Time-series models of pricing the impact of marketing on firm value

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Abstract

Marketers continuously engage in actions such as product launches and advertising that are aimed at generating profitable customer response and increasing key marketing assets such as customer satisfaction and brand equity. To the extent that these efforts are successful, they should enhance the financial outlook of the firm, which is of primordial interest to the investment community. However, the interpretation of the impact of these actions is not straightforward, because the effects tend to play out over time. As a result, it is quite possible that mispricing occurs, i.e. the investment community either overestimates or underestimates the future financial impact of a marketing action or marketing metric. The purpose of this chapter is to review time-series methods as the primary research tool for evaluating the pricing of marketing actions and marketing assets. The main message here is: what is mispricing, what are various forms (especially the difference between contemporaneous and lags), how can we detect, what does it mean for investors/managers, and what do researchers do with the mispricing information? We discuss, in turn, methods for assessing the return (level) and the risk (volatility) of marketing for the investor, and we provide illustrative findings of each.

1.Introduction

Stock prices fluctuate as a result of continuous trading among investors who have different expectations about the firm's future earnings. Thus they represent *consensus forecasts* of the financial value of the firm. As new value-relevant information about the firm or its environment arrives, these forecasts are updated, either immediately or more gradually over time, and either fully or partially. The extent to which such new information is reflected in stock-price adjustments reflects the degree of efficiency in the market.

Time-series methods are well suited to analyze stock-price data and quantify their sensitivity to such new information. In particular, methods that focus on *equal-interval measurements,* such as daily, weekly or minute-by-minute data, are adept at sorting out the magnitude of reaction as well as its distribution over time, i.e. the time lags. Time-series methods can be employed without having to resort to strong a-priori assumptions about investor behavior such as full market efficiency. Thus they can be used to test such assumptions and, where needed, modify them to more accurate representations of investor behavior. Furthermore, time-series methods allow for inferences around the *mean* and the *variance* of stock prices, and as such they connect well to the risk/return paradigm in finance. Finally, time-series techniques can be employed with single equations as well as systems of equations. Such systems allow for the possible feedforward and feedback loops between investor behavior and managerial behavior. In conclusion, time-series methods are ideally suited to test and improve our understanding of the relationships between product markets ("Main Street") and financial markets ("Wall Street") (Luo 2008; Hanssens, Rust, and Srivastava 2009).

This continuous firm value adjustment process is of major importance to senior executives, and in particular to the stewards of demand generation for the firm, i.e. the marketing and sales managers. As argued in Srinivasan and Hanssens (2009), if marketing's contributions were readily visible in quarterly changes in sales and earnings, the task would be simple, because investors are known to react quickly and fully to earnings surprises. However, much of good marketing is building *intangible assets of the firm*, in particular brand equity, customer loyalty and market-sensing capability. Progress in these areas is not readily visible from quarterly earnings, not only because different non-financial "intermediate" performance metrics are used (e.g., customer satisfaction measures), but also because the financial outcomes can be substantially delayed.

Taken in combination, the task of evaluating marketing's impact on firm value is strategically important yet empirically challenging. The purpose of this chapter is to describe the most frequently used empirical time-series methods in the context of modeling stock prices. We begin with a discussion of *mispricing*, i.e. departures from full market efficiency. Mispricing is the key obstacle to the smooth coordination between product markets and financial markets. For example, if investors fail to reward firms that invest in long-term brand building with higher and/or less volatile returns, then why would the managers of these firms engage in such investments? Time-series methods allow us to diagnose and measure the degree to which such mispricing occurs.

Figure 1 presents the classification of mispricing and how time-series models can be employed to test it empirically. Time-series models can be implemented at the stock-portfolio level and at the individual stock/firm level across time periods. They provide insights on the mispricing of both returns and risk due to marketing.

In what follows we will assume that the reader is familiar with standard valuation terminology such as market risk, abnormal stock return and the like. We refer to Srinivasan and Hanssens (2009) for exact definitions. We also assume a basic familiarity with time-series terminology, such as stationarity, autoregression and the like, and we refer to Enders (2005) for specifics. An overview of relevant time-series models is provided in Table 1. Our discussion will cover, first, the pricing of returns due to marketing.

2. Mispricing

This section defines mispricing and how to test mispricing empirically with time-series models. This set of time-series models is quite important for marketing, because ill-specified models may lead to ambiguous and even misleading conclusions. In addition, the task is not trivial because the nascent marketing-finance interface needs solid theoretical and empirical building blocks to recommend appropriate implications, not only for marketers on Main Street but also for investors on Wall Street.

2.1 Definition of Mispricing

According to the efficient market hypothesis (EMH), investors are aware of all publicly available information immediately after the news is announced. As such, stock prices reflect all value-relevant information about the firm. The general stock market (through its buying and selling activities) as a whole should always represent a rational assessment of the economy's strength. No investors can beat the general market by earning abnormal returns once the common risk factors are accounted for.

In any given day, some stocks are positively correlated with the market index, while others are negatively correlated. So, classical portfolio theory suggests that, with complete information, one may diversify away the idiosyncratic risk with these two groups of stocks and thus the market would be efficient (i.e. nobody beats the market). Yet, in reality, information is not complete, and is costly to collect and analyze. That is why analysts can make a living on Wall Street. Hence the EMH is a strong assumption and has come under criticism from the behavioral finance and behavioral economics disciplines (Benartzi and Thaler 1995). So, financial markets may not be fully efficient, as has been demonstrated recently by the global financial crisis. In this context, mispricing may exist theoretically; the challenge is how to test it empirically.

Mispricing can occur in two forms, underpricing and overpricing. At the *portfolio* level, we illustrate these in the context of investor reactions to new information on customer satisfaction. If a strategy of investing in firms that have higher customer satisfaction results in an abnormal portfolio return that is significant and positive (or outperforms the market), that would be evidence of market underpricing. However, if such an investment portfolio underperforms the market wide risk-adjusted benchmark portfolio, we would conclude that overpricing has occurred. Thus, at the portfolio level, testing mispricing due to marketing is a *one-step process*, where researchers construct portfolios and make mispricing inferences based on the abnormal portfolio return. Except for the investment strategy in question (e.g. a strategy focused on customer satisfaction) and the common market-wide risk factors, all other individual firm heterogeneity issues are assumed to be constant and fully diversified away. The abnormal portfolio return itself is a direct test of the stock-price impact of the marketing variable in question. No subsequent regression analyses are needed to test possible mispricing effects (Aksoy et al. 2008; Fornell et al. 2009; Jacobson and Mizik 2009).

By contrast, testing mispricing due to marketing at the stock or firm level is *a two-step process*. First, the abnormal stock return of a firm is obtained. Then, the marketing variables in question with time lags (e.g. lags of customer satisfaction or marketing mix actions) are regressed against the abnormal return obtained in step one. The resultant beta coefficients of the lagged marketing variables identify possible marketing mispricing effects.

2.2 Marketing assets and marketing actions

Generally speaking, studies of the pricing of marketing assets will use a one-step portfolio approach, because the portfolio return of interest is based on the marketing variable in question. Such assets, including brand equity and customer satisfaction, are not easily observable and tend to move slowly over time, so their financial impact is not readily assessed in short-term stock-price movements. Thus it is best to compose hypothetical portfolios of, say, high-asset versus low-asset firms, for the purpose of measuring the importance of the asset.

By contrast, marketing actions such as new-product introductions, sales promotions, sponsorships and advertising campaigns, are immediately visible. Thus they provide an opportunity for investors to update their valuation of the firm if they feel the marketing action is value relevant. In this case the two-step approach is appropriate, using either a stock-return model or an intervention model. Since firm return is observed from the financial market, while the marketing variable in question is observed from the product market, this method enables a direct assessment of the marketing antecedents of a firm’s abnormal stock return.

3. Portfolio-Level Time Series Models for Testing Mispricing

Marketing assets. According to the finance literature, one can test mispricing with the portfolio-level asset pricing models by Fama-French-Carhart (Fama and French 1992, 1993; Carhart 1997). We will illustrate these principles in the context of the possible mispricing of customer satisfaction, based on data from the American Customer Satisfaction Index (ACSI) (Fornell et al. 2006). This is an important issue in the marketing-finance literature. The marketing literature has long acknowledged the beneficial effects of customer satisfaction on repeat buying and, ultimately, long-run business performance. However, achieving high customer satisfaction may be costly, and thus the question arises whether or not Wall Street appreciates and incorporates such efforts by virtue of higher firm valuation.

In gauging the abnormal ACSI portfolio return for a direct test of mispricing customer satisfaction, this section presents several asset pricing models. The intercept term or Jensen's alpha (a_{p0}) is the exact measurement of the abnormal ACSI portfolio return in the Fama-French-Carhart model:

$$R_{pt} = a_{p0} + b_{p1}\, RMRF_t + b_{p2} SMB_t + b_{p3} HML_t + b_{p4} UMD_t + \varepsilon_{pt}, \qquad (1)$$

where the R_{pt} is the month t return on an ACSI portfolio p in excess of risk-free rates, SMB_t is the firm size factor, equal to the average monthly return difference between small and large-cap stocks, and HML_t is the value factor, computed as the average monthly difference in returns between value and growth stocks. UMD_t is the momentum factor that accounts for the tendency for increasing asset prices to increase further, and $RMRF_t$ is the time-series return (in excess of risk-free rates or 30-day Treasury bill rates) of the market index (Fama-French 1993 and Carhart 1997).[1]

If the abnormal ACSI portfolio return is not statistically significant (or Jensen's alpha a_{p0} = 0) in the asset pricing model (1), then the observed ACSI portfolio return is the same as that of the market-wide risk-adjusted benchmark portfolio. In this case, customer satisfaction is priced in financial markets, and there is no systematic mispricing of this "voice of the customer" metric. On the other hand, if Jensen's alpha $a_{p0} > 0$, then customer satisfaction is underpriced. If Jensen's alpha $a_{p0} < 0$, then there is overpricing of customer satisfaction. In other words, the abnormal portfolio return or Jensen's alpha itself is a direct test of the stock-price impact of customer satisfaction. No additional regression models are required.

Empirical studies based on the ACSI index (1995-2005) show that, interestingly, the abnormal return for a high-ACSI portfolio[2] is statistically significant and positive (a_{p0}=0.55%, p<.10 monthly, or 6.6% annualized, for CAPM model; and a_{p0}=0.45%, p<.10 monthly, or 5.4% annualized, for Fama-French 3-factor model). This means that portfolios with the highest level of customer satisfaction tend to outperform the market-wide risk-adjusted benchmark portfolio, in support of customer satisfaction *underpricing*, as suggested in Fornell et al. (2006, 2009a, 2009b). At the same time, the abnormal ACSI portfolio returns for all other ACSI-quintile portfolios (i.e. all but the highest quintile) are statistically insignificant (p>.10). Therefore, these abnormal ACSI portfolio-return results suggest that customer satisfaction is right-priced in the majority of cases. In conclusion, financial markets may exhibit *some* anomalies in the pricing of customer satisfaction (Fornell et al. 2009a)

[1] Portfolio-level models in equation (1) are time-series models because the estimation is done across time (months). More information on the construction of the four factors may be obtained from the website of Professor Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

[2] Details on how to define and construct the ACSI portfolios are discussed in Aksoy et al. (2008) and Fornell et al. (2009).

Marketing actions. Our illustrations so far have focused on the pricing of *marketing assets* such as customer satisfaction and brand equity. An equally interesting question is whether or not investors incorporate *marketing actions* or *events* in their valuation. Single-equation time-series models such as *stock return models* (for continuous marketing actions such as advertising campaigns) and *event studies* (for discrete marketing actions such as new-product introductions) may be used to answer such questions. Researchers can also construct portfolios on the basis of spending on the marketing mix such as advertising, R&D, and others, as well as clean, uncontaminated marketing events. Regardless of what marketing variables are used in the investment strategy and stock portfolio construction, the procedures are the same as those illustrated here with the customer satisfaction example.

4. Firm-Level Time Series Models for Testing Mispricing

As discussed previously, at the firm level, testing mispricing due to marketing is a two-step process. In the first step, the abnormal return of a firm is obtained based on the Fama-French-Carhart model as in equation (1), but operationalized at the firm level.

In the second step, the marketing variables in question with time lags (e.g. lags of customer satisfaction or marketing mix actions) are regressed against the abnormal return obtained in step one. Consistent with finance theory that the stock market only reacts to unexpected news, researchers typically operationalize marketing actions as an unexpected shock (innovation) to the marketing time series. The resultant beta coefficients of the marketing variable lags are used to determine mispricing. If any <u>intertemporal</u> coefficients of the marketing variables are significant, then mispricing of that marketing variable is supported. If any <u>contemporaneous</u> coefficients of the marketing variables are significant, then we conclude that the marketing variables are value-relevant, i.e., have a same time-period effect on stock prices. Dynamic system models such as VAR can track the time-varying coefficients and thus assess the cumulative effects of all marketing-variable lags, while allowing for feedback loops in managerial or consumer behavior.

4.1. Dynamic system models

While stock-return models and event studies are appealing when analyzing the immediate stock-market reaction to a major event, they are subject to some serious limitations in many marketing applications. First, the immediate reaction within a few days of the event may not equal the total investor reaction. For instance, Pauwels et al. (2004) observe that it takes several weeks for automotive stock prices to adjust to a major new-product introduction. In general, the finance literature has observed many such dynamic effects of stock prices, naming them with terms like 'momentum', 'slip' etc. (Carhart 1997). Thus, equating the immediate reaction to the total financial value effect of a major event is only meaningful if one accepts a strong version of the efficient-market hypothesis (e.g. Fama and French 1992, Sorescu and Spanjol 2008).

This issue is more serious when one accepts the proposition that investors will not always correctly and immediately forecast the firm's future returns. For risky marketing actions such as new-product introductions, investors need to correctly assess two major uncertainties: the probability of new-product success and the level of profits associated with the new product (Chaney et al. 1991). On the one hand, the stock market may overreact to a product introduction that eventually does not turn out to be a financial success (ibid). On the other hand, investors may underreact as they focus on current rather than on future revenue streams (Michaely, Thaler and Womack 1995).

Second, many marketing actions do not stand out as a major event, whose announcement day can be pinpointed. Examples are advertising campaigns running over several weeks or even months. While the marketing literature has studied the wear-in and wear-out effects of such actions on consumer and retailer behavior, the stock-market dynamics have received little attention (Joshi and Hanssens 2010). Moreover, the stock market is only supposed to react to unexpected events. If the consumer and retailer reaction to a new campaign is known after the first week, investors may incorporate the expected future earnings from that reaction into the stock price. Consequently, there should be no further stock-price adjustments over the next weeks of the campaign. If such adjustments do occur (i.e. if the lagged effects of the event on stock price changes are significant), the VAR-model findings indicate mispricing.

Finally, a dual causality likely exists between marketing actions and stock market performance (Pauwels, Ghysels, Wolfson and Danneels, 2008). While most marketing-finance studies focus on stock market reaction to marketing events, Markovitz et al. (2005) document how managers adjust their marketing actions based on recent stock-market performance. Even when managers do not read or use the signals in stock-market performance, their future marketing budgets may be affected. For example, successful new products lead to higher revenues and profits that, in turn, can be used to launch additional new products. Likewise, lackluster revenue performance may prompt some companies to engage in aggressive rebate tactics in an effort to boost sales.

Overcoming these three limitations involves modeling a dynamic system of stock market and marketing variables, which (1) provides a flexible treatment of short-term and long-term effects, (2) forecasts an expected baseline for each performance variable, so that we may capture the impact of unexpected events as deviations from this baseline and (3) allows for dual causality. Dynamic system models provide this capability and take the form of Vector Autoregressive Models (VAR, or VARX if exogenous controls are included) or Vector Error Correction models, depending on model specification tests represented in Table 1. Published applications of dynamic system models in marketing-finance are provided in Table 2.

---- Insert Tables 1, 2 about here ----

Dynamic Model Specification

Depending on the treatment of contemporaneous effects, VAR models can be viewed as either structural or reduced form in nature.

Structural Vector Autoregressive Model

The ‘structural’ VAR model is represented as:

$$B_0 y_t = c_0 + B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_p y_{t-p} + \epsilon_t, \tag{2}$$

The nx1 vector of n endogenous variables y is regressed on constant terms (which may include a deterministic time trend and seasonality terms) and on its own past, with p the number of lags and B the nxn coefficient matrix of a given lag. p is the maximum order of lags in the model (also known as the order of the system), and is typically based on Information criteria such as the Akaike or the Schwartz’ Bayes Information Criterion (SBIC), or on lag exclusion tests (Nijs, Srinivasan and Pauwels 2007). Evolving variables are differenced before including them in the model, so that all endogenous variables are stationary.

Note that any contemporaneous effects are captured in the B_0 matrix; as a result the ‘structural’ errors ε are uncorrelated (orthogonal) across equations. For instance, a bi-variate VAR of order 1 (i.e n = 2 and p = 1) is displayed in equation (3):

$$\begin{bmatrix} 1 & B_{0;1,2} \\ B_{0;2,1} & 1 \end{bmatrix} \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} c_{0;1} \\ c_{0;2} \end{bmatrix} + \begin{bmatrix} B_{1;1,1} & B_{1;1,2} \\ B_{1;2,1} & B_{1;2,2} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}, \tag{3}$$

This structural form of the VAR model is of direct interest to decision makers, as it generates predictions of results of various kinds of actions (the orthogonal errors) by calculating their conditional distribution given the action (Sims 1986). In the context of marketing effects on stock price, the structural VAR can thus pick up contemporaneous effects, as predicted by the efficient market hypothesis. It is also the appropriate form for imposing restrictions, typically on the B_0 matrix. Amisano and Giannini (1997) present an excellent overview of different ways of imposing such restrictions, which may be based on theories of investor behavior. For instance, Keating (1990) uses a rational expectations model to impose a set of nonlinear restrictions on the off-diagonal elements of B_0

Structural VARs have seen many applications in economics, but few in marketing. One exception is Freo (2005), who studies the response of store performance to sales promotions. The author causally orders the variables by decreasing Granger exogeneity test statistics and deleting coefficients not significantly different from 0.[3] The key finding is that promotions on heavy household items immediately increase store revenues, but promotions in the textile category immediately decrease store revenues. Thus, the structural VAR model may help marketing-finance researchers uncover diametrically opposite firm value effects of marketing actions in different industries or countries. Likewise, structural VAR models have been used in economics to separate temporary from permanent disturbances (Blanchard and Quah 1989). Applied to the marketing-finance field, this approach can identify which marketing actions are likely to permanently affect firm value (e.g. advertising) and which produce only a temporary increase (e.g. price promotions to move inventory before the end of quarter).

[3] The importance of Granger causality testing and how it is conducted are discussed in Granger (1969) and Luo (2009).

Structural VAR models are subject to at least two challenges relevant to marketing. First, the high degree of collinearity among the estimated coefficients complicates the exclusion assessment (Ramos 1995, Freo 2005). Second, if we follow the test results, the re-estimation of the (appropriately restricted) VAR-models may still induce omitted-variable bias to the other parameter estimates (Sims 1980, Faust 1998). As a general strategy, many econometricians prefer to impose restrictions on the long-run, structural impulse responses (Enders 1995). Pauwels (2004) and Uhlig (2005) adhere to this strategy of restricted impulse response functions based on a reduced-form vector-autoregressive model.

Reduced-Form Vector Autoregressive Model

In the absence of imposed restrictions, we can write the structural VAR model (2) in reduced form by premultiplying each term by B_0^{-1} to obtain:

$$y_t = B_0^{-1}c_0 + B_0^{-1}B_1y_{t-1} + B_0^{-1}B_2y_{t-2} + \cdots + B_0^{-1}B_py_{t-p} + B_0^{-1}\epsilon_t, \quad (4)$$

which can be written as:

$$y_t = c + A_1y_{t-1} + A_2y_{t-2} + \cdots + A_py_{t-p} + e_t \quad (5)$$

with $\Omega = \mathrm{E}(e_te_t') = \mathrm{E}(B_0^{-1}\epsilon_t\epsilon_t'(B_0^{-1})') = B_0^{-1}\Sigma(B_0^{-1})'$ (6)

Note that the residual variance-covariance matrix is no longer diagonal; the reduced-form errors are contemporaneously correlated as they now capture the contemporaneous effects among the endogenous variables.Thus, the researcher needs to identify the model, i.e. assert a connection between the reduced form and the structure so that estimates of reduced-form parameters translate into structural parameters. In the words of Sims (1986), “Identification is the interpretation of historically observed variation in data in a way that allows the variation to be used to predict the consequences of an action not yet undertaken.”

The important advantage of the reduced-form model is that all right-hand-side (RHS) variables are now predetermined at time *t*, and the system can be estimated without imposing restrictions or a causal ordering (this identification issue will come back though when calculating impulse response functions in the next section). Moreover, since all RHS variables are the same in each equation, there is no efficiency gain in using Seemingly Unrelated Regression (SUR) estimation. Even if the errors are correlated across equations, ordinary least squares (OLS) estimates are consistent and asymptotically efficient (Srivastava and Giles 1987, Ch 2). This feature is especially valuable in marketing-finance applications with many endogenous variables. For example, a 5-equation VAR model relating stock price changes, income changes, revenue changes, new product introductions and price rebates (Pauwels et al. 2004) requires estimation of 5x5 = 25 additional parameters for each lag added to the model. In contrast, OLS estimation equation-by-equation implies that only 5 additional parameters have to be estimated.

Vector Error Correction Models are appropriate when a long-term equilibrium exists among two or more endogenous variables (i.e. cointegration). In such a situation, knowing the level of one variable will help us predict the level of another variable: any deviation from the long-term equilibrium will tend to be 'corrected' by the system. Therefore, we relate the evolving endogenous variables in first differences but add the error correction term. For example, consider the relation between the (logarithms of) stock price (S) and the price the firm charges its customers in the product market (P):

$$\Delta \ln(S_t) = c + \alpha_0 \Delta \ln(P_t) + \alpha_2 \left[\ln(S_{t-1}) - \alpha_3 \ln(P_{t-1})\right] + \varepsilon_t \qquad (7)$$

where Δ denotes the first differencing operator (defined *as* $\Delta X_t = X_t - X_{t-1}$). Equation (7) implies that the growth in stock price depends on the growth in the firm's product price and on the deviation from an equilibrium relation between these two variables (Pauwels, Srinivasan and

Franses 2007).

Long-run impact of marketing actions: impulse-response functions

The dynamic system model estimates the *baseline* of each endogenous variable and forecasts its future values based on the dynamic interactions of all jointly endogenous variables. Based on the dynamic system model coefficients, impulse-response functions track the over-time impact of unexpected changes (shocks) to the marketing variables on forecast deviations from baseline for the other endogenous variables. As argued by Mizik and Jacobson (2003), "when an unanticipated change in strategy occurs, the markets react and the new stock price reflects the long-run implications such change is expected to have on future cash flows" (o.c., p. 21).

One potential application of this approach concerns the stock market's reaction to (and possibly mispricing of) customer satisfaction, currently a hotly debated issue. Investors may form expectations of customer satisfaction ratings, e.g. based on their own and their friends' experiences with the brand, on company spending in the area, etc. When actual customer satisfaction differs from this expectation, investors react to the gap with expectations, which may be negative even though the company improved ratings compared to the last period.

To derive the impulse-response functions of a marketing action, we compute two forecasts, one based on an information set without the marketing action, and another based on an extended information set that accounts for the marketing action. The difference between these forecasts measures the incremental effect of the marketing action. This model feature is especially attractive for analyses of stock-market performance, as investors react to *shocks*, i.e. deviations from their expectations. In finance, these expectations are obtained from econometric forecasting models based on the firm's past financial performance records, and the shocks are obtained as the model forecast errors (e.g. Cheng and Chen 1997). The dynamic-system model is a sophisticated version of such an econometric forecast. In addition, the dynamic effects are not a priori restricted in time, sign or magnitude. Most recent studies have adopted the generalized, simultaneous-shocking approach (Dekimpe and Hanssens 1999) in which contemporaneous effects are derived from information in the residual covariance matrix, instead of from an imposed causal ordering among the endogenous variables. Applying this approach, Pauwels et al. (2004) find that automobile companies' valuation does improve immediately upon a new-product introduction, but also continues to increase for several weeks. However, for rebates, the initial positive reaction turns negative in the long run.

Of academic and practical importance is the magnitude of specific impulse response values and their over-time pattern (Pauwels 2004). To judge the statistical significance of each impulse-response value, a one-standard error band is appropriate (Pesaran, Pierse and Lee 1993, Sims and Zha 1999). Finally, many marketing applications sum up all significant impulse-response values to arrive at the cumulative (or total over-time) impact of marketing on performance (Pauwels et al. 2002).

Special care should be taken when interpreting the impulse response of variables that were differenced before inclusion in the model. The model-based impulse response functions represent the effect of/on the first difference of the variable, and thus need to be translated back to a level effect for interpretation. Three scenarios are possible:

1) The marketing variable is stationary, but the financial performance variable is evolving: in this case, significant effects of marketing on performance change indicate a permanent effect of marketing on performance (hysteresis). Several interesting patterns have been observed, including *full hysteresis* (a positive impact of marketing on performance change is not followed by any negative re-adjustment) and *partial hysteresis* (a subsequent negative impact renders the cumulative effect lower than the initial impact) (Hanssens & Ouyang 2002).

2) The marketing variable is evolving, but the performance variable is stationary. For instance, in Dekimpe and Hanssens (1999), a permanent change in the price of a consumer product did not create a permanent change in performance. The cumulative response of performance is given directly by the impulse response function; the researcher simply needs to communicate that this is the impact of a *permanent* change in price, as opposed to a temporary price promotion.

3) Both marketing and performance variables are evolving. In this case, significant effects indicate that a permanent change in marketing yields a permanent change to the performance variable.

Relative importance of marketing actions: forecast error variance decomposition

While impulse-response functions trace the effects of a marketing change on performance, forecast-error variance decomposition (FEVD) determines the extent to which these performance effects are due to changes in each of the VAR variables. Analogous to a 'dynamic R^2', the FEVD calculates the percentage of variation in a response variable that can be attributed to both contemporaneous *and* past changes in each of the endogenous variables.

It is often important to compare the short-run and the long-run FEVD. For example, such a comparison could reveal that the initial movements in stock price are attributed mainly to promotion or advertising shocks, but that over time, the contribution of product innovation gradually becomes stronger. Moreover, if one includes product-market performance metrics, such as sales and profit, FEVD also addresses whether marketing actions affect firm value *only indirectly* through top-line and bottom-line performance (in which case all firm value forecast deviations are attributed to these performance variables), or have a direct effect above and beyond this performance impact. Hanssens (1998) used FEVD on channel orders and consumer demand data to show that sudden spikes in channel orders have no long-term consequences for the manufacturer, *unless* movements in consumer demand accompany them. Pauwels et al. (2004) show that marketing actions impact automotive stock prices above and beyond their effect on revenues and profits.

Figure 2 shows the results of a forecast error variance decomposition of firm value explained by promotions and new product introductions. While sales promotions are initially more important, an increasing percentage of the forecast deviation variance in firm value is attributed to new-product introduction. On average, the ability of a new-product introduction to explain firm value forecast deviations is eight times higher after two quarters than it is in the week of product launch. This indicates that investors struggle to assess the future firm-value impact of an innovation at the time of its introduction.

Forecast Error Variance Decomposition requires the imposition of a causal ordering for model identification purposes. When marketing and finance theory are insufficient to justify such ordering, it is advisable to estimate the Generalized Forecast Error Variance Decomposition (Pesaran and Shin 1998), which is linked to the generalized impulse response function using equation (8):

$$\theta_{ij}^{g}\left(t\right)=\frac{\sum_{l=0}^{t}\psi_{ij}^{g}\left(l\right)^{2}}{\sum_{l=0}^{t}\sum_{j=1}^{m}\psi_{ij}^{g}\left(l\right)^{2}},\ i,\ j=1,\ldots,m. \qquad (8)$$

where $\psi_{ij}^{g}(l)$ is the value of a Generalized Impulse Response Function (GIRF) following a one standard-error shock to variable *j* on variable *i* at time *l*.

4.2 Mispricing volatility: GARCH Extension of Stock Response Models

So far we have discussed time-series models for the levels or changes in firm value in terms of *return* metrics. Equally important is the representation of *risk* or *volatility* of these return metrics. Risk is a vitally important stock performance variable because it is directly related to firms' cost of capital, corporate bankruptcy likelihood, and shareholder wealth (Ang et al. 2006). Benchmarking firm risk and relating it to marketing variables may be accomplished by a class of time-series models called general autoregressive conditional heteroskedasticity (GARCH) models (Engle 1982; Bollerslev 1986). [4]

Note that prior applications in the marketing-finance interface have discussed several approaches to stock volatility (or stock risk). Particularly, total stock risk or volatility of a firm has two parts: systematic and idiosyncratic. The former is the firm's sensitivity to the changes in market returns or to news of broad market changes such as inflation that are common to all stocks. The latter reflects the risk associated with firm-specific strategies such as Corporate Social Performance after the market-wide variation is accounted for (Luo and Bhattacharya 2009; McAlister et al. 2007; Osinga et al. 2011; Rego et al. 2009; Tuli and Bharadwaj 2009). However, most of these studies address cross-sectional volatility (systematic or idiosyncratic), rather than time-series volatility (Bharadwaj, Tuli, and Bonfrer 2011; Jacobson and Mizik 2009; Luo et al. 2010).

The GARCH model offers several appealing properties. First, it can simultaneously test the significance of both stock return (first moment) and volatility (second moment) responses to

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[4] Researchers may user other modeling techniques when dealing with lower-frequency firm value measures (e.g., Tobin's Q). Readers are encouraged to consult Fang, Palmatier, and Steenkamp (2008) and Grewal et al. (2010) for models of Tobin's Q.

marketing actions. In so doing, GARCH also accommodates the tradeoffs between risk and return: stocks with higher volatility are required to earn higher returns, lest no investors would be interested in them (Luo 2009). Though an essential part in the intertemporal capital asset pricing models, these tradeoffs, to our knowledge, have not been explicitly accounted for in prior marketing studies (Jacobson and Mizik 2009).

Second, this method allows for time-varying forecast confidence intervals that can model more precisely the variance of the errors and the confidence intervals. GARCH also generates more efficient estimators because it accounts for heteroskedasticity. Third, it captures autoregressive serial correlation in stock price data by estimating the carry-over effects between historical and future stock returns/volatilities. As such, these advantages suggest that GARCH models can rigorously link marketing actions to firms' stock returns and volatilities over time.

Mathematically, the standard GARCH(1,1) model is specified as:

$$r_t = c + \sum_{l=1}^{L} \rho_l r_{t-l} + \varepsilon_t, \tag{9}$$

$$\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t),$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1},$$

where r_t is stock return, L is the best-fitting autoregressive lag length, ρ is the autoregressive parameter in the conditional mean equation, ε_t is error term, h_t is the latent conditional variance of error terms, and intercept $\alpha_0 > 0$. If the estimates for α_1 and β_1 are positive and significant statistically, then the latent stock volatility is time-varying and heteroskedastic. Clearly, GARCH can account for and model heteroskedasticity because h_t is allowed to vary over time. In addition, GARCH accommodates autoregressive serial correlation or state dependency because it includes historical lags of both returns and volatilities in the models. According to this GARCH(1,1) model specification, investors update their estimates of stock return and volatility in each period based on the newly revealed surprises only in last period's information (lag =1).

Higher-order GARCH (*p*,*q*) models are developed so as to accommodate the possibility that investors may update their expectations using a series of historical surprises of volatility and forecasted variances (i.e. lags greater than 1). Put differently, it may take some time to fully impound the information content of unexpected news in the financial markets. In higher-order GARCH models, *p* represents the order of autoregressive ARCH terms, and *q* is the order of moving-average GARCH terms. The standard GARCH (*p*,*q*) model is specified as:

$$r_t = c + \sum_{l=1}^{L} \rho_l r_{t-l} + \varepsilon_t, \tag{10}$$

$$\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t),$$

$$h_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} .$$

GARCH can also test the tradeoffs between stock return and stock volatility based on Merton's (1973) theory of the intertemporal capital asset pricing model. More specifically, if stock volatility is introduced into the stock-return equation, we obtain the GARCH-in-mean (GARCH-m) model as follows:

$$r_t = c + \sum_{l=1}^{L} \rho_l r_{t-l} + \nu \operatorname{Log}(h_t) + \varepsilon_t, \tag{11}$$

$$\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t),$$

$$h_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} ,$$

where the parameter (ν) captures the risk-return tradeoff. If $\nu \neq 0$, then there is a significant tradeoff between stock return and stock volatility in GARCH-m models. This means investors would require higher returns for buying stocks associated with higher risks.

In order to test the impact of marketing actions on stock returns and stock volatilities, we introduce shocks in marketing actions as follows:

$$r_t = c + \sum_{l=1}^{L} \rho_l r_{t-l} + \nu \operatorname{Log}(h_t) + \sum_{m=1}^{M}\sum_{n=1}^{N} \zeta_{m,n} Shock\_MKG_{m,t-n} + \varepsilon_t, \tag{12}$$

$$\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim GED(0, h_t),$$

$$h_t = \alpha_0 + \sum_{m=1}^{M}\sum_{n=1}^{N} \xi_{m,n} Shock\_MKG_{m,t-n} + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} ,$$

where $SHOCK\_MKG_{m,t-n}$ is the unexpected shock in the m^{th} marketing variable at lagged time period t-n. All models in the GARCH system of equations are estimated simultaneously along with bootstrapping methods (Lundblad 2007). Shocks or unanticipated information of marketing actions can be derived based on VAR models described previously. As such, this GARCH system now provides a direct test of the hypothesis regarding the impact of marketing actions on stock returns and volatilities. The null hypothesis is that $\zeta_{m,n} = 0$, which would suggest that marketing actions have no impact on stock returns. The alternative hypothesis is that $\zeta_{m,n} \neq 0$, which supports the impact of marketing actions on stock returns. In addition, if $\xi_{m,n} = 0$, marketing actions have no impact on stock volatilities. Otherwise $\xi_{m,n} \neq 0$, which would support the stock volatility implications of marketing actions.

On the basis of monthly data of dissatisfaction of consumption experience in the airline industry (1999-2005), Luo (2009) finds that negative consumer word-of-mouth (NWOM) has a significant impact on firm risk. Particularly, GARCH results show that both *contemporaneous* coefficients and *intertemporal* coefficients of NWOM are significant. NWOM induces higher stock volatilities of the firm (total impact of the intertemporal coefficients b=0.0338 with multiple lags t = 10 past months). This suggests a substantial amount of mispricing of the information of negative word-of-mouth. The market is not able to impound the full information of WOM immediately but rather may take up to 10 months to fully reflect the damaging impact of NWOM. These results indicate that NWOM is value-relevant and has mispricing effects (i.e., lasting effects on firm stock prices) with significant underreactions to NWOM information. The harm of NWOM on customer loyalty and brand value may last for a long time, during which the market prices the damaging impact *gradually*. Firms with poor ratings in consumer WOM are punished with higher financial risks in a multi-period setting. Thus, firms should communicate in a timely manner the full impact of WOM and disclose marketing information to analysts and investors for improved market efficiency.

5. Conclusions and Future Research Opportunities

If society is to benefit from a smooth market-driven coordination between resource allocation in product markets and financial markets, then investors should place the proper value on what firms and their marketing managers do, i.e. creating marketing assets such as brands, and engaging in specific marketing actions such as product launches. This chapter has introduced a range of time-series methods to investigate empirically whether or not such efficient pricing occurs, at the level of stock returns as well as stock volatility.

The application of these methods to various aspects of marketing valuation has revealed that, while investors generally incorporate the value relevance of marketing assets and marketing actions, documented cases exist of over-pricing, under-pricing and delayed pricing. As a result, there is opportunity for future research to diagnose not only the existence of mispricing, but also its causes, and to recommend remedies to reduce their influence. More specifically, three potential causes merit additional investigation. The first is *disclosure*, i.e. mispricing may occur because investors do not have access to the right metrics. For example, if reported revenue were broken down by revenue from new vs. existing customers, separate time-series models on these two revenue sources would likely provide superior projections than those generated by combined models. A similar argument can be made for revenue generated at base price vs. revenue realized at a discounted price. The second is *consumer response dynamics*. Time series models on consumer sales, especially diffusion models for new products, can be used to project more realistic revenue projections for companies that rely on technological innovation for their growth. The third is *corporate communications*. Since these are expected to represent an optimistic view of the company's future, a time series analysis on anticipated vs. realized stock returns may quantify and adjust for the biasing influence of such communications. Much remains to be discovered in these and related areas by future research on the marketing-finance interface.

Table 1

Methodological Building Blocks

Methodological approach	*Relevant literature*	*Research questions*
1.Unit root tests and cointegration tests		
Augmented Dickey-Fuller test	Dickey and Fuller (1979)	Are performance and marketing variables stationary (mean-reverting) or evolving (unit root)?
Unit root test accounting for endogenous structural breaks	Zivot and Andrews (1992)	
Cointegration test	Johansen and Juselius (1990)	Do evolving variables move together?
2. VAR model		
Vector Autoregressive model	Enders (1995) Dekimpe and Hanssens (1995)	How do performance, product introduction and promotion variables interact, accounting for exogenous factors?
3. Impulse response analysis		
Performance response to a unit marketing shock	Hamilton (1994) Dekimpe and Hanssens (1995) Pauwels et al. (2002)	What is the long-term performance impact of a marketing shock?
Generalized Impulse Response Function	Pesaran and Shin (1998) Pauwels (2004)	What is the long-term performance impact of marketing, without imposing a causal ordering?
4. Variance decomposition analysis		
Forecast error variance decomposition of performance variables Generalized FEVD	Hamilton (1994) Hanssens (1998) Nijs, Srinivasan, Pauwels (2007)	What fraction of performance variance comes from each marketing action? Without imposing a causal ordering?

Table 2

Dynamic system model studies connecting marketing actions to firm value

Authors	***Methodology***	***Findings***
Pauwels, Silva-Risso, Srinivasan and Hanssens (2004)	Vector-Autoregression Impulse Response Function Forecast Error Variance Decomposition	New product introductions benefit firm value in the short run and the long run, while rebates hurt firm value in the long run. It takes several weeks for these effects to wear in.
Luo (2009)	Vector-Autoregression Impulse Response Function	Negative word-of-mouth hurts firm value and increases volatility in the short run and in the long run. It takes 4 months for these effects to wear in.
Joshi and Hanssens (2010)	Vector-Autoregression Impulse Response Function Forecast Error Variance Decomposition	Advertising has a direct effect on firm value, beyond its indirect effect through market performance. The advertiser benefits, while competitors of comparable size get hurt.

Figure 1
Classification of mispricing and matched time-series models

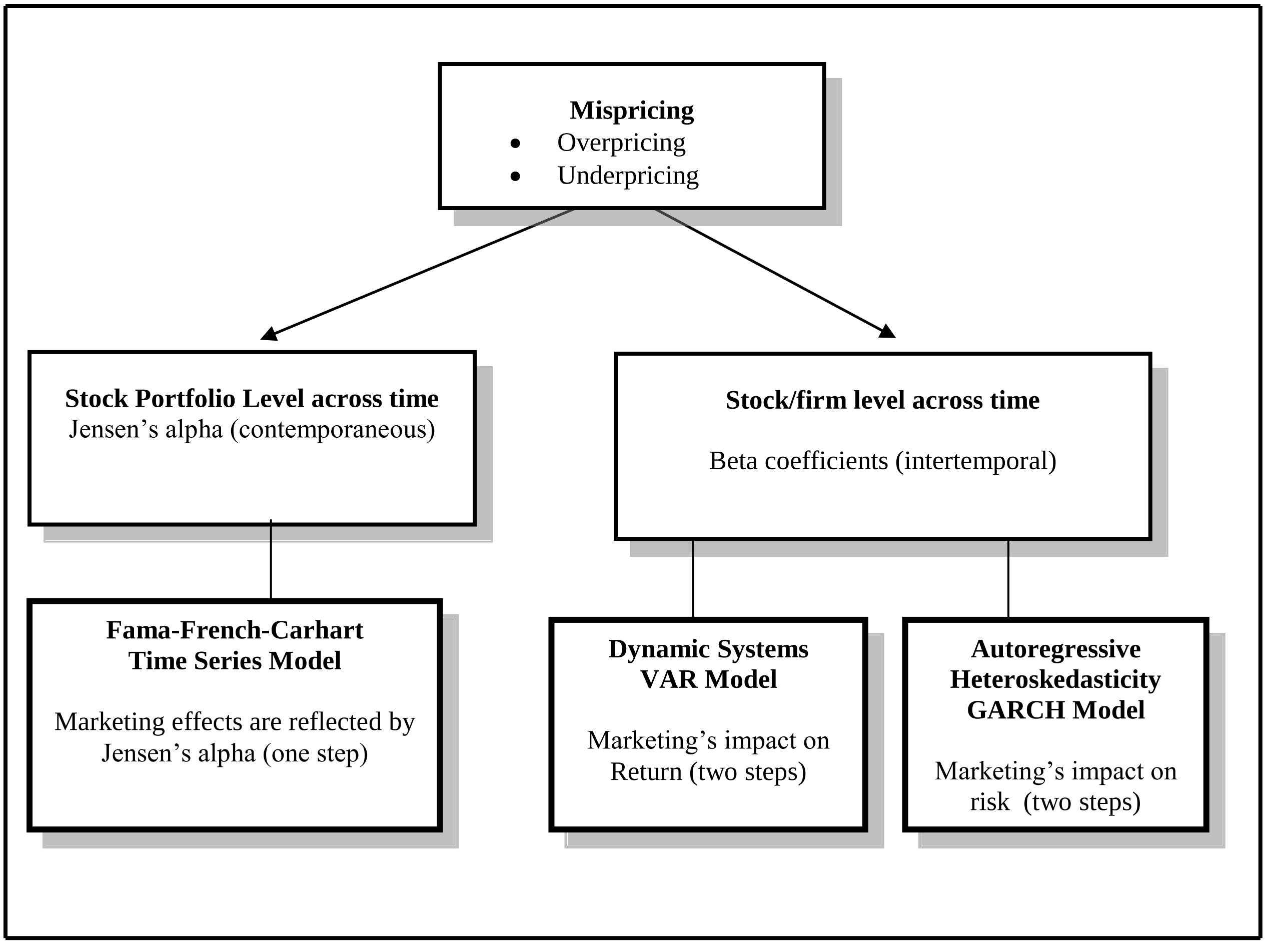
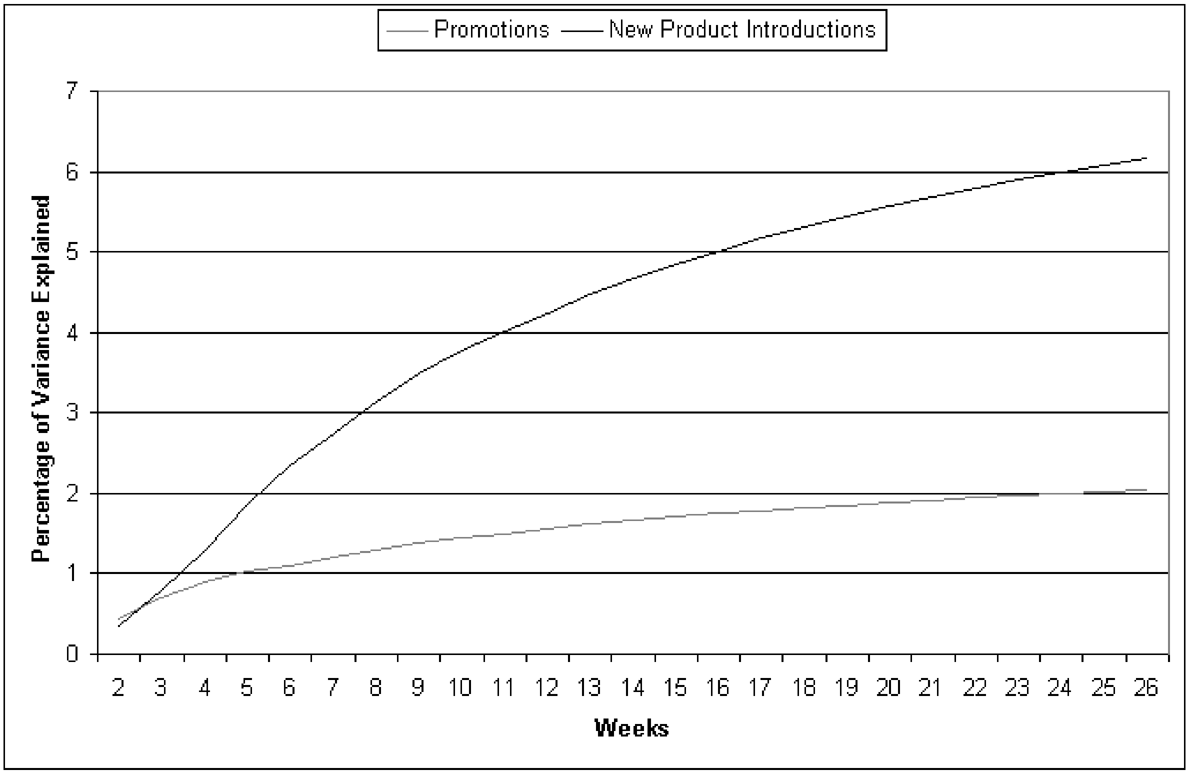


Figure 2

Forecast Error Variance Decomposition of Firm Value*



*Source: Pauwels et al. (2004)

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