Marketing Spending and the Volatility of Revenues and Cash Flows

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ABSTRACT

While volatile marketing spending, as opposed to even-level spending, may 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 responsiveness of own marketing spending, and by competitive reactivity. From market response theory, we derive predictions about the influence of these variables on revenue and cash-flow volatility. Based on a broad sample of 99 pharmaceutical brands in four clinical categories and four European countries, the authors test for the empirical relevance of our predictions and assess the magnitude of the different sources of marketing-induced performance volatility.

The authors find broad support for the expected volatility effects. The results suggest that volatile marketing spending may incur negative financial side effects such as greater financing costs or higher opportunity costs of cash holdings. Thus common volatility-increasing marketing practices such as advertising pulsing may be effective at the top-line, but could turn out to be ineffective after all costs are taken into account.

Keywords: Revenue/Cash-Flow Volatility, Marketing Volatility, Econometric Models, Marketing Metrics

In order to be effective, marketing executives often deploy their resources in spending bursts, i.e. regimes characterized by on-again, off-again marketing actions, including advertising campaigns, sales promotions and new-product launches. Inasfar as such *pulsing* causes revenues and cash flows to become more volatile, it may have an unintended negative consequence on their firms' financial performance. Indeed, senior executives dislike cash-flow volatility since it increases investors' perceived uncertainty about future cash flows, incurs additional financing costs for the firm and, accordingly, hurts firm value. Top executives report that they are actively involved in earnings management in order to diminish cash-flow volatility, and are even willing to sacrifice real economic gains (Graham, Harvey, and Rajgopal 2005).

Such revenue or cash-flow volatility has traditionally not been of major concern to marketers. However, as marketing moves away from a sole focus on customer-demand impact to a focus on firm-value impact (e.g., Rust et al. 2004; Srinivasan and Hanssens 2009), it adopts an investor perspective, which includes a strong concern about the stability of revenues and cash flows. Marketing spending may indeed be a key source of revenue and cash-flow volatility, which is controllable by the company. For example, Rao and Bharadwaj (2008) show analytically that marketing actions can affect the probability distribution of sales as well as the cash requirements, which in turn influences the distribution of cash flows. Using a single-period model, they argue that the shareholders' wealth of the firm can be influenced by such actions.

Marketing actions that are routinely carried out by brand managers potentially generate performance volatility. Specifically, how brand managers allocate marketing spending over time may affect cash-flow volatility because it impacts the volatility of brand revenues as well as that of costs. Following the pulsing argument, marketing managers may increase marketing spending volatility to improve brand sales, but it may also increase revenue and cash-flow volatility. As long as they are not aware of the potential negative financial effects of such policy, they have no incentive to reduce spending volatility and the resulting cash-flow volatility. Thus, there may be a potential conflict between sales maximization and stable cash-flow generation.

In theory, a multi-division firm can diversify its marketing-induced volatility away by strategically coordinating marketing activities across brands and/or regional markets. For example, a beverage manufacturer could ensure that a major campaign for its ice-tea brand does not coincide with another campaign for its bottled-water brand. In practice, however, such coordination is unlikely to occur, because individual brands are treated as profit centers, and regional markets often decide on their own budget allocations. Take, for example, a global consumer packaged goods (CPG) company that markets 100 brands in 50 countries (comparable to P&G) and sets advertising budgets for each quarter of the fiscal year. This requires to coordinate 20,000 spending decisions (100×50×4) per year – obviously a challenging task. In fact, an analysis of inter-brand expenditure correlation of manufacturers of our data sample suggests that expenditures are *not* coordinated across brands, business unit, or regions (see the Appendix A for details). In conclusion, marketing resource allocation at the brand level cannot easily be managed so as to dampen marketing-induced revenue and cash-flow volatility. It is therefore important to study the *drivers* and *consequences* of this *volatility* at the *brand level,* which is the primary focus of this study. Specifically, this paper addresses three important, yet unanswered questions:

- Can we make reasonable predictions about how marketing spending affects the volatility of revenues and cash flows based on market response theory?
- Do we find these effects in practice and how large are they?
- What are the implications for managerial decision making?

We will approach these questions as follows. First, we use market response theory to derive the volatility effects of marketing spending. Specifically, we consider the *level* and the *volatility* of marketing spending –as well as the customer *responsiveness* to marketing spending as important drivers of revenue and cash-flow volatility. In addition, we derive results on the impact of competitor behavior on volatility. Second, we use a database of 99 pharmaceutical brands from four European countries to test for the expected effects and measure the magnitude of the impact of the various volatility drivers. Third, based on the insights from the conceptual and empirical analysis, we offer recommendations for managers to improve their marketing decisions.

The remainder of the article is organized as follows. Following a brief literature review, we develop predictions about the effects of marketing spending on revenue and cash-flow volatility. Next we describe our research methodology to measure the predicted effects. We then present empirical results 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.

Prior Research on Marketing-Related Volatility Effects

Many marketers believe in the effectiveness of a *pulsing* strategy, which implies an uneven distribution of expenditures over time. 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 studies have shown that pulsing is a superior strategy that leads to higher revenues and cash flows, provided that market response is subject to threshold effects (e.g., S-shaped response) or differential stimulus effects (e.g., Sasieni 1971;

Simon 1982; Dubé, Hitsch, and Manchanda 2005). Hence, both marketing theory and practice suggest that marketing managers use pulsing tactics in order to increase revenues and cash flows. However, these tactics may also increase volatility in revenues and cash flows, and thus, create additional financing costs to the firm. In addition to the *level* of cash flows, which has been the focus in pulsing studies so far, their *distribution* is also relevant because it determines how much capital must be mobilized over time to finance a specific pulsing strategy. In the Appendix B, we present an example that illustrates the additional financial burden that may arise from a pulsing strategy. The implications for shareholders' wealth from volatile marketing expenditures are also analyzed by Rao and Bharadwaj (2008).

Only a few empirical studies have addressed the relationship between marketing and revenue/cash-flow volatility to date. Raju (1992) examines the drivers of category sales variability and finds that the magnitude of discounts is positively associated with sales volatility whereas frequency is negatively correlated. By adopting an EGARCH approach, Vakratsas (2007) shows that marketing-mix variables including price, advertising, and distribution affect market-share volatility via the error term. Gruca and Rego (2005) analyze the impact of satisfaction on cash-flow volatility at the firm level, 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).

While these prior studies provide valuable insights, they do not address the volatility impact on *brand* revenues and cash flows coming from marketing spending *level*, spending *variation* and sales *responsiveness*. Such a focus is more actionable for marketing managers, but still offers a close link to the company's financial performance.

Marketing-Induced Volatility Effects

We start the discussion of volatility effects with the impact of marketing spending behavior on the volatility of revenues, followed by its effects on the volatility of cash flows. We do this, in turn for a single-firm marketing scenario and for a scenario with competitive actions. Our general argument is that the volatility, the average level and the sales responsiveness of marketing expenditures together affect the volatility of revenues and cash flows.[1]

Market Response Theory

Our conceptual development is rooted in market response theory, as knowledge of the market response function is important for determining optimal marketing budgets (e.g., Dorfman and Steiner 1954). We assume that (aggregated) brand sales follow a concave relationship with marketing expenditures. By varying conditions such as responsiveness to marketing, we derive predictions about our focal volatility variables. Some of these predictions are straightforward, while others are not.

The assumption of a concave response function is justified for several reasons. First, it is theoretically attractive because it allows for diminishing returns which are a prerequisite for marketing budget optimization. Second, it is by far the most frequent type of response function encountered in empirical research.[2] In contrast, empirical evidence for S-shaped aggregate response functions or response functions with differential stimulus variables is rather weak (Hanssens, Parsons, and Schultz 2001, pp. 106-109). Since we also do not find evidence for these response types but for a log-log response model in our data, our assumption is consistent with the later empirical analysis. Finally, the results may be generalized to S-shaped and differential stimulus response. Assuming rational behavior, budgets vary within the concave part of these functions.

Marketing responsiveness is measured by the slope parameter of the response function. It recognizes changing returns to scale and relates actual input (marketing expenditures) in a realistic and straightforward way to actual output (sales). In addition, it is an important parameter for the derivation of optimal marketing budgets (e.g., Dorfman and Steiner 1954) and may easily be converted to elasticity measures that are comparable across units of analysis.

We consider two measures of volatility: the *range* (i.e. the difference between maximum and minimum values) and the *variance* of marketing expenditures, revenues, and cash flows. Variance is a common measure of variability. Range is a useful metric as well (Alizadeh, Brandt, and Diebold 2002), especially in our brand-level context. Indeed, when managers decide about the temporal distribution of a given marketing budget, they need to determine the extreme points, i.e. when and at what level to set the highest and the lowest spending. We will use a graphical analysis on the range measure to derive volatility effects. For variance, we derive the predictions mathematically. Details are provided in the Appendix C.

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). 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 $R_{1B}(X)$ is twice as large as $R_{1A}(X)$. On the ordinate, $R_{1A}(REV)$ and $R_{1B}(REV)$ reflect the ranges of revenues associated with these two conditions. Our first prediction follows directly from Figure 1: Ceteris paribus, a higher volatility of spending translates into a higher volatility of revenues (*prediction I)*.

=== Insert 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}(REV) and R_2(REV) are the corresponding ranges of revenues. We conclude that, ceteris paribus, the volatility of revenues decreases with a higher mean level of marketing expenditures (*prediction II*). The predicted effect of a higher mean spending applies to both a change in spending level for one brand over time (Figure 1 illustrates this case) as well as across brands. Empirically, we expect the effect to come out stronger from a cross-sectional analysis because the cross-sectional variance in spending levels is likely to be higher than the variance over time. In addition, brand differences in spending levels contribute to differences in brand equity and brand loyalty that impact volatility (McAlister, Srinivasan, and Kim 2007; Rego, Billet, and Morgan 2009).

Finally, we consider the effect of higher marketing *responsiveness* 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(REV). Figure 2 shows that, the more responsive the market is to marketing spending (i.e. f_1 is steeper than f_2) the wider the range of revenue realizations. Hence, ceteris paribus, higher marketing responsiveness turns into a larger volatility of revenues (*prediction III*).

=== Insert Figure 2 about here ===

Effects on Cash-Flow Volatility. The results on revenue volatility cannot be automatically applied 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 gross margin ratio) and marketing costs.[3] 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 (marketing budget) function. These properties may lead to results that are different from 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 do not demonstrate this straightforward effect in Figure 3. The corresponding prediction is: Ceteris paribus, a larger volatility of marketing spending translates into a larger volatility of cash flows (*prediction IV)*.

=== Insert 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 inflexion point of the U-shaped curve lies behind the optimal level of spending.[4] 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 inflexion point to be rather far behind the optimal spending level for many brands. The following prediction reflects our argumentation: Ceteris paribus, the volatility of cash flows follows a U-shape with higher levels of marketing expenditures (*prediction V)*.

Finally, higher marketing responsiveness should also lead to a higher volatility of cash flows. This prediction, however, assumes that the average spending level is smaller or equal to the optimal spending level. Under this assumption, the difference between incremental revenues and marketing costs is larger for higher responsiveness making the cash-flow function steeper. The situation reverses for budgets larger than the optimal level when incremental return is negative. Since marketing costs stay the same but incremental revenues are higher due to higher responsiveness the cash-flow function is less steep. Hence, ceteris paribus, higher marketing responsiveness turns into a larger volatility of cash flows, provided the mean level of marketing expenditures does not exceed the optimal level. In our empirical analysis, we expect the effect to be positive because it is unlikely that firms permanently operate in the loss part of the cash-flow function (*prediction VI*).

Our predictions so far are derived from a scenario without competitors (or at least without competitive reactions). We now extend these volatility predictions to account for the impact of competitive actions.

Impact of Competition

Consistent with economic theory, we assume that firms are profit maximizers and interact with each other. Depending on the number of competitors, the time horizon, the level of information (i.e. the observability of competitive behavior) and the type of competitive interaction (e.g., Nash behavior), an equilibrium in marketing variables such as price or advertising may exist. We do not have evidence that firms engage in expenditure volatility games, in which they set their spending volatility in function of the volatility decisions of their competitors. In fact, it is not clear that firms even observe the volatility in marketing spending of their competitors in advance. Thus, we assume that marketing spending volatility is a result of budget setting behavior, not volatility setting behavior under competitive conditions.

In the following, we study the impact of competitors' marketing spending on the volatility of the focal brand's revenues and cash flows. We do not assume a specific competitive game but rather adopt a reduced-form view that studies observed marketing budgets as a result of competitive interaction. We discuss the effects of competitors' marketing expenditure volatility and the focal firm's reaction behavior on the volatility of its revenues and cash flows. Again, predictions are derived under the assumption that the effects of other variables such as market trend, own marketing mix volatility, etc. are held constant. We do not consider the mean level of competitive spending as a driver of volatility, for lack of a clear understanding how this relates to the volatility of market response for the focal firm. We also do not discuss the effect of a brand's demand responsiveness to competitive activities on the focal volatility variables, because its variation in our dataset is too low to conduct a powerful test of this effect.

Competitive-expenditure volatility. The effect of competitive marketing on own brand sales (cross-effect) may be implicitly embedded in the demand function, such as in market-share attraction models, or it can be made explicit by including competitor variables among the predictors. If brand sales is the dependent variable, the cross-effect of competitive expenditures 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:

Ceteris paribus, a larger volatility of competitive marketing expenditures leads to a larger volatility of own revenues and cash flows (*prediction VII*). 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.

Competitive-reaction behavior. 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/her spending behavior with that of his/her competitors, which induces a positive correlation between the expenditures. In reality, reaction occurs with a certain time lag that may lead to divergent correlation structures. With quarterly data as ours, however, this effect vanishes and we should observe a positive correlation if expenditures are synchronized. The effectiveness of the competitive 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 expect that a higher correlation between own and competitive marketing expenditures reduces 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. We conclude: Given a *negative* cross-effect of competitive marketing expenditures, a higher correlation between own and competitive marketing expenditures *reduces* the volatility of own revenues and cash flows. Given a *positive* cross-effect of competitive marketing expenditures, a higher correlation between own and competitive marketing expenditures *increases* the volatility of own revenues and cash flows (*prediction VIII*).

In case (2), a negative correlation between own and competitive expenditures results from counter-cyclical spending relative to competition. This does not alter our prediction about the effect of our correlation variable. 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 1 summarizes our predictions that we now test with a large dataset from the pharmaceutical industry.

=== Insert Table 1 about here ===

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 Health, 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), revenues, and aggregate marketing expenditures on detailing, journal advertising and other communications media. Detailing has the lion's share in expenditures with more than 90%. 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 sixteen product markets (4 categories × 4 countries). We analyze data on 99 brands, which were marketed by 26 pharmaceutical firms.

Table 2 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 2. Volatility is particularly high with respect to marketing spending. Moving variance is about $151.1 million (or $0.4 million in terms of standard deviation) and 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. This volatility also translates into substantial volatility at the portfolio level (see the Appendix A, Table A.1 again).

=== Insert Table 2 about here ===

METHODOLOGY

The empirical testing of the expected 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. We also test whether market response is subject to threshold or differential stimulus effects that would justify pulsing as an optimal spending strategy. This market response model provides us with brand-specific estimates of marketing responsiveness. In a second step, these responsiveness estimates are used as predictor variables in a model that explains differences in volatility of revenues and cash flows (*volatility models*).[5] 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. Brand expenditures are not subject to trend or seasonality as specification tests revealed.

Market Response Model

We apply the multiplicative interaction model, a standard response model, to explain brand unit sales. This functional form has received large empirical support, has been found useful in normative applications, and incorporates interaction effects in a parsimonious way (e.g., Hanssens, Parsons, and Schultz 2001). To allow for pulsing as a superior strategy we augment the model with a differential-stimulus effect (Simon 1982) that captures any extra demand lift due to pulsing (see the Appendix D for the exact specification).

We include variables that are relevant to the international markets over the ten-year sample period. Specifically, the response model incorporates own and competitive marketing expenditures on detailing, professional journal advertising, and direct marketing, including lagged effects. More than 90% of expenditures are allocated to detailing. We account for brand heterogeneity in demand, e.g., quality, brand equity, order of entry, by estimating brand-specific fixed effects. The model further includes three types of covariates, i.e., seasonal dummies, a trend variable (elapsed time since launch of a brand) to control for life-cycle effects, and a country's gross domestic product (GDP) as a proxy of the overall economic condition of a country. *Distribution* and *price are not relevant* variables in our context. In the European countries covered by our data, pharmacies are required to list every approved drug, resulting in 100% distribution for the drugs in our sample. Prices were highly regulated during the observation period and therefore not used as a tactical marketing instrument. Details on model estimation are provided in the Appendix D.

Volatility Models

*Structural Equations***.** Let V(REV) denote the volatility of revenues measured in terms of variance or range, respectively, V(MKT) represent the volatility of own marketing expenditures, A(MKT) be the average level of own marketing expenditures, V(CMKT) denote the volatility of competitive marketing expenditures, CORR represent the correlation between own and competitive marketing expenditures, RESP denote total marketing responsiveness (including lagged and current effects), **X** denote a vector including the remaining variables of the brand sales model as specified in Equation (A.11) in the Appendix D (i.e., brand-fixed effects to control for order of entry, quality, etc., trend, seasonality, and GDP as surrogate for general demand), $\boldsymbol{\gamma}$ 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:

$$V(REV) = \gamma_0 V(MKT)^{\gamma_1} A(MKT)^{\gamma_2} V(CMKT)^{\gamma_3} Exp(\gamma_4 CORR + \gamma_5 RESP + \mathbf{X}\boldsymbol{\gamma} + \nu), \quad \text{with } \nu \sim N(0, \xi). \tag{1}$$

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 market response theory discussion. The correlation between own and competitive marketing expenditures and the estimated marketing responsiveness parameter appear as part of an exponential function because they may become negative.[6] The parameters $\gamma_{1\text{-}3}$ can be directly interpreted as elasticities and facilitate the comparison of volatility drivers. We subsequently describe how we transform the dataset to remove the X-variables, which are not the focus in this study.

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

$$V(CF) = \delta_0 V(REV)^{\delta_1} V(MKT)^{\delta_2} A(MKT)^{\delta_3} \operatorname{Exp}\left[\delta_4 A(MKT) + \upsilon\right], \quad \text{with } \upsilon \sim N(0,\psi), \tag{2}$$

where V(CF) denotes the volatility of cash flows, **δ** is a parameter vector to be estimated, and υ represents an error term with variance ψ. The effects of competitive-marketing-expenditure volatility, competitive reaction, marketing responsiveness, and X-variables 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 (2) allows for a U-shaped influence of the level of marketing expenditures on cash-flow volatility, consistent with our prediction V. 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 seasonality, 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.[7]

The volatility of the adjusted revenues and cash flows is measured by the variance or 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 volatility measure 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 volatility measures of adjusted revenues and cash flows (moving-window analysis). This procedure is also applied to compute moving volatilities for own and competitive marketing expenditures and the moving average of own marketing expenditures. We denote moving volatilities with MV and moving averages with MA.

The application of moving-window analysis is well established in the accounting literature (e.g., Kothari 2001) and is 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.

Estimation Equations. The use of moving windows is helpful to increase the power of statistical tests due to the increase in degrees of freedom, but it is also likely to generate serially correlated errors in the time series of adjusted revenues and cash flows. We therefore transform expressions (1) and (2) into a series of relative differences. By taking the total differentials of the log-transformed equations (1) and (2), we obtain (see the Appendix E for details):

$$\frac{\Delta MV(AREV)_{ikst}}{MV(AREV)_{ikst-1}} = \gamma_1 \frac{\Delta MV(MKT)_{ikst}}{MV(MKT)_{ikst-1}} + \gamma_2 \frac{\Delta MA(MKT)_{ikst}}{MA(MKT)_{ikst-1}} + \gamma_3 \frac{\Delta MV(CMKT)_{ikst}}{MV(CMKT)_{ikst-1}} + \gamma_4 \Delta MA(CORR)_{ikst} + \Delta \nu_{ikst}, \quad (3)$$

$$\frac{\Delta MV(ACF)_{ikst}}{MV(ACF)_{ikst-1}} = \delta_1 \frac{\Delta MV(AREV)_{ikst}}{MV(AREV)_{ikst-1}} + \delta_2 \frac{\Delta MV(MKT)_{ikst}}{MV(MKT)_{ikst-1}} + \delta_3 \frac{\Delta MA(MKT)_{ikst}}{MA(MKT)_{ikst-1}} + \delta_4 \Delta MA(MKT)_{ikst} + \Delta \upsilon_{ikst}, \quad (4)$$

where,

$MV(AREV)_{ikst}$	=	Moving volatility of adjusted revenues of brand i in therapeutic area k, country s and period t
$MV(MKT)_{ikst}$	=	Moving volatility 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
$MV(CMKT)_{ikst}$	=	Moving volatility 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.
$MV(ACF)_{ikst}$	=	Moving volatility of adjusted cash flows of brand i in therapeutic area k, country s and period t
Δ	=	First-difference operator.

Equations (3) and (4) represent the original equations (1) and (2) in terms of relative differences. Unlike absolute differences, this representation not only reduces serial correlation, 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.

Equations (3) and (4) establish an equation system with possibly correlated errors across equations. Revenue volatility is the only endogenous variable occurring at the right hand side of Equation (4). Thus, the system is recursive and Generalized Least Squares (GLS) provides efficient estimates (Zellner 1962). Since first-differencing may not completely remove serial correlation we also allow for equation-specific autocorrelation coefficients in the variance-covariance matrix.

The first-differencing procedure eliminates the time-invariant marketing responsiveness variable that is part of the revenue volatility model (1).[8] To measure its influence, we linearize (1) 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 Ordinary Least Squares (OLS). However, the marketing-responsiveness parameters of the first stage are measured with sampling error that vanishes in the limit. As a consequence, OLS estimates from the second stage regression will be consistent but their standard errors may be biased (Murphy and Topel 1985). Following Nijs, Srinivasan, and Pauwels (2007), we obtain corrected standard errors by a bootstrapping procedure with 10,000 replications.

RESULTS

Brand Sales Model

We estimate the multiplicative brand sales model with and without the differential stimulus (DS) effect (see Equation A.11 in the Appendix D again). The DS-effect is insignificant in all markets where estimation was feasible, and information criteria such as the Schwartz Information Criterion (SC) disfavor the models with DS-effect. Alternatively, we estimate an S-shaped response model (details are available from the authors). This specification also turned out to be inferior compared to the standard log-log model. Hence, we conclude that market response follows a diminishing-returns pattern in the analyzed markets, which does not justify a pulsing policy. All following results are thus based on the log-log model without DS-effect.

The multiplicative brand sales model describes sales evolution in the markets very well. The average total marketing elasticity, weighted by relative standard errors to account for estimation uncertainty, is .192, which is well in line with recently reported results (e.g., Fischer and Albers 2009). 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 use as a predictor in our volatility models. Recall that we use the total effect which is the sum of current and lagged marketing elasticity.

Volatility Models

Table 3 shows the estimation results for the revenue and cash-flow volatility models by using either (adjusted) variance or range as dependent variable. Our focal predictor variables explain a substantial part of variance in observed (i.e. unadjusted) revenue and cash-flow volatility in estimation and holdout samples underlining the relevance of marketing activities for performance volatility. To form holdout samples we excluded the last four quarters (20% of total cases) in the first-difference models and the last 20 brands (20% of cases) in the cross-sectional model.

=== Insert Table 3 about here ===

In the following discussion we focus on variance as volatility measure and on the results from first-difference models. Since the effect of marketing responsiveness, which does not vary within but across brands, can only be estimated by a cross-sectional model we also report on the results of the cross-sectional regression model. 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.

We discuss first estimates from the revenue volatility model and then turn to the cash-flow volatility model. The volatility of marketing expenditures measured by their variance increases the volatility of revenues and supports our first prediction, with an estimated elasticity of .273 ($p<.05$).[9]

The first-difference model also supports our second prediction on the influence of the level of marketing expenditures on revenue volatility; but the coefficient is not significant at $p<.05$. We obtain a significant negative effect from the cross-sectional regression (-1.99, $p<.05$). Note that this variable has been divided by average brand unit sales in order to control for brand-size effects. As expected, the effect comes out stronger in a pure cross-sectional regression.

Marketing responsiveness drives revenue volatility (8.11, $p<.05$), supporting our third prediction. The associated elasticity of .811 ($=8.11\times.10$) is substantial. We do not find significant effects ($p>.05$) for the volatility of competitive marketing expenditures in the first-difference regression and the cross-sectional regression. The correlation of own and competitive marketing expenditures shows a significant negative effect on revenue volatility (-.262, $p<.05$). Since the effect of competition is predominantly substitutive in our data, the sign of the effect is consistent with our expectation.

As expected, revenue volatility is an important driver of cash-flow volatility, with an elasticity of 1.36 ($p<.05$). Its lower boundary value is the squared profit margin, 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 .535 ($p<.05$). This coefficient represents the volatility effect due to the cost component of marketing expenditures. In order to fully evaluate the predicted effect of expenditure volatility on cash-flow volatility, we need to consider the total effect.

Table 4 displays the total effects in terms of elasticity, which facilitates the interpretation and comparison of the magnitude of effects. The total effect of expenditure volatility on cash-flow volatility amounts to .906 ($=1.36\times.273+.535$; $p<.05$). Hence, we find strong support for our fourth prediction. Interestingly, this elasticity is more than three times higher than for revenue volatility. We also find strong support for the expected U-shaped influence of the level of marketing expenditures on cash flows (-2.38, p<.05 and .003, p<.05; see table 4). The direction of the influence of marketing responsiveness on cash-flow volatility is also consistent with our prediction. Its elasticity is high with a value of 1.10 (p<.05). The volatility effect of the volatility of competitive marketing expenditures is not significant, which may be due to the fact that the estimated cross-effects are rather small and not uniform in sign across all categories. We find, however, support for the expected cash-flow volatility effect of the correlation of own and competitive marketing expenditures though the associated elasticity is small (-.003; p<.05).

=== Insert Table 4 about here ===

Both tables 3 and 4 show also the results for models when we take range instead of variance as volatility measure. Overall, the results are consistent with the results using variance as volatility measure.

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 were similar but model fit deteriorated, underlining that the 8-quarter window is the best choice for our dataset. Second, we created volatility variables that do not overlap over time periods. For example, the first observation of an 8-quarter-based variance 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 only 292 observations. The results did not change materially, though the standard errors increased. Third, we estimated a linear model and a semi-log model in addition to the already reported brand slaes models. The results of the Davidson-McKinnon comparative test (Greene 2004) support our log-

log specification. Fourth, we verified whether 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 study provides insights that invite marketing decision makers to think differently about the consequences of their actions. First, our results show 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, product launches 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, their impact on cash-flow volatility is larger than on revenue volatility. Second, stronger 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/her expenditures produce higher returns. On the other hand, higher responsiveness has a dark side since it makes revenues and cash flows more volatile, even if spending volatility itself does not change. Third, we find that a higher mean 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. That level is *greater* than the optimal spending level.

Some marketing tactics, such as advertising campaigns, are used frequently and involve a volatile deployment of the marketing budget. Sometimes these tactics improve a brand's top-line results, sometimes they do not, but in either case, we expect them to have an effect on the volatility of both revenues and cash flows, as our conceptual and empirical analysis suggest.

Since volatility incurs additional financial costs, even revenue-effective volatile marketing tactics may turn out to be harmful to the bottom line. This creates a managerial tradeoff, as illustrated in Figure 4. The matrix provides brand managers with a means to evaluate their marketing policy. If the effect of marketing volatility on the level of revenues/cash flows is small or non-existent, there is no need to increase marketing volatility, and in fact it should be avoided. If the effect on sales is high, managers need to find the right balance between that positive impact and its negative financial side effect.

=== Insert Figure 4 about here ===

The volatility of brand expenditures in our data was quite high. In particular, we observed several new brand entries for which firms adopted highly volatile spending behavior in the first two years after launch, a time when marketing spending often exceeds brand revenue. In contrast to that, we do not find evidence for a market response that justifies pulsing. As a consequence, managers are in the "double jeopardy" scenario of Figure 4; and there is no economic reason to deploy volatile marketing tactics as it only adds financing costs to the losses that are already being incurred.[10] For the newly introduced brands in our observation period (61 brands out of 99), we estimate these costs to amount to US$ 5.1 million on average (median = 1.8 million) in the first two years after launch.

Similarly, different brands have different levels of marketing spending and our results show that those with higher spending *levels* enjoy protection against performance volatility, especially cash-flow volatility, so long as their expenditures are economically reasonable, i.e. they are not too far beyond the Dorfman-Steiner optimal levels. On the other hand, higher spending *quality* (as assessed by responsiveness) comes at a cost of increased performance volatility in connection with volatile spending behavior, and in that sense good marketing and stable business performance are difficult to reconcile.

Research Implications

Our findings 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; Rao and Bharadwaj 2008) has focused on marketing's potential to *reduce* volatility and its associated financial side effects at the firm level, 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 responsiveness 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 a sizeable effect on revenue volatility, and its effect on cash-flow volatility is even higher. Marketing 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 is similar to the firm-level finding of McAlister, Srinivasan, and Kim (2007) that marketing spending reduces the systematic risk of the firm. Thus while generous marketing spending may be favorable for the firm in the long run, at the same time, allocating these budgets across brands in a pulsing pattern may be less favorable.

Revenue and cash-flow volatility may also arise from other marketing-mix activities such as promotions and new-product introductions. The extant promotion literature shows that promotions lead to higher revenues, at least in the short run (e.g., Blattberg, Briesch, and Fox

1995). Even though the long-term consequences of promotion activities may not be beneficial to the firm's bottom line, this marketing tactic is heavily used by CPG companies and retailers because of its immediate impact on revenues (e.g. Srinivasan et al. 2004). In addition, the financial benefits of new-product introductions have been acknowledged (e.g., Pauwels et al. 2004). For example, Sorescu and Spanjol (2008) report that the average CPG company in their sample introduced 237 new products during the period 1985-2003. Typically, these new-product introductions are not evenly distributed across the year, possibly causing performance volatility.

Limitations and Future Research

Our research is subject to limitations that may stimulate future research. First, we have quantified the magnitude of volatility drivers in eight prescription-drug markets. 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, multi-divisional firms may be able to manage volatility across their portfolio of products, at least in principle. Even though full diversification is unlikely to be achievable for firms with many allocation units, future research should investigate to what extent individual marketing plans can be adjusted across products and regions so as to maintain an acceptable level of cash-flow volatility at the corporate level. Finally, we discussed the cost-benefit trade-off 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.

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TABLE 1

Summary of Expected Effects

	Expected effect on the … *Volatility of Revenues*		*Volatility of Cash flows*	
Volatility of own marketing expenditures	Increase	+	Increase	+
Level of own marketing expenditures	Decrease	-	Decrease first, then increase	-/+
Sales responsiveness to own marketing expenditures	Increase	+	Increase[1)]	+
Volatility of competitive marketing expenditures	Increase	+	Increase	+
Correlation between own and competitive marketing expenditures	Decrease for negative cross-effect	-	Decrease for negative cross-effect	-
	Increase for positive cross-effect	+	Increase for positive cross-effect	+

[1)] This prediction assumes that, on average, firms choose spending levels that do not exceed the optimal level. Note that the marginal return turns negative behind the optimal level.

TABLE 2

Descriptive Statistics (Period = Quarter)

Level variables	*Mean*	*Std. dev.*	*Volatility variables*	*Mean*	*Std. dev.*
Unit sales in th. daily dosages	17,817	20,392	Moving variance of adjusted revenues in th. US$	7,524,430	40,764,000
Revenues in th. US$	9,342	10,400	Moving variance of adjusted cash flows in th. US$	3,310,330	17,186,000
Cash flows in th. US$	5,022	6,385	Moving variance of marketing expenditures in th. US$	151,134	347,868
Marketing expenditures in th. US$	1,053	872	Moving variance of competitive marketing expenditures in th. US$	2,300,460	2,525,510
Competitive marketing expenditures in th. US$	5,008	3,390	Moving range of adjusted revenues in th. US$	3,754	6,749
Moving average of marketing expenditures in th. US$	960	732	Moving range of adjusted cash flows in th. US$	2,692	4,383
Moving average correlation between own and competitive marketing expenditures	0.35	0.40	Moving range of marketing expenditures in th. US$	854	756
			Moving range of competitive marketing expenditures in th. US$	3,675	2,322

Notes: All variables before log-transformation that is used in estimation. All values in 1996 dollars deflated by country-specific consumption price index.

TABLE 3

Estimation Results for the Volatility Models

	Expected sign	*Revenue volatility* First-difference model: Variance	Range	*Revenue volatility* Cross-sectional model: Variance	Range	*Cash-flow volatility* First-difference model: Variance	Range
Constant		-		-11.120 (9.70)	-6.537 (4.883)	-	
Volatility of revenues	+	-		-		1.359 (.029)***	1.155 (.018)***
Volatility of marketing expenditures	+	.273 (.024)***	.101 (.024)***	1.926 (.699)***	2.214 (.819)***	.535 (.032)***	.227 (.023)***
Level of marketing expenditures	-	-.245 (.237)	.139 (.076)	-1.988[1] (.665)***	-1.008[1] (.327)***	-2.042 (.369)***	-.307 (.079)***
Exp(Level of marketing expenditures)	+	-		-		.003 (.001)***	.001 (.000)***
Volatility of competitive marketing expenditures	+	-.006 (.023)	.018 (.020)	-.222 (.143)	-.449 (.285)	-	
Correlation between own and competitive marketing expenditures	+/-	-.262 (.095)***	-.066 (.026)**	-2.337 (3.19)	-1.019 (1.481)	-	
Marketing responsiveness	+	-		8.110 (4.75)**	3.974 (2.078)**	-	
Variance explained in estimation/holdout samples[2]		.245/.202	.339/.215	.201/.600	.241/.647	.724/.585	.771/.721
Total no. of observations		2,104		99		2,104	

Notes: Standard errors in parentheses. One-sided t-test applies to unidirectional expectations, two-sided t-tests otherwise. *** p < .01; ** p < .05

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

[2] Variance in log-transformed focal volatility variable explained by predictor variables. Estimation sample includes 80%, holdout sample 20% of cases.

TABLE 4

Total Effects in Terms of Elasticity (When Applicable)

	Expected sign	*Revenue Volatility*		*Cash-flow volatility*	
Dependent variable variance					
Variance of marketing expenditures	+	.273	(.024)***	.906	(.070)***
Level of marketing expenditures[1)]	-	-.245	(.237)	-2.375	(.490)***
Exp(Level of marketing expenditures)[1)]	+	-		.003	(.001)***
Marketing responsiveness[2)]	+	.811	(.474)**	1.102	(.645)**
Variance of competitive marketing expenditures	+	-.006	(.023)	-.009	(.031)
Correlation between own and competitive marketing expenditures[2)]	+/-	-.002	(.001)***	-.003	(.001)***
Dependent variable range					
Range of marketing expenditures	+	.101	(.024)***	.344	(.051)***
Level of marketing expenditures[1)]	-	.139	(.076)	-.147	(.118)
Exp(Level of marketing expenditures)[1)]	+			.001	(.000)***
Marketing responsiveness[2)]	+	.397	(.208)**	.459	(.240)**
Range of competitive marketing expenditures	+	.018	(.020)	.021	(.023)
Correlation between own and competitive marketing expenditures[2)]	+/-	-.001	(.000)***	-.001	(.000)***

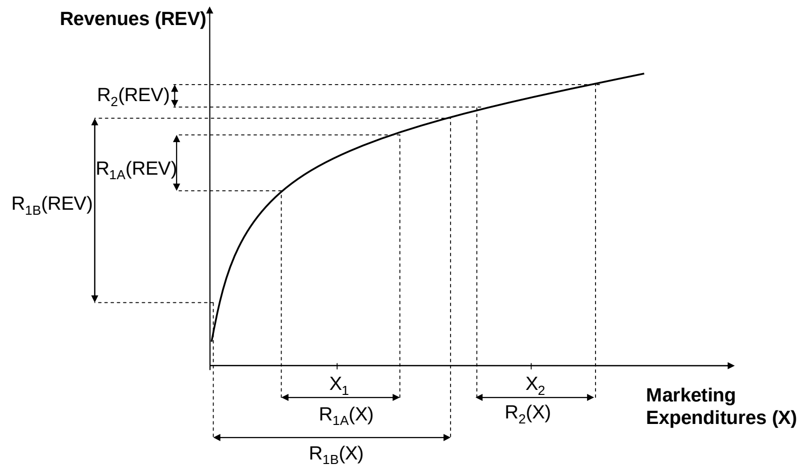
Notes: (Approximated) standard errors in parentheses. Results are based on first difference models except for marketing responsiveness which are based on cross-sectional models. *** $p < .01$; ** $p < .05$

1) Results reflect parameters of a non-monotonic function, not elasticities.

2) Elasticities are not constant and are evaluated at sample means for responsiveness and expenditure correlations, respectively.

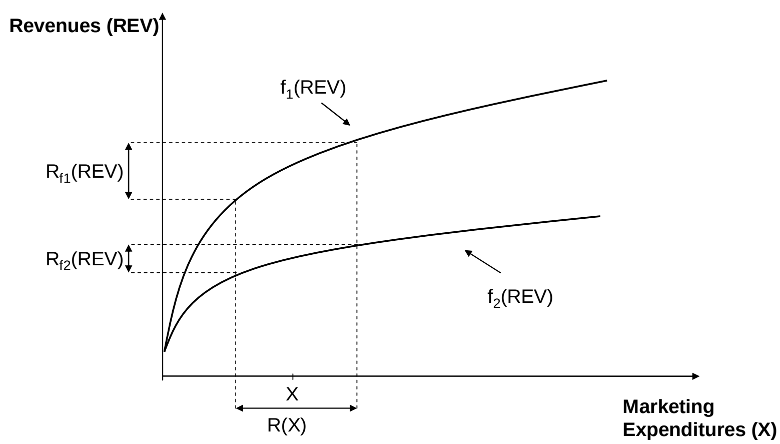
FIGURE 1

Effects of Volatility and Level of Marketing Expenditures on Revenue Volatility



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

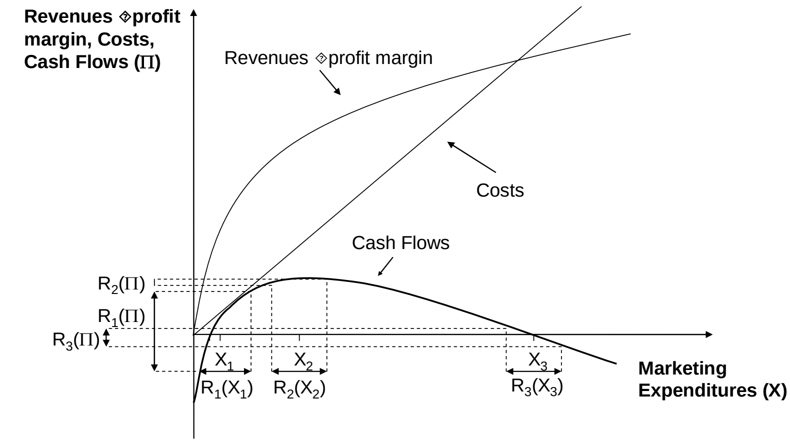
FIGURE 2
Effects of Marketing Responsiveness on Revenue Volatility



Notes: R(REV) = Range of revenues; R(X) = Range of marketing expenditures; f(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(Π) = 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 volatility on level of revenues/cash flows

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

APPENDIXES

Appendix A: Correlation between Brand Expenditures

In theory, a multi-division firm can deploy volatile marketing tactics that do not affect portfolio volatility by strategically coordinating marketing campaigns across brands and regions. In that case, we would expect marketing expenditures to be predominantly negatively correlated. However, given that many firms operate their brands, business units, or regions as profit center, we argue that such strategic coordination is less likely to occur in reality. For example, it may be a conflict to centralize (i.e. coordinate) spending decisions at the portfolio level when individual brand managers or regional managers are held accountable for their decisions. In addition, coordinating expenditures of many spending units in a large portfolio quickly turns out to be a very challenging task.

To investigate whether pharmaceutical firms in our sample are involved in strategic coordination of their brand expenditures we conducted an empirical test on the co-movements of brand expenditures for three multi-brand pharmaceutical firms operating in several country markets. Consistent with our arguments that strategic coordination is not likely to happen, we expect a firm's marketing expenditures across brands or regions to be either uncorrelated or positively correlated (when they move in sync with third factors such as seasonality and overall budget fluctuations). As shown in Table A.1, the intercorrelations are predominantly insignificant or positive, when measured either in levels or in differences. The number of negative intercorrelations is very small, ranging from 0% to 8%, consistent with our anticipation.

=== Insert Table A.1 about here ===

Appendix B: Illustrative Example of Financial Cost of Spending Volatility

This section illustrates the additional financial burden that may arise from a pulsing strategy. Consider a brand manager with a budget of $400,000 to be spent over the fiscal year (see Table A.2). Under even spending we assume s/he invests $100,000 in marketing activities every quarter. Under the alternative pulsing strategy, we assume $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 marketing, i.e. sales do not drop immediately to their base level when expenditures are reduced to zero.

The upper panel of Table A.2 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. The figures are generated by a market response function that accounts for carryover from the last quarter and a differential stimulus effect (similar to specification A.11 in Appendix D). Total marketing spending elasticity is assumed to be .20 and corresponds to our findings for the analyzed markets (see Appendix Table A.3). Consistent with the idea of the differential stimulus effect (Hanssens and Levien 1983; Simon 1982), incremental revenues are higher under pulsing. The last two columns show the incremental cash flows (net revenues minus marketing expenditures). Pulsing generates cash flows that are 5% higher than those from even spending which is at the top of the range of reported gains of 1% to 5% (Dubé, Hitsch, and Manchanda 2005; Mahajan and Muller 1986).

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 A.2.

=== Table A.2 about here ===

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 due to the incremental cash flows generated by marketing in previous periods. 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 in this example if the aim is to maximize shareholder value.

Appendix C: Proof of Predictions I-VI for Variance as Volatility Measure

In this section, we show by formal analysis that our predictions also hold when we measure volatility in terms of variance instead of range. Consistent with our conceptual development, we focus on volatility effects with respect to own marketing expenditures.

Definitions

Let P denote price, C marginal cost, and Q(MKT) unit sales that depends on own marketing expenditures MKT. Revenues, RV, and cash flows, CF, are given by the following expressions:

$$RV(MKT) = P \cdot Q(MKT) \tag{A.1}$$

$$CF(MKT) = (P - C)Q(MKT) - MKT\ . \tag{A.2}$$

Q(MKT) is a nonlinear, twicely differentiable function with Q'(MKT) > 0 and Q''(MKT) < 0. Assuming profit maximization together with response functions (e.g., S-shaped) that suggest pulsing as an optimal strategy implies that firms operate in the concave part of the response function. Hence, our assumptions about Q''(MKT) still hold. Let MKT be a random variable with mean (average spending level), μ, and variance, Var(MKT). Since Q(MKT) is nonlinear we need to approximate its variance (Greene 2004). For this purpose, we use the linear Taylor series approximation and choose μ, without loss of generality, as expansion point:

$$Q(MKT) \cong \left[Q(\mu) - Q'(\mu)\mu\right] + Q'(\mu)MKT\ . \tag{A.3}$$

The variance of Q(MKT) is then given by

$$Var\left[Q(MKT)\right] \cong \left[Q'(\mu)\right]^2 Var(MKT) \tag{A.4}$$

and we can write for the variance of revenues

$$Var\left[RV(MKT)\right] \cong P^2\left[Q'(\mu)\right]^2 Var(MKT) \tag{A.5}$$

and the variance of cash flows

$$Var\left[CF(MKT)\right] \cong \left[(P - C)Q'(\mu) - 1\right]^2 Var(MKT). \tag{A.6}$$

Proofs of Predictions

We derive first predictions with respect to revenues followed by cash flows.

Prediction I: Ceteris paribus, a higher variance of spending translates into a higher variance of revenues.

Proof. Differentiate (A.5) w.r.t. Var(MKT) to obtain $P^2[Q'(\mu)]^2$ wich is always greater than 0.

Prediction II: Ceteris paribus, the variance of revenues decreases with a higher mean level of marketing expenditures.

Proof. Differentiate (A.5) w.r.t. μ

$$\frac{\partial Var\left[RV\left(MKT\right)\right]}{\partial \mu} = 2P^2 Q''\left(\mu\right)Q'\left(\mu\right)Var\left(MKT\right) < 0 .$$

Because Q''(MKT) < 0 and all other terms are > 0 this expression holds.

Prediction III: Ceteris paribus, higher marketing responsiveness turns into a larger variance of revenues.

Proof. Higher responsiveness means that Q'(MKT) is larger. Hence, we differentiate (A.5) w.r.t. Q'(μ) and obtain $2P^2Q'(\mu)$Var(MKT) which is always greater than 0.

Prediction IV: Ceteris paribus, a larger variance of marketing spending translates into a larger variance of cash flows.

Proof. Differentiate (A.6) w.r.t. Var(MKT) to obtain $[(P-C)Q'(\mu)-1]^2$ which is always greater than 0.

Prediction V: Ceteris paribus, the variance of cash flows follows a U-shape with higher mean levels of marketing expenditures

Proof. Differentiate (A.6) w.r.t. μ

$$\frac{\partial Var\left[CF\left(MKT\right)\right]}{\partial \mu} = 2Q''\left(\mu\right)\left[\left(P-C\right)Q'\left(\mu\right)-1\right]Var\left(MKT\right). \tag{A.7}$$

Note, Q'(μ) > 0 but at a decreasing rate. Since Q''(μ) < 0 we have

$$\left.\frac{\partial Var\left[CF\left(MKT\right)\right]}{\partial \mu}\right|_{\mu<\mu^*} < 0, \quad \left.\frac{\partial Var\left[CF\left(MKT\right)\right]}{\partial \mu}\right|_{\mu=\mu^*} = 0, \text{ and } \left.\frac{\partial Var\left[CF\left(MKT\right)\right]}{\partial \mu}\right|_{\mu>\mu^*} > 0, \tag{A.8}$$

where Q'(μ*) = 1/(P-C). Hence, with (A.8) we conclude that the variance of cash flows decreases in μ for μ < μ*, achieves a minimum at μ*, and then increases in μ for μ* > μ.

Prediction VI: Ceteris paribus, higher marketing responsiveness turns into a larger variance of cash flows, provided that the mean expenditure level does not exceed the (Dorfman-Steiner) optimal expenditure level.

Proof. Differentiating (A.6) w.r.t. Q'(μ), we obtain

$$\frac{\partial Var\left[CF\left(MKT\right)\right]}{\partial Q'\left(\mu\right)} = 2\left[\left(P-C\right)Q'\left(\mu\right)-1\right]Var\left(MKT\right). \tag{A.9}$$

Define $\varepsilon_{Q,\mu}=Q'(\varepsilon)\mu/Q$ as marketing elasticity. We can write for (A.9)

$$\frac{\partial Var\left[CF\left(MKT\right)\right]}{\partial Q'\left(\mu\right)} = 2\left[\varepsilon_{Q,\mu}\frac{\left(P-C\right)Q}{\mu}-1\right]Var\left(MKT\right) \tag{A.10}$$

From Dorfman and Steiner (1954), we know that the optimal expenditure level has to satisfy $\varepsilon^*_{Q,\mu} = \frac{\mu^*}{(P-C)Q^*}$. For $\mu<\mu^*$, i.e. the mean expenditure level is lower than the (Dorfman-Steiner) optimal level, the expression in (A.10) is greater than zero. Hence, cash-flow volatility increases in marketing responsiveness.

Appendix D: Brand Sales Model

Specification of Brand Sales Model

The market response model is specified as follows:

$$\begin{aligned} q_{ikst} &= \alpha_{0i} MKT_{ikst}^{\alpha_{1i}} MKT_{ikst-1}^{\alpha_{2i}} CMKT_{ikst}^{\alpha_{3ks}} CMKT_{ikst-1}^{\alpha_{4ks}} GDP_{st}^{\alpha_{5ks}} \left(\prod_{l=6}^{8} \alpha_{l,ks}^{SD_{l,t}}\right) \\ &\cdot DS_{ikst}^{\alpha_{9ks}} Exp\left(\alpha_{10ks} ET_{ikst} + \varepsilon_{ikst}\right), \\ &\text{with } DS_{ikst} = \max\left\{MKT_{ikst} - MKT_{ikst-1}, 1\right\}, \\ &\varepsilon_{ikst} = \rho_1 \varepsilon_{ikst-1} + \rho_2 \varepsilon_{ikst-2} + \mu_{ikst}, \text{ and } \mu_{ikst} \text{ i.i.d. } N\left(0, \sigma_\mu^2\right), \end{aligned} \tag{A.11}$$

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
DS_{ikst}	=	Differential stimulus for brand i in therapeutic area k, country s and 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, σ^2	=	Error terms and variance
ρ_1, ρ_2	=	First and second order autocorrelation coefficients
i	=	1, …, I (number of brands)
k	=	1, …, K (number of therapeutic areas)
s	=	1, …, S (number of countries)
t	=	1, …, T_i (number of observation periods for brand i).

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. 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. The total (long-term) effect on sales in period t is simply the sum of the two effects, i.e., α_{1i} and α_{2i}. We use this measure as marketing responsiveness measure, RESP, in our volatility equations (1) and (3). We account for brand heterogeneity in demand (e.g., quality, brand equity) via brand-specific intercepts, i.e. fixed effect terms.

Estimation of Brand Sales Model

We transform the brand sales equation (A.11) into a log-log specification, construct deviations from the group mean to remove the fixed effects, and estimate the model with generalized least squares. Hence, the effects of order of entry, quality, and other time-invariant variables are implicitly controlled for (e.g., Berndt et al. 1995).

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. In addition, this result implies that the variables are not co-integrated. Consistent with specification (A.11), 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.

We acknowledge that marketing expenditures may be endogenous and therefore apply the Hausman-Wu test (Greene 2004) to check the exogeneity assumption for own and competitive marketing expenditures in each product market. All exogenous variables of Equation (A.11) together with the three and four-period lagged first differences of own and competitive marketing expenditures were used in the first-stage regressions, which always yielded F-values above 10 indicating that our instruments are not weak (Stock, Wright, and Yogo 2002). The lagged difference variables provide the overidentifying restrictions for the Hausman-Wu test (Greene 2004). We do not find any evidence that the exogeneity assumption is violated. Detailed test statistics with respect to the tested time-series properties and exogeneity assumptions are available from the authors upon request.

In table A.3, we provide detailed summary statistics on the estimated total own and competitive marketing elasticities. Standard errors are White-corrected for heteroskedasticity (Greene 2004).

=== Insert Table A.3 about here ===

Appendix E: Derivation of Estimation Equations for Volatility Models

In this section, we derive the estimation equations (3) and (4) from equations (1) and (2). We start with a log transformation of equations (1) and (2):

$$\begin{aligned}\ln R(REV) = \ln\gamma_0 + \gamma_1 \ln R(MKT) + \gamma_2 \ln A(MKT) + \gamma_3 \ln R(CMKT) + \gamma_4 CORR +\\ \gamma_5 RESP + \mathbf{X\gamma} + \nu\end{aligned} \tag{A.12}$$

$$\ln R(CF) = \ln\delta_0 + \delta_1 \ln R(REV) + \delta_2 \ln R(MKT) + \delta_3 \ln A(MKT) + \delta_4 A(MKT) + \upsilon. \tag{A.13}$$

Then we take the total differentials to obtain our estimation equations (3) and (4):

$$\begin{aligned}\frac{1}{R(REV)} dR(REV) = \frac{\gamma_1}{R(MKT)} dR(MKT) + \frac{\gamma_2}{A(MKT)} dA(MKT)\\ + \frac{\gamma_3}{R(CMKT)} dR(CMKT) + \gamma_4 dCORR + \gamma_5 dRESP + \mathbf{dX\gamma} + d\nu.\end{aligned} \tag{A.14}$$

$$\begin{aligned}\frac{1}{R(CF)} dR(CF) = \frac{\delta_1}{R(REV)} dR(REV) + \frac{\delta_2}{R(MKT)} dR(MKT) + \frac{\delta_3}{A(MKT)} dA(MKT)\\ + \delta_4 dA(MKT) + d\upsilon.\end{aligned} \tag{A.15}$$

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APPENDIXES TABLES

TABLE A.1

Correlation Pattern of Marketing Expenditures for Pharmaceutical Firms

		Expenditures in levels			*Expenditures in differences*		
		Significant ($p < .05$)		Insignificant	Significant ($p <.05$)		Insignificant
	No. of products	$\rho < 0$	$\rho > 0$	$\rho = 0$	$\rho < 0$	$\rho > 0$	$\rho = 0$
Firm 1	13	4 (5%)	29 (37%)	45 (58%)	4 (5%)	12 (16%)	62 (79%)
Firm 2	9	3 (8%)	9 (25%)	24 (67%)	0 (0%)	8 (22%)	28 (78%)
Firm 3	7	1 (5%)	3 (14%)	17 (81%)	1 (5%)	2 (10%)	18 (85%)

Notes: Values in cells are counts of bivariate correlations.

TABLE A.2

An Example of the Financial Costs of Spending Volatility

Statement of cash flows (quarterly) in Thousand US$

	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	154	20	-46
Quarter 2	100	0	120	87	20	87
Quarter 3	100	200	120	154	20	-46
Quarter 4	100	0	120	87	20	87
Total	400	400	480	484	80	84
Std. dev.	0	100	0	34	0	66
Range[1)]	0	200	0	67	0	133

Cash balance sheet (quarterly) in Thousand US$

	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	-46	100	200	4	8
Quarter 2	40	42	80	46	3	2
Quarter 3	60	-4	60	158	2	6
Quarter 4	80	84	40	4	1	0
Total			280	408	10	16

[1)] Range = Maximum expenditure – Minimum expenditure

TABLE A.3

Summary Statistics of Estimated Marketing Effects on Brand Sales

	Therapeutic areas		*Total*
	Cardio-vascular	Gastro-intestinal	
Own marketing effectiveness (total effect)			
Mean	.134	.290	.192
Median	.164	.296	.200
SD	.154	.183	.182
Minimum	-.140	-.033	-.140
Maximum	.566	.705	.705
Competitive marketing effectiveness (total effect)			
Mean	-.022	.018	-.007
No. of brands	71	28	99

Notes: Estimates are weighted by their relative standard error to account for estimation uncertainty. For competitive marketing effectiveness, only the mean is reported since a homogenous effect is estimated for each category (in total 4 effects from four clinical categories).

FOOTNOTES

[1] We acknowledge that there are other potential sources of volatility that are either exogenous (e.g., trend, seasonality) or endogenous (e.g., price setting behavior) to the firm. We derive our predictions under the assumption that these other sources are controlled for.

[2] It encompasses, for example, the log-log model and the semi-log model among sales models.

[3] We make abstraction of non-marketing fixed costs, which have no bearing on our analysis.

[4] The inflexion point is approached faster the smaller the volatility of spending and the steeper the curve around the profit maximum. 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.

[5] We subsequently present the econometric specifications of our volatility models. One could also think of just using the calibrated brand sales model to demonstrate and test the proposed volatility effects. Although market response theory represents a sound theoretical foundation, it should be recognized that it is still a simplified reflection of reality. In order to increase the external validity of our findings, we attempt to provide empirical evidence on the existence and magnitude of the proposed effects under real market conditions.

[6] Conceptually, own marketing responsiveness should be bounded by zero. However we may find cases with negative values due to estimation inaccuracy.

[7] 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.

[8] First-differencing also eliminates brand-specific factors such as quality that may explain different volatility levels among brands. Note that, together with the procedure to adjust revenues, we have therefore completely removed the impact of the X-variables of Equation (1) in our final estimation equations.

[9] 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.

[10] One may argue that in our data these additional financing costs do not arise because detailing cost, which is the primary expenditure element, are fixed. Even with fixed cost we still have an indirect effect on cash-flow volatility via revenue volatility which is substantial (elasticity = .371). However, many pharmaceutical firms use contract sales force, which is paid out-of-pocket, for new product launches in order to create a maximum in detailing power.