms as instruments to identify equation (6).

The first-differencing procedure eliminates the time-invariant marketing effectiveness variables that are part of the revenue volatility model (3). To measure their influence, we linearize (3) first via log-transformation and then build a cross-sectional regression model by obtaining averages of all time-varying variables. The resulting equation can be estimated with OLS. However, the marketing-effectiveness parameters of the first stage are measured with sampling error that vanishes in the limit. As a consequence, OLS estimates from the second stage regressions will be consistent but their standard errors may be biased (Murphy and Topel 1985). Following Nijs, Srinivasan, and Pauwels (2006), we obtain corrected standard errors by a bootstrapping procedure with 10,000 replications.

Empirical Study

Data

Data on prescription drugs from two therapeutic areas (cardio-vascular and gastro-intestinal) that cover four product categories are available. Two categories, calcium channel blockers and ACE inhibitors, comprise drugs for the treatment of cardio-vascular diseases. Drugs in the two other categories, H2 antagonists and proton pump inhibitors, are used in gastro-intestinal therapies. These four categories are among the largest prescription-drug categories. They differ in their therapeutic principles to treat diseases like hypertension or acid related gastro-intestinal disorders. Data, collected by IMS, are available on a quarterly basis for a time period of 10 years (1987-1996) covering the growth and maturity phases of the analyzed categories. They include unit sales (normalized over different application forms of the drug and transformed into daily dosages by a brand-specific dosage factor), daily dosage price, quality, launch date, and marketing spending on detailing, journal advertising and other communications media. Quality is measured as an objective quality index, based on international medical evaluation standards. Monetary values are in 1996 US\$ and have been deflated by country-specific consumption price indexes. The data cover four European countries: France, Germany, Italy, and the UK, and comprise eight product markets (2 categories \times 4 countries). We analyze data on 99 brands, which were marketed by 26 pharmaceutical firms.

Table 3 shows the descriptive statistics of the variables used in the estimation equations. Revenues average about \$9.2 million per quarter, cash flows are about \$5.0 million, and average marketing spending amounts to about \$1.0 million. There is also considerable variation in the data across brands and time, as indicated by the standard deviations and the volatility measures in Table 3. Volatility is particularly high with respect to marketing spending. The moving range

is about \$0.8 million, virtually as high as the mean spending. Plots of marketing spending over time (not shown) reveal substantial volatility for many brands in our sample.

== Table 3 about here ==

Estimation Results

Brand Sales Model. The multiplicative market response model (1) describes sales evolution in the markets very well. We verified the stationarity of the brand-sales time series by applying the pooled unit-root test procedure for unbalanced data (Maddala and Wu 1999). We found the log-transformed series of unit sales, own and competitive marketing expenditures to follow an $I(0)$ process. Hence, there is no need to first-difference the data. Consistent with specification (1), we allowed for autocorrelation and tested for the order by using the Schwartz Bayesian Criterion (Enders 1995). We find three of the gastrointestinal country markets to be best represented by an $AR(1)$ process, whereas $AR(2)$ is more appropriate for the other country markets.¹¹ The average marketing elasticity is .10, which is within the range of reported results in the literature (see Manchanda and Honka 2005). In addition, if we weigh the estimates by their relative standard errors, the mean value rises to .192. The impact of competitive marketing activities is negative, with a mean value of -.01. In general, there is substantial variation in the marketing impact estimates, which we expect to explain by our marketing effectiveness model.

Marketing Effectiveness Model. Estimation results for the marketing effectiveness model are shown in Table 4. The predictor variables explain more than two thirds of the variance of the effectiveness estimates. Many of them are significant and in line with our expectations. For example, marketing effectiveness is higher at the beginning of the brand-life cycle, and is reduced by competition, as measured by the level of competitive marketing spending. Moreover,

¹¹ Due to space limitations we do not show the results of the first stage regression in detail. Additional information may be obtained from the authors.

higher-priced brands have higher marketing effectiveness. Since the innovativeness of a drug and its price are positively correlated we interpret this finding to reflect the influence of innovativeness on effectiveness.

== Table 4 about here ==

Most importantly for the context of this study, *the volatility of marketing spending has a positive impact on marketing effectiveness*. Based on its mean value for the range of marketing expenditures in the sample, we calculate an elasticity of .484 ($.572 \times 10^{-4} \times 846 / .10$) which is substantial. That means that the effectiveness of own marketing expenditures increases by ca. 50% if expenditure volatility is doubled. As a result, we find strong evidence for the existence of a differential stimulus effect in our data.

Volatility Models. Table 5 shows the estimation results for the revenue and cash flow volatility models. We present the results of the model in relative first differences. Since the effect of marketing effectiveness, which does not vary within but across brands, can only be estimated by a cross-sectional model we also present the results of a cross-sectional regression. However, due to the missing time variation and the substantially lower number of observations in this model, the effects for the time-varying variables should be interpreted with caution.

== Table 5 about here ==

We focus first on the estimates from the revenue volatility model and then turn to the cash-flow volatility model. The volatility of marketing expenditures measured by their range increases the volatility of revenues and supports hypothesis 1, with an estimated elasticity of .106 ($p < .01$).¹²

¹² The estimate obtained from the cross-sectional model is very large but, as already pointed out, should be interpreted with caution since it is only based on cross-sectional variation and not normalized by brand size.

The first-difference model does not support hypothesis 2 on the influence of the level of marketing expenditures on revenue volatility, as the coefficient is positive and significant at $p < .05$. However, a highly significant negative effect, consistent with hypothesis 2, is found in the cross-sectional regression ($-.101$, $p < .01$). Note that this variable has been divided by average brand unit sales in order to control for brand-size effects.

Own marketing effectiveness drives revenue volatility (4.16 , $p < .05$), supporting hypothesis 3. The effect is substantial since the associated elasticity is $.416$ ($1.52 \times .10$). We do not find significant effects ($p > .10$) for the volatility of competitive marketing expenditures in the first difference regression and for competitive marketing effectiveness in the cross-sectional regression (hypotheses 7 and 8). While the coefficient for the volatility of competitive marketing expenditures is in the right direction, the coefficient for competitive marketing effectiveness does not have the expected sign. However, it is difficult to establish an impact for the effectiveness variable in our data, since variation is based on only eight data points (2 therapeutic areas \times 4 countries). The correlation of own and competitive marketing expenditures shows a significant negative effect on revenue volatility ($-.057$, $p < .05$). Since the effect of competition is predominantly substitutive in our data, the sign of the effect is consistent with our hypothesis 9a.

As expected, revenue volatility is an important driver of cash-flow volatility, with an elasticity of 1.67 ($p < .01$). Its lower boundary value is 1, which would be achieved if cash flows consisted only of revenues multiplied by the profit margin. The direct effect of the volatility of marketing expenditures is positive and significant, with a value of $.173$ ($p < .01$). This coefficient represents the volatility effect due to the cost component of marketing expenditures. The indirect effect via revenue volatility is also positive and adds to the direct effect, resulting in a total elasticity of $.350$ ($=1.67 \times .106 + .173$). Hence, we find strong support for hypothesis 4.

Interestingly, this elasticity is more than three times higher than for revenue volatility. We also find strong support for hypothesis 5 that posits a U-shaped influence of the level of marketing expenditures on cash flows (-.288, $p < .01$ and .00039, $p < .01$). The direction of the influence of marketing effectiveness on cash-flow volatility is consistent with hypothesis 6 since we measured a significant positive effect in the revenue volatility model that is mediated by the significant revenue volatility effect. The associated elasticity of .688 ($=1.67 \times .412$) is substantial. The effects of the volatility of competitive marketing expenditures and the correlation of own and competitive marketing expenditures on cash flow volatility are also mediated through the revenue volatility. They lend directional support for hypothesis 7 and substantiate our argument with respect to the correlation of marketing expenditures.

Robustness of Findings

We performed several analyses to verify the robustness of these results. First, we varied the window of the volatility measures. Instead of 8 quarters we computed volatility measures based on 4 quarters and 12 quarters. The results remained the same. Second, we used moving variances instead of ranges as volatility measures. The correlation between the two measures is very high, averaging .91 across the volatility variables. The regression results were very similar. Third, we created volatility variables that do not overlap over time periods. For example, the first observation of an 8-quarter based range variable includes the first 8 quarters, the second observation is based on the subsequent 8 quarters and so forth. This procedure reduces the sample size to 258 observations. The results did not change materially, though the standard errors increased. Fourth, we verified if the results are influenced by collinearity. The condition indices of the models were well below the critical value of 30 (Greene 2004).

Discussion

Managerial Implications

Our empirical analyses revealed that the effectiveness of marketing expenditures varies strongly across brands, due to factors such as the life-cycle stage and innovativeness of a brand. These factors are exogenous or can hardly be influenced by the brand manager in the short run. On the other hand, we also find strong support for the existence of a *differential stimulus effect* that suggests a pulsing strategy will improve marketing productivity. Our discussions with pharmaceutical brand managers and sales executives confirm that they actively vary their expenditures over time because they believe in wearout effects of detailing and other physician oriented marketing activities.

Consequently, a brand's top-line results can be improved by making marketing spending more volatile. However, such marketing volatility may create a *financial side effect* that reduces or even surmounts its positive effect on revenues. This creates a managerial tradeoff, as illustrated in Figure 4. The matrix provides brand managers with a means to evaluate their spending policy. If the differential stimulus effect is small or non-existent, there is no need to increase marketing volatility, and in fact volatility should be avoided. If the differential stimulus effect on sales is high, managers need to find the right balance between that positive impact and its negative financial side effect.

By applying the framework of Table 1 and the logic of Figure 4 to the brands in our sample, we identified several cases where the differential stimulus effect generated remarkable incremental cash flows compared to an even-spending strategy.¹³ However, we also encountered a number of cases where the financial side effect exceeded the incremental cash flows from

¹³ The degree of marketing volatility differs across brands. We compare the financial outcome from actual pulsing strategies with those from a simulated even-spending strategy representing the extreme case of zero marketing volatility.

pulsing. These situations occurred most often during the first two years after launch, when firms usually spend more resources on marketing than can be covered by brand revenues. While such “launch spending” has its own justification, we are not aware of arguments in favor of pulsing over even-spending in the early years. Thus *pulsing may not be an advisable spending strategy during product launch* because it only adds financing costs to the losses that are already being incurred.

== Figure 4 about here ==

Research Implications

Our findings also contribute to the advancement of knowledge in marketing. Cash-flow volatility has been overlooked in marketing for a long time (Srivastava, Shervani, and Fahey 1998). While recent research (e.g. Gruca and Rego 2005; McAlister, Srinivasan, and Kim 2007) has focused on marketing’s potential to *reduce* volatility and its associated financial side effects, our study is the first to describe its potential to *increase* volatility. We do so by relying on extant market response theory, which allows us to make the formal connection between marketing spending, marketing effectiveness, and revenue and cash-flow volatility.

The empirical application of our theoretical framework to a large dataset from the pharmaceutical industry creates interesting findings. We learn that the volatility of marketing expenditures has only a minor effect on revenue volatility, but its effect on cash-flow volatility is much higher. In contrast, market responsiveness has a strong effect on revenue volatility, which translates into a substantial impact on cash-flow volatility. Finally, our analysis shows that higher marketing-spending levels help reduce the volatility of revenues and cash flows. This conclusion corroborates the finding of McAlister, Srinivasan, and Kim (2007) that marketing spending reduces the systematic risk of the firm.

Limitations and Future Research

Our research is subject to some limitations that may stimulate future research. First, we have quantified the magnitude of volatility drivers in four prescription-drug categories. It would be interesting to extend this analysis to other industries. Second, we do not claim to have analyzed all marketing related drivers of volatility. In particular, new-product introductions and sales promotions may also contribute to volatility, and should be explored in future research. Third, we referred primarily to the financing cost as a side effect of volatility, but this is not the only cost. The finance literature emphasizes the link between cash-flow volatility and the opportunity cost of cash holdings as well as the relationship between cash-flow volatility and firm's cost of capital. Future research should establish a link between marketing activities and these cost categories, both conceptually and empirically. Fourth, multi-divisional firms may also manage volatility across their portfolio of products, at least in principle. Future research should investigate to what extent individual marketing plans can be adjusted across products so as to maintain an acceptable level of cash-flow volatility at the corporate level. Finally, we established the cost-benefit tradeoff of volatility-driving marketing practices such as pulsing, but we did not derive the optimal level of volatility. Future research should develop a normative model that includes the benefits and the costs of volatility-increasing marketing activities.

Appendix

In this section, we derive the estimation equations (5) and (6) from equations (3) and (4).

We start with a log transformation of equations (3) and (4)

$$\ln R(REV) = \ln \gamma_0 + \gamma_1 \ln R(MKT) + \gamma_2 \ln A(MKT) + \gamma_3 \ln R(CMKT) + \gamma_4 CORR + \gamma_5 EFF + \gamma_6 CEFF + v \quad (A.1)$$

$$\ln R(CF) = \ln \delta_0 + \delta_1 \ln R(REV) + \delta_2 \ln R(MKT) + \delta_3 \ln A(MKT) + \delta_4 A(MKT) + v. \quad (A.2)$$

and take the total differentials:

$$\begin{aligned} \frac{1}{R(REV)} dR(REV) &= \frac{\gamma_1}{R(MKT)} dR(MKT) + \frac{\gamma_2}{A(MKT)} dA(MKT) \\ &+ \frac{\gamma_3}{R(CMKT)} dR(CMKT) + \gamma_4 dCORR + \gamma_5 dEFF + \gamma_6 dCEFF + dv. \end{aligned} \quad (A.3)$$

$$\begin{aligned} \frac{1}{R(CF)} dR(CF) &= \frac{\delta_1}{R(REV)} dR(REV) + \frac{\delta_2}{R(MKT)} dR(MKT) + \frac{\delta_3}{A(MKT)} dA(MKT) \\ &+ \delta_4 dA(MKT) + dv. \end{aligned} \quad (A.4)$$

By using moving ranges and averages for the respective variables in the transformed equations we can write the discrete-time analogs to (A.3) and (A.4) as done in (5) and (6) in the paper.

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Table 1 An example of the financial side effect of spending volatility

<i>Statement of cash flows (quarterly) in Thousand US\$</i>						
	Marketing expenditures		Incremental revenues net of cost of goods due to marketing expenditures		Incremental cash flows due to marketing expenditures	
	Even spending	Pulsing spending	Even spending	Pulsing spending	Even spending	Pulsing spending
Quarter 1	100	200	120	150	20	-50
Quarter 2	100	0	120	92	20	92
Quarter 3	100	200	120	150	20	-50
Quarter 4	100	0	120	92	20	92
Total	400	400	480	484	80	84
Std. dev.	0	100	0	29	0	71
Range ¹⁾	0	200	0	58	0	142

<i>Cash balance sheet (quarterly) in Thousand US\$</i>						
	Cumulated cash flows due to marketing expenditures		Required cash holdings		Financing costs for capital lockup (3.8% per quarter)	
	Even spending	Pulsing spending	Even spending	Pulsing spending	Even spending	Pulsing spending
Quarter 1	20	-50	100	200	4	8
Quarter 2	40	42	80	50	3	2
Quarter 3	60	-8	60	158	2	6
Quarter 4	80	84	40	8	2	0
Total			280	416	11	16

¹⁾ Range = Maximum expenditure – Minimum expenditure

Table 2 **Summary of hypotheses**

	Expected effect on the ...			
	<i>Volatility of Revenues</i>		<i>Volatility of Cash flows</i>	
Volatility of own marketing expenditures	Increase	(H1)	Increase	(H4)
Level of own marketing expenditures	Decrease	(H2)	Decrease first, then increase	(H5)
Own marketing effectiveness	Increase	(H3)	Increase	(H6)
Volatility of competitive marketing expenditures	Increase	(H7)	Increase	(H7)
Competitive marketing effectiveness	Increase	(H8)	Increase	(H8)
Correlation between own and competitive marketing expenditures	Decrease for negative cross-effect	(H9a)	Decrease for negative cross-effect	(H9a)
	Increase for positive cross-effect	(H9b)	Increase for positive cross-effect	(H9b)

Table 3 **Descriptive statistics**

<i>Level variables</i>	<i>Mean</i>	<i>Std. dev.</i>	<i>Volatility variables</i>	<i>Mean</i>	<i>Std. dev.</i>
Unit sales in th. daily dosages	18,036	20,591			
Revenues in th. US\$	9,229	10,421	Moving range of adjusted revenues in th. US\$	3,295	5,955
Cash flows in th. US\$	4,962	6,395	Moving range of adjusted cash flows in th. US\$	2,405	3,901
Marketing expenditures in th. US\$	1,039	869	Moving range of marketing expenditures in th. US\$	846	756
Competitive marketing expenditures in th. US\$	5,146	3,331	Moving range of competitive marketing expenditures in th. US\$	3,675	2,322
Moving average of marketing expenditures in th. US\$	943	729			
Moving average correlation between own and competitive marketing expenditures	0.35	0.40			
Order of entry ¹⁾	4	n.a.			
Quality	1.01	0.18			
Elapsed time since launch in years	6.23	5.57			
Gross domestic product in bill. US\$					

Notes: All variables before log-transformation. N.a. – not applicable. All values in 1996 dollars deflated by country-specific consumption price index

¹⁾ Median instead of mean reported.

Table 4 Estimation results for the marketing effectiveness model

	<i>Expected sign</i>	<i>Coefficient estimate (standard error)</i>
Constant	+	.144 (.071)**
Standard deviation		.055 (.010)***
Range of marketing expenditures ¹⁾	+	.572 (.119)***
Daily dosage price	+/-	.071 (.036)**
Competitive marketing expenditures ¹⁾	-	-.153 (.036)***
Quality	+	-.054 (.064)
Order of entry	-	.008 (.005)
Elapsed time since launch ²⁾	-	-.140 (.055)**
No. of observations		99
Pseudo R ²		.682

Notes: Two-sided t-tests. *** p < .01; ** p < .05; * p < .10

¹⁾ Multiplied by 10,000 for reading convenience.

²⁾ Multiplied by 100 for reading convenience.

Table 5 Estimation results for the volatility models

	<i>Expected sign</i>	<i>Revenue volatility</i>		<i>Cash flow volatility</i>
		First difference model (3SLS)	Cross-sectional model	First difference model (3SLS)
Constant		-	-6.47 (5.50)	-
Range of revenues	+	-	-	1.67 (.232)***
Range of marketing expenditures	+	.106 (.024)***	2.22 (.794)***	.173 (.034)***
Level of marketing expenditures	-	.152 (.073)**	-1.01 (.345)***, ¹⁾	-.288 (.090)***
Exp(Level of marketing expenditures)	+	-	-	.394 (.164)***, ²⁾
Range of competitive marketing expenditures	+	.010 (.019)	-.459 (.256)	-
Correlation between own and competitive marketing expenditures	+/-	-.057 (.026)**	-1.21 (1.49)	-
Own marketing effectiveness	+	-	4.16 (2.24)**	-
Competitive marketing effectiveness	+	-	-3.92 (4.71)	-
No. of observations		2,104	99	2,104
R ²		.104	.259	.324

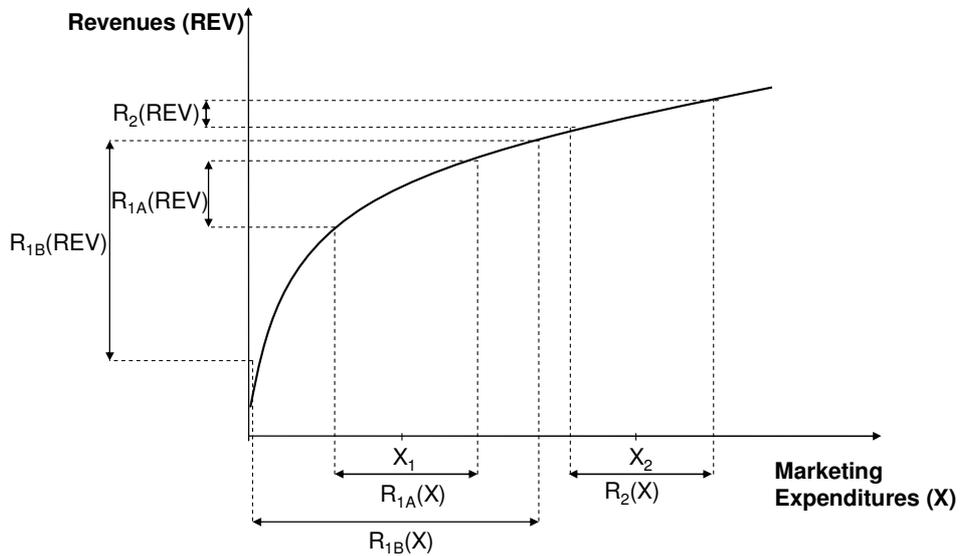
Notes: Standard errors in parentheses. One-sided t-test applied to unidirectional hypotheses, two-sided t-tests otherwise.

*** p < .01; ** p < .05; * p < .10

¹⁾ Level of marketing expenditures was divided by the mean level of unit sales for a brand to account for brand size effects.

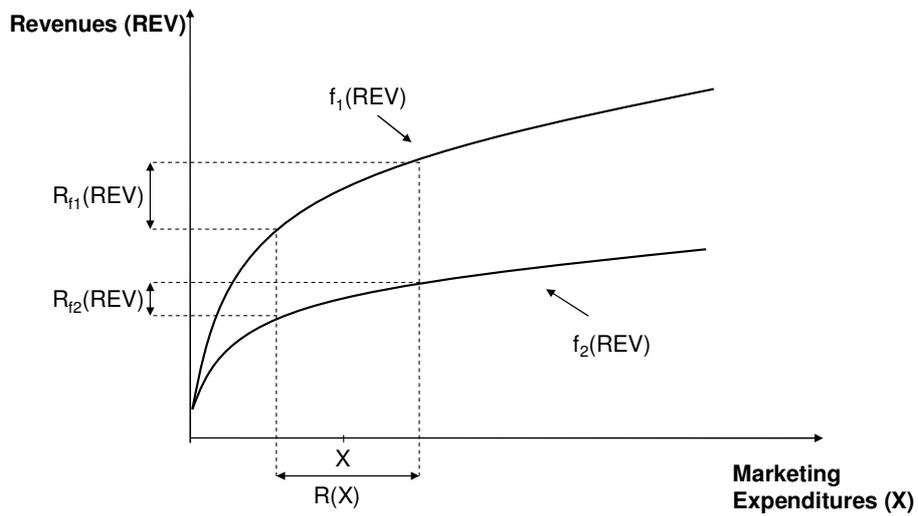
²⁾ Multiplied by 1,000 for reading convenience.

Figure 1 Effects of volatility and level of marketing expenditures on revenue volatility



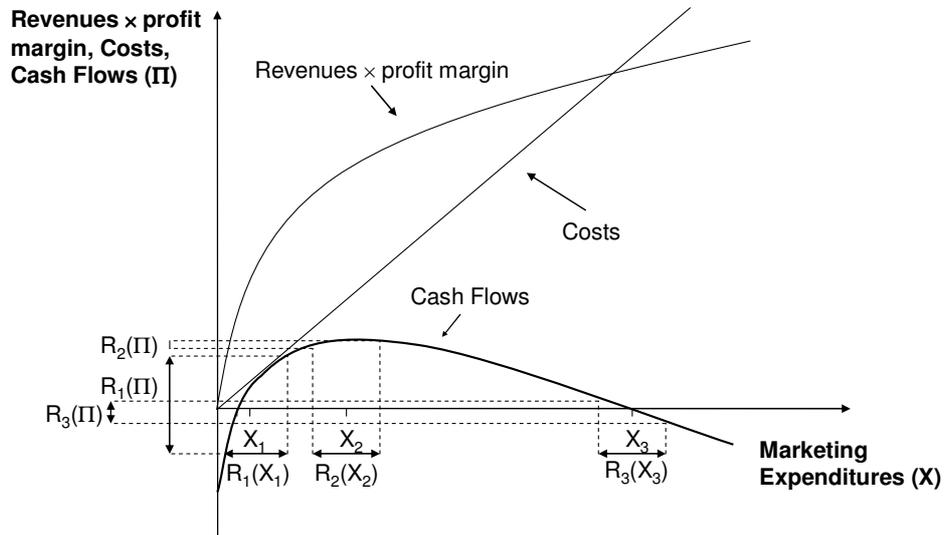
Notes: $R(\text{REV})$ = Range of revenues; $R(X)$ = Range of marketing expenditures
Range is measured as difference between maximum and minimum value.

Figure 2 Effects of marketing responsiveness on revenue volatility



Notes: $R(\text{REV})$ = Range of revenues; $R(X)$ = Range of marketing expenditures; $f(\text{REV})$ = Revenue function
Range is measured as difference between maximum and minimum value.

Figure 3 Effects of volatility and level of marketing expenditures on cash flow volatility



Notes: $R(\Pi)$ = Range of cash flows; $R(X)$ = Range of marketing expenditures
 Range is measured as difference between maximum and minimum value.
 Costs include marketing expenditures

Figure 4 Tradeoff-Matrix

Impact of marketing spending volatility on level of cash flows (differential stimulus effect)

		Low	High
Degree of marketing spending volatility	Low	Do not change policy!	Check if effectiveness can be improved by increasing volatility of spending!
	High	Double jeopardy!	Check if higher volatility of spending does pay off!