Introduction

An important concern in marketing theory is the relationship between marketing strategy and shareholder value (Day and Fahey 1988; Srivastava, Shervani, and Fahey 1998). Yet, despite the relationship's supposed importance, the focus on microlevel tactical issues (for example, coupon promotions and redemption) has led to concerns that marketing’s strategic role is steadily shrinking (Day 1992). Others have argued, however, that marketing continues to play an important role in a firm’s strategy dialogue. These scholars have explored marketing’s participatory role in decisions at the corporate and business unit levels (Varadarajan 1992; Varadarajan and Jayachandran 1999). However, even these proponents would agree that marketing has not adequately demonstrated its impact on performance metrics that matter to senior management. Consequently, senior management has tended to leave marketing issues in the hands of functional managers. Simultaneously, there have been questions about the payoff of marketing investments (Sheth and Sisodia 1995). The key concern is that marketing has been unable to demonstrate the value relevance of its actions in terms that matter to senior management.
Against this backdrop, the event study method, which relates the announcement of marketing strategy initiatives (for example, celebrity endorsements, name changes, or brand extensions) to the creation (or destruction) of shareholder wealth, seems particularly relevant. The purpose of this chapter is to provide a concise description of the event study method to test models that relate marketing strategy initiatives to changes in shareholder wealth.

There is considerable interest in the effect of an economic event on the value of a firm. Given assumptions of market efficiency, perfect information, and rationality of investors (Fama 1970), the effect of an event should be immediately reflected in stock prices. Hence, any event's economic impact on the wealth of shareholders can be measured by changes in the firm's stock prices over a relatively short time period. Event studies have been widely used in accounting, law, and finance to assess how a firm's stock price is affected by firm-specific events such as mergers and acquisitions, earnings announcements, product recalls, and issues of new debt or equity, as well as how a firm's stock price is affected by macroeconomic events such as interest rate changes and trade deficits.

The first researcher to publish an event study was Dolley (1933), who examined how the stock splits of 95 firms affected their stock prices. In the late 1960s, important papers by Ball and Brown (1968) and Fama et al. (1969) introduced the event study method that is still widely used. Since these early studies, there have been several refinements to the basic event study method.

**Intuition behind the Event Study Method**

The price of a stock reflects the time- and risk-discounted present value of all future cash flows that are expected to accrue to the holder of that stock (Rappaport 1997). According to the semistrong version of the efficient-market hypotheses, all publicly available information is reflected completely and in an unbiased manner in the price of the stock, such that it is not possible to earn economic profits on the basis of this information. Therefore only an unexpected event can change the price of the stock, which is equal to the anticipated changes in the future cash flows of the firm adjusted for the risk of those cash flows. Information resulting in a positive (negative) change in expected future cash flows will have a positive (negative) effect on the stock's price. For example, announcements of new product introductions positively impact the stock prices of the firms making the announcements, with the effect of the announcements expected to vary with the newness of the product (Chaney, Devinney, and Winer 1991). Thus, an event has an impact on
the financial performance of the firm if it produces an abnormal movement in the price of the stock.

Event studies are popular because they eliminate the dependence on accounting-based measures of profits, which have sometimes been criticized as being questionable indicators of the true economic performance of the firms. For example, managers can manipulate accounting profits because they can select accounting procedures (Benston 1985). Stock prices, on the other hand, are not as subject to easy manipulation by insiders, and incorporate both the risk and the return profile of the event announced by the firm (Bharadwaj, Bharadwaj, and Konsynski 1999). From a pragmatic perspective, the event study method is relatively easy to implement because the only data necessary are the names of the publicly traded firms, event dates, and stock prices.

Event studies rely on some key assumptions. Specifically, event studies assume that (1) financial markets are efficient, (2) shareholders are the only relevant group of stakeholders for a firm, (3) researchers can isolate the share price reaction to the event of interest, and (4) an appropriate benchmark model is used to compute the abnormal returns.

It is important to note that event studies test both whether the event has an impact on the stock price of the firm and whether the stock market is efficient. In this respect, an important issue is the extent to which individual investors can integrate all the information pertaining to the firm and the event. However, as Friedman (1953) argues, even when people do not make all the necessary calculations reflected in a proposed economic model, they may still act as if they do so. Further, even if individual investors do not have all the relevant information, markets exhibit information aggregation behavior, through which they act as if they were rational (Hayek 1945; Ball 1995).

Guide to Event Studies

An event study consists of five steps: event identification, defining of criteria for inclusion of the event, calculation of normal and abnormal returns, estimation of the normal performance model, and performance of statistical and hypotheses tests.

Event Identification

The first step in an event study is to define the event of interest and the event window—that is, the period over which the stock prices of the firm involved in this event will be studied. For example, if the interest is in looking at how the announcement of a brand extension affects daily stock price data, the event will be
the announcement of the brand extension and the event window might be the day of the announcement. In implementation, because the announcement may have been made after the stock market closes for the day, the event window is often opened up to one or more days after the event to capture the price effects of the announcement. Sometimes the event window may also include one or more days before the announcement date to capture leakages, if any, in the announcement. For example, the fact that a celebrity will be endorsing a brand may be revealed to the marketplace before the endorsement formally occurs.

**Defining of Criteria for Inclusion of Event**

It is important to define the criteria for the inclusion of a firm's event in a study. For example, in a study on the effects of brand extensions on shareholder value, the researcher may elect to exclude certain industries (for example, services and hospitals) from the study because of prior theoretical considerations. The criteria for inclusion may be broad (for example, the researchers may accept events of any firm listed on the New York Stock Exchange or the American Stock Exchange) or narrow (restricted, for example, to events of firms in a given industry of interest to the researcher). The events are typically identified through an extensive search of databases (such as Factiva) that contains newspaper articles and newswire reports. This ensures that the time and date of the first public announcement is clearly defined.

**Calculation of Normal and Abnormal Returns**

To assess the event's impact on the firm's shareholder value, we require a measure of the abnormal return on the stock price. The abnormal return is the actual ex post return of the stock during the course of the event window minus the expected normal return of the firm during the same time frame if the event had not taken place. For each firm $i$ and event date $t$

$$
\epsilon_{it}^{*} = R_{it} - E[R_{it} | X_t]
$$

where $\epsilon_{it}^{*}$, $R_{it}$, and $E[R_{it}]$ are the abnormal, actual, and normal returns respectively for the time period $t$. $X_t$ is the conditioning information for the normal performance model for the stock. The two most widely used approaches for modeling are the constant mean return model and the market model. The constant mean return model assumes that the mean return of a given stock is constant over time, while the market model assumes a linear relationship between the return on the market and the stock's return. These models are discussed next.
Estimation of the Normal Performance Model

After selecting the normal performance model, the parameters of the model are estimated using a portion of the data known as the estimation window. The estimation window includes days on which no information related to the event is released to ensure that the normal performance model parameter estimates are not biased by the event of interest. While the estimation window can be either before the event, after it, or both, generally the period before the event is chosen. For example, in an event study using daily data, the normal performance model parameters are estimated over the 250 days prior to the event. For event studies using daily data, typically a 45-day window separates the estimation window from the event window.

Performance of Statistical and Hypotheses Tests

Once the parameter estimates for the normal performance model are estimated, the abnormal returns can be computed, and the significance of the abnormal returns can be determined using both parametric and nonparametric tests. In addition, empirical tests of cross-sectional models of characteristics of the firm and the event may also be tested. The results of the empirical tests will generate insights about the theoretical mechanisms by which the firm's event affects its stock prices. Typically, additional analyses may be performed to establish the robustness of the results and to exclude competing explanations.

Models for Measuring Market Performance

There are two different approaches to calculating normal performance model parameters: statistical and economic. Models in the statistical group imply only statistical assumptions about the behavior of the stock returns and are not contingent on any economic assumptions. Models in the economic group make strong assumptions about investors' behavior over and above the statistical assumptions.

In the statistical approach, it is assumed that the abnormal returns are jointly multivariate normal and independently and identically distributed over time. These distributional assumptions are sufficient for the accurate specification of the normal market performance model and allow for the estimation of exact finite-sample distributional results for the estimators and statistics. The inferences are robust to deviations from these assumptions.

The different statistical models include the constant mean return model, the market model, and the factor model (see MacKinlay 1997 for a description of the different models). In practice, the market model is better than the constant
mean return model, and the benefits of the factor model over the market model are limited. Hence, we describe only the market model in detail below.

Two common economic models are the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT). The CAPM model was widely used in the 1970s, but in the last decade or so some limitations of the CAPM method have been identified, and it is no longer used in event studies. The use of APT complicates the estimation of abnormal returns while offering no tangible benefits over the market model. See Fama and French (1996) for more details. In sum, the economic models provide no distinctive advantage over statistical models but make stronger assumptions about investor behavior. As a result, statistical models are the most widely used models in event studies.

The Market Model

The market model is a statistical model that relates the return of a given stock to the return of the market portfolio. Assuming joint normality of asset returns results in a linear specification of the model. For a given stock $i$, we have

$$R_i = \alpha_i + \beta R_m + \varepsilon_i$$

where $R_i$ and $R_m$ are the period-$t$ returns on stock $i$ and the market portfolio respectively, and $\varepsilon_i$ is the zero mean disturbance term. $\alpha_i$, $\beta$, and $\sigma^2_{\varepsilon_i}$ are the parameters of the market model. In practice, a broad-based stock index such as the S&P 500 index, the CRSP value-weighted index, or the CRSP equal-weighted index is used for the market portfolio. By removing the portion of the stock’s return that is related to variations in the market’s return, the variance of the abnormal return is decreased, resulting in an increased ability to detect the effect of the event on the stock’s returns. The better the fit of the market-model regression, the greater the variance reduction of the abnormal return and the greater the gain in the efficiency of the event study.

Measurement of Abnormal Returns

We start by defining the notation. We index returns in event time using $\tau$ (Figure 1). Defining $\tau = 0$ as the event date, $\tau = T_1 + 1$ to $\tau = T_2$ represents the event window, and $\tau = T_0 + 1$ to $T_1$ constitutes the estimation window. Let $L_1 = T_1 - T_0$ and...
Let \( L_2 = T_2 - T_1 \) be the length of the estimation and the event window respectively. If the event being considered is an announcement on a given date, then \( T_2 = T_1 + 1 \) and \( L_2 = 1 \). \( L_1 \) is the length of the estimation window and \( L_2 \) is the length of the event window.

**Figure 1**

**Timeline for an Event Study**

<table>
<thead>
<tr>
<th>(estimation window)</th>
<th>(event window)</th>
<th>(post-event window)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_0 )</td>
<td>( T_1 )</td>
<td>( T_2 )</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>( T_3 )</td>
</tr>
</tbody>
</table>

The market model for stock \( i \) and observation \( \tau \) in the event time expressed in Equation 2 can be expressed as a regression system in matrix notation as below:

\[
R_i = X \dot{\theta}_i + \epsilon_i \tag{3}
\]

where \( R_i \) is an \((L_1 \times 1)\) vector of returns from the estimation window, \( X \) is an \((L_2 \times 2)\) matrix with a vector of ones in the first column and the vector of market return observations \( R_m \) in the second column, and \( \dot{\theta}_i \) is the \((2 \times 1)\) parameter vector. \( X \) has the subscript \( i \) because the width of the estimation window may be specific to firm \( i \).

Ordinary least squares (OLS) is a consistent estimation procedure for market-model parameters. Given the market-model parameter estimates, the abnormal returns are specified as:

\[
\hat{\epsilon}_i = R_i - \hat{\alpha}_i - \hat{\beta}_i R_m = R_i - X_i \hat{\theta}_i \tag{4}
\]

where \( R_i \) is an \((L_2 \times 1)\) vector of event window returns, \( X_i \) is an \((L_2 \times 2)\) matrix with a vector of ones in the first column and the vector of market return observations \( R_m \) in the second column, and \( \hat{\theta}_i \) is the \((2 \times 1)\) parameter vector estimate.

Conditional on the market return over the event window, the abnormal returns will be jointly normally distributed with a zero conditional mean and a conditional covariance matrix such that for large estimation windows \( L_1 \), the abnormal returns over time will become independent asymptotically. Under the null hypothesis \( H_0 \), the given event has no impact on the mean on variance of returns.
\( \hat{\varepsilon}_i^* \sim N(0, V_i) \) where \( V_i = E[\hat{\varepsilon}_i^* \hat{\varepsilon}_i^* | X_i^*] \) (5)

where \( V_i \) is the conditional covariance matrix of the abnormal returns.

**Aggregation of Abnormal Returns and Statistical Tests**

Abnormal returns for events are generally aggregated both over time and across firms to generate inferences about the events. We first consider aggregation over time for an individual stock and then across firms and over time.

The cumulative abnormal return can include several days within the event window. Define \( CAR_i(T_1, T_2) \) as the cumulative abnormal return for stock \( i \) from \( T_1 \) to \( T_2 \) where \( T_1 < T_1^* \leq T_2^* \). Let \( \gamma \) be an \((L_2 \times 1)\) vector with ones in positions \( T_1 - T_1^* \) to \( T_2 - T_1^* \) and zeroes elsewhere. Then,

\[
CAR_i(T_1, T_2) = \gamma^T \hat{\varepsilon}_i^* \sim N(0, \Sigma_i^*(T_1, T_2)). 
\]

We construct a test of \( H_0 \) for stock \( i \) by using \( SCAR_i(T_1, T_2) \), the standardized cumulative abnormal return for stock \( i \) from \( T_1 \) to \( T_2 \). It follows from the assumptions of normality of abnormal returns that:

\[
SCAR_i(T_1, T_2) = \frac{CAR_i(T_1, T_2)}{\hat{\sigma}_i(T_1, T_2)}.
\]

Under the null hypothesis, the distribution of \( SCAR_i(T_1, T_2) \) is student \( t \) with \((L_2 - 2)\) degrees of freedom. From the properties of the student \( t \) distribution, the expectation of \( SCAR_i(T_1, T_2) \) is 0 and the variance is \((L_2 - 2) / (L_2 - 4)\). For a large estimation window (e.g., \( L_2 > 30 \)), the distribution of \( SCAR_i(T_1, T_2) \) is approximated by the standard normal distribution.

The above result applies to one event and can be extended to the aggregation of several events. To aggregate across stocks and through time, it is assumed that the abnormal returns of the different stocks are uncorrelated. The stocks' abnormal returns can be averaged using the abnormal returns from Equation 4. Given a sample of \( N \) events, the sample average of the \( N \) abnormal returns is as follows:

\[
\bar{\varepsilon}^* = \frac{1}{N} \sum_{i=1}^{N} \hat{\varepsilon}_i^* 
\]

\[
Var[\bar{\varepsilon}^*] = \frac{1}{N^2} \sum_{i=1}^{N} V_i 
\]
where $V_r$ is the conditional covariance matrix of the abnormal returns described in Equation 5.

We next describe the statistical tests that can be performed to determine the statistical significance of the abnormal returns.

**Parametric Tests.** For $N$ events, we can aggregate the sample cumulative abnormal returns for each stock $i$. Thus, for $N$ events, we have

$$\text{CAR}_{\text{average}}(\tau_1, \tau_2) = \frac{1}{N} \sum_{i=1}^{N} \text{CAR}_i(\tau_1, \tau_2)$$  \hspace{1cm} (9)

$$\text{VAR}[\text{CAR}_{\text{average}}(\tau_1, \tau_2)] = \sigma^2(\tau_1, \tau_2) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2(\tau_1, \tau_2)$$

where $\text{CAR}_{\text{average}}(\tau_1, \tau_2)$ is the cumulative abnormal return from $\tau_1$ to $\tau_2$ where $T_1 < \tau_1$ to $\tau_2 <= T_2$ and is distributed normally as $N[0, \sigma^2(\tau_1, \tau_2)]$ because, under the null hypothesis, the mean of the abnormal returns is zero. In practice, because $\sigma^2(\tau_1, \tau_2)$ is unknown, we can use

$$\hat{\sigma}^2(\tau_1, \tau_2) = \frac{1}{N^2} \sum_{i=1}^{N} \hat{\sigma}_i^2(\tau_1, \tau_2)$$

as a consistent estimator and test $H_0$ using the following statistical test:

$$J_1 = \frac{\text{CAR}_{\text{average}}(\tau_1, \tau_2)}{(\hat{\sigma}^2(\tau_1, \tau_2))^{1/2}} \sim N(0,1).$$  \hspace{1cm} (10)

The intuition behind $J_1$ is that computed variance of the estimated CARs is being used in the parametric test. A second method of aggregation is to equally weight each individual $\text{SCAR}_i$ instead of the $\text{CARs}$. Defining $\text{SCAR}_{\text{average}}(\tau_1, \tau_2)$ as the average over $N$ stocks from event time $\tau_1$ to $\tau_2$, we have

$$\text{SCAR}_{\text{average}}(\tau_1, \tau_2) = \frac{1}{N} \sum_{i=1}^{N} \text{SCAR}_i(\tau_1, \tau_2).$$  \hspace{1cm} (11)

Assuming that the event windows of the $N$ stocks do not overlap in calendar time, under $H_0$, $\text{SCAR}_{\text{average}}(\tau_1, \tau_2)$ will be normally distributed in large samples with a mean of zero and a variance of
Then, the null hypothesis can be tested using

\[ J_2 = \left( \frac{N(L_1 - 4)}{L_1 - 2} \right)^{1/2} \text{SCAR}_{\text{average}}(\tau_1, \tau_2) \sim N(0,1). \]  

(12)

The choice of the statistical tests \( J_1 \) or \( J_2 \) depends on the alternative hypothesis under consideration. If the true abnormal return is constant across the stocks, then it is appropriate to give greater weight to the stocks with the lower abnormal return variance, which means that one would use \( J_2 \). On the other hand, if the true abnormal variance is larger for stocks with higher variance, then it would be appropriate to use \( J_1 \), because that test gives equal weight to the realized cumulative abnormal return of each stock. Empirical studies indicate that the test results are robust to the choice of either statistical test.

**Nonparametric Tests.** The parametric tests assume that the distribution of abnormal returns is normal. There are two alternative nonparametric tests that do not make any distributional assumptions about the abnormal returns. They are the sign test and the rank test.

The sign test, which is based on the sign of the abnormal returns, requires that the abnormal returns and cumulative abnormal returns be independent across stocks. The expected proportion of positive (or negative) abnormal returns under the null hypothesis is .5. Under the null hypothesis it is equally probable that the \( \text{CAR} \) will be positive or negative. If, for example, the alternative hypothesis is that there is a positive (or negative) abnormal return associated with a given event, the null hypothesis is \( H_0 : \rho \leq .5 \) and the alternative is \( H_2 : \rho > .5 \) where \( \rho = Pr(\text{CAR}_i \geq 0) \). To calculate the test statistic, we need the number of announcements for which the abnormal return is, say, positive \((N+)\) and the total number of cases \((N)\). If \( J_3 \) is the test statistic, then asymptotically as \( N \) increases, we have

\[ J_3 = \left[ \frac{N+}{N} - .5 \right] \frac{N^{1/2}}{\sqrt{.5}} \sim N(0,1). \]  

(13)

For a test of size \((1 - \alpha)\), \( H_0 \) is rejected if \( J_3 > \Phi^{-1}\alpha \). A weakness of the sign test is that it may not be well specified if the distribution of abnormal returns is skewed, as might be the case with daily stock data. To address this weakness,
Corrado (1989) proposed a nonparametric rank test for abnormal returns that tests the null hypothesis that there is no abnormal return on the event day or during the multiple-day event window.

Consider a sample of \( L_2 \) abnormal returns for each of \( N \) stocks. To implement the rank test, each stock is ranked on abnormal returns from 1 to \( L_2 \). Define \( K_{\tau} \) as the rank of the abnormal return of stock for event time period \( \tau \). \( \tau \) ranges from \( T_1 + 1 \) to \( T_2 \) and \( \tau = 0 \) is the event day. The rank test assumes that the expected rank under the null hypothesis is \( \frac{(L_2 + 1)}{2} \). The test statistic for the null hypothesis of no abnormal returns on the event day is

\[
J_4 = \frac{1}{N} \sum_{i=1}^{N} \left( K_{\tau,0} - \frac{L_2 + 1}{2} \right) / s(L_2)
\]

Tests of the null hypothesis can be implemented using the result that the asymptotic null distribution of \( J_4 \) is standard normal. Typically, the nonparametric and the parametric tests are not used independently, but in conjunction with each other. Generally, the nonparametric tests are used to check the robustness of the parametric tests.

**Cross-sectional Regression Modeling of Abnormal Returns**

Theoretical models often suggest that there should be an association between the magnitude of abnormal returns and characteristics specific to the event. For example, in the marketing context, researchers may be interested in investigating how abnormal returns to announcements of different marketing strategy decisions differ.

To investigate this relationship, the appropriate method is a cross-sectional regression model of abnormal returns on the characteristics of the event that are of interest. To set up the model, define \( y \) as the cumulative abnormal return observations and \( X \) as the matrix of characteristics. In the case of the brand extension example, for instance, \( X \) may include both characteristics of the event (such as number of brand extension variants, markets in which the extensions are being launched, relatedness of the brand extension to the parent brand, and so on) and characteristics of the firm (such as product portfolio, size, advertising budget, market share, and so on). Then, for the cross-sectional model, we obtain the following regression equation:
\[ y = X\theta + \eta \]  \hspace{1cm} (15)

where \( \theta \) is the coefficient vector and \( \eta \) is the disturbance vector.

In many situations, the abnormal returns witnessed in the event window are related to firm characteristics not only through the valuation effect of the event but also through the event's relationship to the firm characteristics and the extent to which the event may be anticipated. This can happen when investors rationally use the firm's characteristics to forecast the likelihood of the event's occurrence. The relation between firm characteristics and the extent of anticipation of the event introduces a selection bias. The assumption that the regression residual is uncorrelated with the regressors \( E[X' \eta] = 0 \) breaks down, and the OLS estimators are inconsistent. However, despite possible misspecification, under weak conditions, the OLS approach can be used for inferences and the \( t \)-statistics can be interpreted as lower bounds of the true significance level of the estimates. An appropriate approach in this situation is to calculate heteroskedasticity consistent \( t \)-statistics and standard errors following White (1980). For a good overview of the theoretical and empirical issues surrounding the application of event studies to substantive issues in areas outside finance and accounting, see McWilliams and Siegel (1997).

Other Empirical Issues in Event Studies

Researchers who make use of event studies must consider such empirical issues as the practical significance of the results obtained from event studies, the statistical power of event studies, the size of the event window, event date uncertainty, inferences in clustering, and other possible biases. They should also be aware of recent developments in event studies.

Practical Significance of Event Study Results

The significance of the event can be determined by calculating the total wealth gain or loss attributable to the event. Specifically, the absolute dollar gain or loss at time \( t \) (\( \Delta W_t \)) attributable to the event is defined by:

\[ \Delta W_t = CAR_t \times MKTVAL_0 \]

where \( MKTVAL_0 \) is the market value of the firm at a date prior to the event window interval and \( CAR_t \) is the cumulative residuals to date \( t \) for the firm.

The percent abnormal return times the market value of the firm yields the total dollar wealth gain or loss in the market value of the firm. For example, a study
on announcement of new product launch delays in 101 firms (median market value of $1.95 billion) discovered that the delays led, on average, to a market value loss of $119.3 million in 1991 dollars (Hendricks and Singhal 1997), indicating that new product introductions have a substantial impact on firms’ overall wealth.

**Statistical Power of Event Studies**

If an event changes firm value by a specific amount, say by 2%, or if an event has no impact on firm value, can the event study method make this inference with statistical precision?

The power of a test statistic is considered in the context of a null hypothesis and an alternative hypothesis. In the context of event studies, generally the null hypothesis is that the event has no impact on firm value. An alternative hypothesis is that the event increases the firm value (let’s say by 2%). Under the assumption that the alternative hypothesis is true, the power of the event study is the probability of observing a statistically significant test statistic. Brown and Warner (1980, 1985) and MacKinlay (1997) show that the power of the event study technique improves as the number of firms in the sample increases, as the number of days in the event window decreases, and as the alternative of a smaller abnormal return is considered against the null of zero abnormal return.

**Size of the Event Window**

If the timing of an event is known precisely, then the ability to statistically identify the effect of the event will be higher for smaller event windows—that is, event windows of shorter duration. The increases in precision result from a reduction in the variance of the abnormal return without affecting the mean of the abnormal return. In addition, the larger the event window, the greater the likely contamination of the abnormal returns due to the effect of other possibly confounding events. Hence, reducing the size of the event window substantially increases the power of the event study.

**Event Date Uncertainty**

In some cases it is difficult to identify the exact date of the event (for example, when collecting event dates from financial publications such as the *Wall Street Journal*). When the event announcement appears in the newspaper, one cannot be certain whether the market was informed before the close of the market on the prior trading day. If it was, then the prior day is the event day; if not, the current day is the event day. The usual method of handling this situation is to expand the event window to two days—Day 0 and Day 1. While expanding the window results in
reduced power, the statistical properties of two-day event windows are still good, suggesting that it is worth the costs to avoid the risk of missing the event.

**Inferences in Clustering**

In analyzing aggregated abnormal returns, we have assumed that abnormal returns on individual stocks are uncorrelated in the cross-section. This is a reasonable assumption if the event windows of the included stocks do not overlap. The assumption enables the calculation of the aggregated sample cumulative abnormal returns without covariances between individual CARs, because they are zero. However, when the event windows overlap, the covariances between the abnormal returns may not be zero, and the distributional assumptions are violated. For methods to handle problems related to clustering, see Bernard (1987) and Schipper and Thompson (1983).

**Other Possible Biases**

Event studies are subject to a number of possible biases, including the nonsynchronous trading that occurs when prices are assumed to be recorded at time intervals of one length when they are actually recorded at time intervals of other, possibly irregular, lengths. For example, the daily prices of stocks in event studies are generally closing prices, prices at which the last transaction in each of those stocks occurred during the trading day. These closing prices do not generally occur at the same time each day, but by calling them daily prices, it is implicitly assumed that they are equally spaced at 24-hour intervals. This assumption can induce a bias in the calculation of the abnormal returns. See Campbell, Lo, and MacKinlay (1997) for possible corrections.

The statistical analysis of abnormal returns is based on the assumption that returns are jointly normal, temporally independent, and identically distributed. Any departure from this assumption can result in biases. The normality assumption is important for the exact finite-sample results. However, Brown and Warner (1985) show that this assumption is usually not a big issue for event studies as the test statistics converge to the asymptotic distributions quickly.

Finally, there can be an upward bias in cumulative abnormal returns because of the observation-by-observation rebalancing to equal weights implicit in the calculation of the aggregate cumulative abnormal returns, combined with the use of transaction prices, which can represent both the bid and the ask side of the market. This bias can be large for studies using low-market-capitalization firms, which have, in percentage terms, wide bid-ask spreads (Blume and Stambaugh 1983).
Recent Developments in Event Study Methods

During the past decade, an increasing number of finance studies have considered abnormal returns for long-horizon windows of several years. Such studies have considered abnormal returns over 12 to 60 months after the announcement of various corporate events, including mergers, share repurchases, initial public offerings, stock splits, and the issuing of dividends. Some examples of long-run event studies include Ikenberry, Lakonishok, and Vermaelen (1995), Loughran and Ritter (1995), Brav and Gompers (1997), and Desai and Jain (1999).

There are two reasons why long-horizon event studies may be informative. First, the market may be unable to fully interpret and incorporate the impact of the announcement on the company's value right at the time of the announcement. Over time, the market gets the opportunity to understand and incorporate the impact of the event on the company's value more completely. Second, new information pertinent to an announcement may only become known to the market participants in the months or years after the announcement, so that the full impact of the event on the firm's performance may only be known several years later. There is ongoing debate about the specification and power of event studies with long-horizon windows of several years (Barber and Lyon 1997; Kothari and Warner 1997; Lyon, Barber, and Tsai 1999).

Use of Event Studies in Marketing

Table 1 contains a summary of representative event studies in marketing. A review of the table indicates that despite the considerable potential of the event study method to relate marketing strategy initiatives to changes in shareholder wealth, event studies have been underutilized in marketing. Event studies have been used to investigate the effect of a corporate name change (Horsky and Swyngedouw 1987), new product introductions (Chaney, Devinney, and Winer 1991), celebrity endorsements (Agrawal and Kamakura 1995), brand extensions (Lane and Jacobson 1995), joint ventures (Houston and Johnson 2000), and the addition of an Internet distribution channel (Geyskens, Gielens, and Dekimpe 2002). All these studies used daily abnormal returns around the day of the announcement of the marketing initiative. One study (Agrawal and Kamakura 1995) used statistical tests, while all the others used cross-sectional regression models that related the characteristics of the event to the abnormal returns attributable to the announcement of the event. Importantly, the findings across the different event studies indicate that these marketing strategy initiatives had a significant impact on the shareholder wealth of the firm.
Table 1: Representative Event Studies in Marketing

<table>
<thead>
<tr>
<th>Authors and Study Year</th>
<th>Context</th>
<th>Method</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horsky and Swyngedouw (1987)</td>
<td>Company name change (N = 58)</td>
<td>Daily abnormal returns and cross-sectional testing using regression</td>
<td>Empirical results support a contingency model with most name changes being associated with a positive return. The greatest returns were seen for firms in industrial goods and for firms with poor performance.</td>
</tr>
<tr>
<td>Chaney, Devinney, and Winer (1991)</td>
<td>New product introductions (N = 1685)</td>
<td>Daily abnormal returns and cross-sectional testing using regression</td>
<td>New product introductions are associated with positive returns, but not for all firms. The effect varies across industries and with the firm's systematic risk and the number of announcements made over the 10-year period, the number of products in the announcement, and whether the products are truly new.</td>
</tr>
<tr>
<td>Agrawal and Kamakura (1995)</td>
<td>Celebrity endorsements (N = 110)</td>
<td>Daily abnormal returns; univariate statistics</td>
<td>On average, celebrity endorsements are associated with positive returns, suggesting that celebrity endorsement contracts are generally viewed as a worthwhile investment in advertising.</td>
</tr>
<tr>
<td>Lane and Jacobson (1995)</td>
<td>Brand extensions (N = 89)</td>
<td>Daily abnormal returns and cross-sectional testing using regression</td>
<td>The stock market's response to brand extension announcements indicated the tradeoffs inherent in brand leveraging, depending interactively and monotonically on brand attitude and familiarity.</td>
</tr>
<tr>
<td>Houston and Johnson (2000)</td>
<td>Joint ventures and contracts (N = 208)</td>
<td>Daily abnormal returns</td>
<td>The abnormal returns in joint ventures and contracts are the same, primarily accruing to the supplier firms. Horizontal joint ventures (where partners are at the same level in the value chain) provide bilateral, synergistic wealth gains.</td>
</tr>
<tr>
<td>Geyskens, Gielens, and Dekimpe (2002)</td>
<td>Introduction of Internet channel for newspapers (N = 98)</td>
<td>Daily abnormal returns and cross-sectional testing using regression</td>
<td>Introduction of Internet channel additions are, on average, positive net-present value investments. Firm characteristics, order of entry, publicity, and marketplace characteristics influence the direction and magnitude of the stock market reaction. The impact is stronger for firms with more channel power, early followers, and more publicity.</td>
</tr>
</tbody>
</table>
While these studies offer valuable insights into the effects of marketing initiatives, we note that there is an opportunity to use the event study methodology to investigate the relationship between marketing strategy and shareholders' wealth creation or destruction. Such research assumes special importance given the increased emphasis among marketing academics on relating the marketing function and marketing strategy initiatives to shareholder value (Srivastava, Shervani, and Fahey 1998). Specifically, we believe that the event study methodology could shed light on the following areas in marketing strategy:

- Effects of marketing strategy decisions (for example, ad campaigns, deconglomeration)
- Effect of competitive interactions on marketing decisions (for example, competitive market entry)
- Crisis events in marketing (such as product failures, product recalls)
- Role of marketing capabilities and resources (such as intellectual and relational assets)

Conclusion

Much has been learned from a large body of research in economics and finance that has used the event study methodology. Most generally, event studies have shown that, as might be expected, in a rational marketplace, prices respond to the new information conveyed by the event. Surprisingly, however, event studies have not seen widespread use in marketing.

Over the past few years, both marketing academics and practitioners have shown increasing interest in the relationship between marketing and shareholder wealth. We hope that the event study method, which is one way to generate insights into such relationships, will emerge as a valuable tool in marketing strategy research.

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Notes
1. The efficient-market hypothesis has been subject to extensive empirical testing and most empirical studies find evidence to support it. Controversy still lingers over the definition and measurement of risk and the relationship between risk and return. There is, however, agreement that these issues notwithstanding, the event study methodology is useful to investigate changes in share prices. See Fama and French (1990) and Brown and Warner (1980, 1985).

2. The specification requires that the asset weights in the market portfolio remain constant. However, changes over time in the market portfolio weights are so small in actuality that they have a negligible effect on empirical estimation. Additionally, a conservative approach here would be to utilize an autocorrelation- and heteroskedasticity-consistent approach such as the generalized method of moments.

References


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