Buy, Sell, or Hold?

An Event Study Analysis of Significant Single Day Losses in Equity Value

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ABSTRACT

Many active investors might be concerned with what position to take (buy, sell, or hold) following a significant single-day loss in the value of one of his or her securities. This paper examines this question through the use of an event study. Our event study presents the post-event performance of stocks that have suffered single-day losses in price of –20% or more relative to the market. The data set used in the study was restricted to a thirty-six year window during which the stock returns of the largest 500 publicly traded U.S. domiciled companies in each year were analyzed. Our findings, which use several different economic models and statistical techniques, show statistically significant negative abnormal performance for up to twelve months post-event. Based upon this technical analysis alone, our results would indicate that one should immediately liquidate his/her position following this type of event.

INTRODUCTION

The Problem Statement Defined

Any active participant in the U.S. stock market during the last year can most likely recall several instances when a large-cap company made an announcement that triggered a significant single-day loss in shareholder value. It was for these instances that our sponsor, a mutual fund manager, wanted advice on how to react. Should he buy, sell, or hold his position?

There are a variety of considerations that should go into making such a decision. Certainly the effects of taxes, transaction costs, and portfolio diversification should all be considered. However, these decision guidelines are often specific to each occurrence of an event and specific to each investor. Our paper is an effort to search for an average post-event trend in the case of significant single-day losses in shareholder value. We look to arrive at a single decision rule that, on average, is justified by the performance of these stocks post-event.

At the heart of our question is the often-debated topic of market efficiency. Just how fast does the stock market incorporate new information into the price of equities? Although many previous academic studies conclude that markets are efficient at least for large-cap companies on a day-to-day basis, there is a growing acceptance of market trends explained only through the controversial field of behavioral finance. By analyzing past events via an event study, we can attempt toy understand historical reactions to similar events and use this insight to guide a portfolio manager's future actions to earn excess returns for his or her shareholders.

Outline of Discussion

Our paper begins by providing the reader an overview of the various forms of market efficiency and their implications to our study. This section leads into a brief discussion of the strengths and shortcomings of event studies in general. Next, we discuss some of the empirical findings and explanations for momentum investing. Our final overview section explains the economic intuition behind the Capital Asset Pricing Model and the Fama and French Multi-factor Model.

After this broad overview of existing literature and theory, we go through the details of the collection of data for our event study. We explain our choices and methods of data collection followed by an analysis of the resulting data set of event observations and any possible statistical anomalies contained therein.

From our discussion of the data set, we move to a description and explanation of our methods of analyzing the data for abnormal returns. We discuss our choice of both daily and monthly models and explain how abnormal returns are aggregated and measured over time. Finally, we detail the statistical methods used to test our results.

In the results section of the paper, we provide a qualitative overview and interpretation of the tables and graphs presented in Exhibit A. We conclude the paper with a summary of our analysis and a final caveat to investors.

OVERVIEW OF RELATED FINANCIAL THEORY

Efficient Markets Overview

The Efficient Markets Hypothesis ("EMH") states that a company's stock price incorporates the subjective interpretation of all information that could be used to value the company. There are varying degrees of information reflected in prices, which correspond to three forms of the EMH:

- The "weak" form states that only historical information pertaining to past stock prices is impounded in the current stock price,
- The "semi-strong" form states that both past stock price information and publicly available information is impounded in the current stock price,
- The "strong" form states that all available information whether public or private is impounded in the current stock price.

In this context, stocks that exhibit a sudden, large drop in price are simply reflecting new information. Thus, even the weak-form EMH would suggest that one should not be able to make risk adjusted excess returns in a stock simply given knowledge that a large drop had previously occurred. For a more complete discussion of the EMH and its ramifications, we recommend Bodie (1999).

Event Studies Overview

An event study is a commonly employed research method used as an attempt to isolate the effect of a particular event on a stock's return for some post-event estimation period. As MacKinlay (1997) discusses, economists have used event studies since the early 1930's. Most often, event studies assume that markets react immediately and rationally to new information and are therefore a test of the null hypothesis that the weak-form EMH is correct. The traditional steps in conducting an event study can be summarized as follows:

- Define the event to be tested,
- Define what is meant by abnormal performance,
- Define the pre-event, event, and post-event observation windows,
- Collect a set of events from an unbiased dataset,
- Measure and test aggregate abnormal performance post-event.

In the last twenty years, economists have used event studies to test the effects of any and every type of event imaginable on the value of firms. Such studies include events such as earnings announcements, initial public offerings, share repurchases, mergers, acquisitions, stock splits, etc. Defining what is meant by abnormal performance involves choosing a model that suggests how a security is expected or predicted to behave. Many of the models traditionally used in event studies have been shown to have wide-ranging deficiencies, but still provide valuable insights to practitioners. Some models require significant pre-event returns data to be useful, but almost all models suffer from well-documented weaknesses as the post-event estimation window increases. Academics generally use either daily or monthly returns when testing for post-event effects. These post-event effects are usually separated into short-term effects (one month or less) and long-term effects (one month to five years). The effects are separated as such because there are a variety of different statistical issues used to measure abnormal performance over short and long-term horizons. Fama (1998) notes that methodology is critical to the conclusions drawn in event studies, and, in fact, when different statistical approaches are applied, the conclusions drawn in these studies becomes "marginal or disappear."

Yet event studies continue to be used and methodologies continue to be improved. For a more detailed discussion of these studies we recommend Campbell, Lo, and MacKinlay (1997).

Momentum Investing Overview

A number of academic long-term horizon event studies have suggested market inefficiency in the form of market under or overreaction to new information; these findings are associated with the real-world field known as momentum investing. Several prominent portfolio managers, including the managers of the Twentieth Century Ultra, AIM Constellation, Putnam OTC Emerging Growth, & Louis Navellier funds, lend credibility to the results of these academic papers. These and other portfolio managers actively implement strategies based on the belief that a piece of good or bad corporate news is rarely an isolated event. Momentum investors typically focus on stock price momentum, but many also take long or short positions in a stock if they see significant momentum in other metrics such as earnings, revenues, etc.

A behavioral model that supports the theory that abnormal returns can be made through momentum investing maintains that investors underreact to information that is eventually fully incorporated into stock prices. This "conservatism bias" suggests that individuals underweight new information in updating their prior information.

Jegadeesh and Titman (1999) summarize several other behavioral models that support the practice of momentum investing in the short term and support long-term reversals to fundamental values. The representative heuristic model highlights the tendency of individuals to identify an uncertain event by the degree to which it is similar to the parent population. The representative heuristic may lead investors to mistakenly conclude that firms realizing extraordinary earnings growths will continue to experience extraordinary growth in the future. Proponents of this model such as Barberis, Shleifer and Vishny (1997) argue that although the conservatism bias, examined in isolation, leads to underreaction, this bias together with the representative heuristic can lead to long horizon negative returns for the momentum portfolios.

Daniel, Hirshleifer and Subrahmanyam (1998) present an investor overconfidence behavioral model to explain empirically observed abnormal returns from momentum investing. Their model is based on two psychological biases: investor overconfidence and self-attribution. The first bias is related to the overconfidence of an investor that leads him/her to overestimate the precision of his or her private information signal, but not of public information signals. The second bias is based on the idea that investors observe positive signals about a set of stocks, some of which perform well after the signal is received. Due to these two cognitive biases, overconfident traders attribute the performance of ex-post winners to their stock-selection skills and that of ex-post losers to bad luck. Based on their increased confidence in their positive signals, they push up the prices of the winners above fundamental values.

In essence, Daniel, et al., maintain that stock prices overreact to private information signals and underreact to public signals. As public information arrives, the stock price moves closer to the full-information value. Delayed reaction thus leads to momentum profits that are eventually reversed as stock prices revert to their fundamentals as further public information arrives. The authors argue that biased self-attribution implies short-run momentum and long-term reversals.

The Hong and Stein (1997) model addresses both overreaction and underreaction in an integrated manner by compartmentalizing investors into two groups of investors who trade on different sets of information. One group, the informed investors, obtain signals about future cash flows but ignore information about past price history. Information obtained is transmitted with a delay and hence only partially incorporated in the prices when first revealed to the market. This part of the model contributes to underreaction, resulting in momentum profits. The other set of investors trade on the basis of a limited history of prices and does not observe any fundamental information. These traders extrapolate based on past prices and tend to push prices of past winners above their fundamental values. Returns reversals are observed when prices eventually revert to their fundamentals.

"Prospect theory" also predicts a payoff to momentum investing. Prospect theory predicts that investors will tend to hold on to losing positions in the hope that prices will eventually recover. In contrast investors will be risk averse as they experience gains. Risk aversion to gains will cause them to sell too quickly into rising stock prices, thereby depressing prices relative to fundamentals. Conversely, risk seeking behavior for losses will cause investors to hold on too long when prices decline, thereby causing the prices of stocks with negative momentum to overstate fundamental values (Scott, Stumpp and Xu, 1999).

As far as trading on historical performance is concerned there are two main strategies. Clearly one method of acting on historical metrics is to implement a strategy of buying past winners and selling past losers, often referred to as a relative-strength trading strategy. Jegadeesh and Titman (1993) point out that a majority of mutual funds show a tendency to buy stocks that have increased in price over the prior quarter. Further, they refer to the predictive power of Value Line rankings, rankings that are based in large part on past relative strength.

In contrast to relative-strength strategies, contrarian strategies involve buying past losers and selling past winners. Contrarian strategies are based upon behavioral models that promote the idea that momentum profits arise due to inherent biases in the way that investors interpret information. Contrarian strategists often subscribe to the behavioral bias termed as the over extrapolation effect: human beings develop, and stick to, stronger views than warranted by impartial analysis of data (Scott, Stumpp and Xu, 1999). For example, abnormal returns to low P/E investing or value investing may be explained by a tendency that the average investor over extrapolates past problems into the future. An overconfidence bias is also put forward by contrarian strategist to suggest that investors adjust their expectations with a time lag; a theory that would explain a post-event drift in stock prices.

It must be noted here though that evidence of momentum investing is still not fully documented in academic research. In a recent paper, Scott, Stumpp and Xu (1999) present a framework for the application of behavioral biases to various investment strategies such as growth, GARP (growth at a reasonable price), value investing, momentum investing, etc. In the paper, the authors attempt to identify specific categories of stocks for which each behavioral bias will be strongest. Interestingly, although they support the theory that risk and loss aversion creates bias in stock prices, they find little support for strategies that rely exclusively on momentum. In addition, Daniel and Titman (1998) maintain that the momentum effect is strong in growth stocks, but is weak or non-existent in value stocks. In addition, anecdotal popular press news articles suggest that there has been an over-growth in the number of momentum investors and that this has attracted many transaction-intensive short-term trading arbitragers who seek to rebalance the scales of market efficiency for their gain at the expense of the momentum investors.

There exist a variety of alternative explanations for previously documented abnormal returns from various momentum strategies. Some of the major issues being debated include:

- *Seasonality/January Effect* – Jegadeesh and Titman (1993) find a striking seasonality in momentum profits. They document that the winners outperform losers in all months except January but the losers significantly outperform the winners in January. In a more recent study (1999), Jegadeesh and Titman observe a similar January seasonality effect in the more recent sample period (1990 to 1997).
- *Time Horizon* – Our survey of the literature shows us that it is important to conduct an investigation around as broad a time horizon as reasonably possible in order to study returns over

relatively short and long time horizons. Many of the disagreements in academic literature surround the time horizon of the investigations conducted by proponents of relative-strength and contrarian strategies. Jegadeesh and Titman (1993) maintain that contrarian strategies are rewarding in the short term, i.e., contrarian strategies that select stocks based on their returns over the previous week or month generate significant abnormal returns. They attribute the success of contrarian strategies to the presence of short-term price pressure or a lack of liquidity in the market rather than overreaction. With regard to relative-strength investing, Jegadeesh and Titman (1993) provide evidence of positive returns over a three to twelve month period. In a fairly recent paper, Jegadeesh and Titman (1999) acknowledge that there may be evidence that return reversals or corrections in stock prices occur when the length of the investigation was extended beyond the investigation conducted by the same authors in 1993. They acknowledge that while they found no evidence of return reversal in the two to three years following the formation date, there are significant return reversals four to five years after the formation date. With regard to mutual fund performance and relative-strength investing, Carhart (1997) suggests that buying the previous year's winners is an actionable strategy for capturing the Jegadeesh and Titman one-year momentum effect. Carhart also provides evidence of return reversal in the years thereafter (i.e. after the first year).

- *Compensation for Risk* – Arguments have been made in literature that returns from momentum investing strategies have been the result of not adequately compensating for risk in the momentum portfolio. Conrad and Kaul (1998) argue that the profitability of momentum strategies could be entirely due to cross-sectional variations in mean returns rather than to any predictable time-series variations in stock returns. Specifically, they note that stocks with high (low) unconditional expected rates of return in adjacent time periods are expected to have high (low) realized rates of returns in both periods. Hence, they maintain that momentum strategies will yield positive average returns even if the expected returns on the stock are constant over time. The volatility of individual stocks and the idiosyncratic risk of individual stocks that may be giving rise to abnormal returns may be erroneously attributed to momentum investing. However, Jegadeesh and Titman (1999) strongly refute – by providing evidence - the claim that observed momentum profits can be explained completely by the cross-sectional dispersion in expected returns.
- *Data Mining* – Given the availability of stock market returns data and inexpensive computing capabilities, undoubtedly many academics and practitioners have independently tested a wide variety of trading strategies that resulted in little or no statistical significance and, therefore, went unreported. In this context, the data mining or data mining bias, challenges the significance of

individual studies that detail the profitability of a particular trading strategy. However, Jegadeesh and Titman (1999) point out that the fact that the momentum profits observed in the eight years subsequent to the Jegadeesh and Titman (1993) sample are very similar to the profits found in the earlier investigation. They maintain that this reproducibility is evidence against data mining biases.

To conclude our overview of momentum investing, we should point out that while our analysis certainly fits into this category of trading on prior performance metrics, to our knowledge, there has never been a significant academic study that addresses the issue of a dramatic one-day drop in stock price.

Capital Asset Pricing Model Overview

Earlier we discussed the generic steps in conducting an event study. One of the most important steps in the process is defining abnormal performance. In this and the following section of the paper, we introduce two of the most popular models used to measure abnormal performance.

Sharpe, Lintner, and Mossin developed the first model we will discuss nearly forty years ago. The intuition behind the model begins with a statement that the realized holding period returns of a stock could be explained by the following equation:

$$r_i = E(r_i) + m_i + \varepsilon_i \qquad \underline{\text{Equation 1}}$$

Where:

$E(r_i)$ is the expected future return of the stock i at the beginning of a holding period

m_i is the effect of unanticipated macro event returns on stock i (expected value = 0)

ε_i is the unanticipated stock i specific return (expected value = 0)

From here, we can recognize that the magnitude of an individual firm's reaction to a macroeconomic event varies with some observable correlation. This prompts us to include the addition of a sensitivity coefficient, β, to [Equation 1] resulting in the following new equation:

$$r_i = E(r_i) + \beta_i F + \varepsilon_i \qquad \underline{\text{Equation 2}}$$

Where:

F is some macroeconomic factor

Since a macroeconomic factor is expected to affect all securities and the magnitude of this effect is relatively easy to measure, we can say that the rate of return on a broad index of the market is a reasonable proxy of this factor. The resulting equation for holding period excess return, also known as the security characteristic line, can be written as:

$$E[r_i] - r_f = \alpha_i + \beta_i \left(E[r_m] - r_f\right) + \varepsilon_i$$ Equation 3

Where:

α_i is stock *i's* expected return if the market is neutral

$\beta_i(E[r_m] - r_f)$ is stock *i's* return due to macroeconomic events

ε_i is the unanticipated stock *i* specific return (expected value = 0)

[Equation 3] can be utilized to calculate the return of a portfolio of N securities each equally-weighted:

$$E\left[r_p^e\right] = \frac{1}{N}\sum_{i=1}^{N}\alpha_i + \left(\frac{1}{N}\sum_{i=1}^{N}\beta_i\right) \cdot E\left[r_m^e\right] + \frac{1}{N}\sum_{i=1}^{N}\varepsilon_i$$ Equation 4

If one allows the value of N to increase to infinity, a useful equation is uncovered. This equation is known by as the Capital Asset Pricing Model ("CAPM") equation (Z. Bodie et al., 1999):

$$E[r_i] - r_f = \beta_i \left(E[r_m - r_f]\right)$$ Equation 5

We use the CAPM as one of our basic models later in this paper to determine if there is a predictable value and sign to the firm-specific abnormal return, ε_i.

Fama and French Multi-factor Model Overview

The single-market CAPM model attributes all of the systematic risk in a security to the single beta term. However, many academics criticize the lumping of all systematic variance into a single coefficient. Fama and French illustrated a lack of correlation between CAPM and average returns in their paper, "Cross Section of Expected Stock Returns" in 1992. Fama and French suggested the inclusion of two additional coefficients to further explain systematic stock variance and returns. In the Fama-French Multi-factor Model, the additional factors include:

- *SMB= small minus big: excess return of small stocks over big stocks*
- *HML= high minus low: return of portfolio stock with high book to market values in excess of the returns on a portfolio of stocks with low book to market ratios.*

Combining these variables with the CAPM yields the Fama-French Multi-factor asset pricing equation:

$$E[r_i] - r_f = \beta_{i1}\left(E[r_m] - r_f\right) - \beta_{i2} HML - \beta_{i3} SMB$$ Equation 6

Where:

$\beta_{i1}\left(E[r_m]-r_f\right)$ is stock *i's* return due to macroeconomic events

$\beta_{i2}HML$ is stock *i's* return due to the difference in returns between large and small stocks

$\beta_{i3}SMB$ is stock *i's* return due to the difference in returns between high book to market value stocks and low book to market value stocks

Essentially, this model in many ways is simply an extension of the intuition developed by Sharpe, Lintner, and Mossin for the CAPM. Accordingly, we will be using this model in the same was as the CAPM to determine if there is a predictable value and sign to the firm-specific abnormal return, $\varepsilon_{i.}$

Additionally, one could imagine that there might be many other coefficients included in this model, and academics have indeed tried to find other meaningful explanatory factors. However, the economic intuition remains puzzling as to why the addition of a size factor and book to market factor would increase the explanatory power of the CAPM (in our testing the average explanatory power of the regression, or the r-squared, increased by nearly 25% with the addition of the Fama and French factors). Many suggest that these two factors are by themselves economically unimportant, but result in empirical improvements to the CAPM because they serve as proxies for some other important pricing mechanism (such as a type of risk that investors care about, but is not captured by the covariance with a broad market index).

DATA SET

Choice of Data

As mentioned, our event study was specifically designed to address the buy / hold / sell dilemma faced by a large-cap portfolio manager after one of his or her portfolio companies suffered a significant single-day loss in equity value due to a decline in stock price. Based on advice from our sponsor, we chose to limit the scope of our analysis to companies with approximately $5 billion in equity value and to stocks traded on the NYSE, AMEX, or NASDAQ exchanges.

Today, there are approximately 500 common stock issues that meet this size criterion for inclusion in our analysis. Thus, for our historical analysis, we chose to screen only the largest 500 common stock issues in any given year for significant single-day losses. A beneficial by-product of eliminating smaller stocks from our analysis is that we also eliminated the statistical havoc thinly traded micro-cap stocks wreak on the soundness of event study results.

Collection of Data

As we have defined our problem statement, our best-case collection of raw data would be a set of stock returns for the 500 largest companies on any given trading day of the year for the past seventy plus years. However, there were several limitations to our collection of raw data.

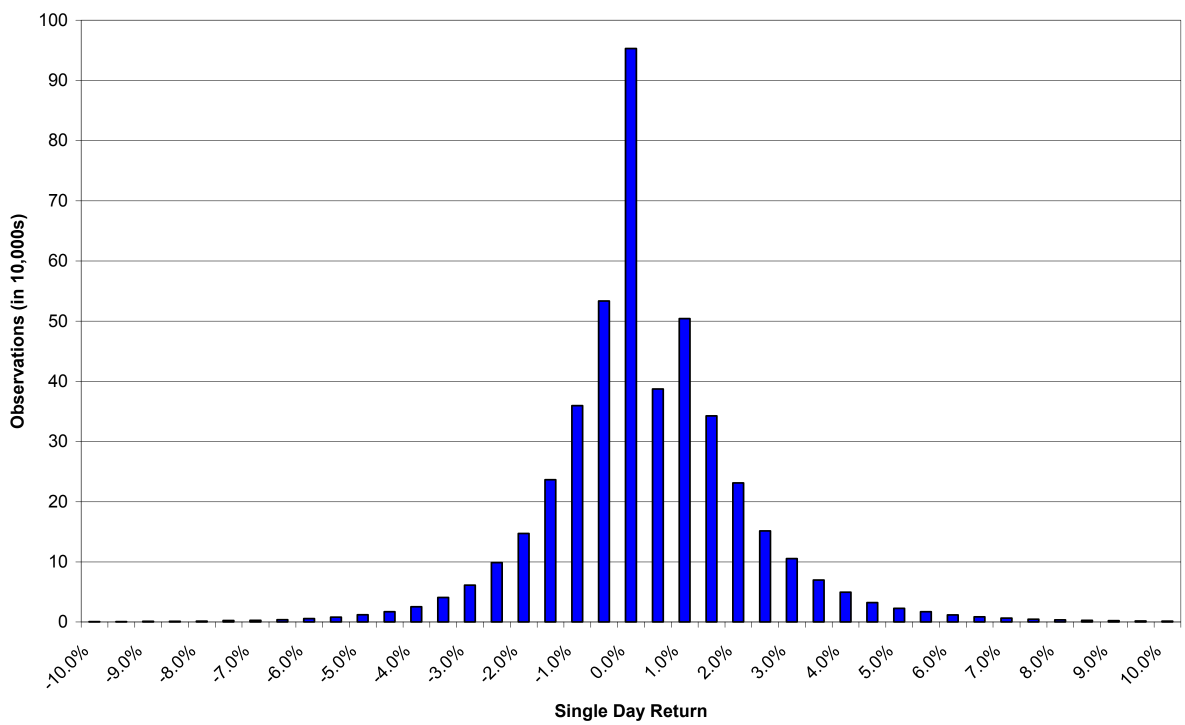
To begin with, we chose to obtain our data, like many academic studies, by accessing the Center for Research in Security Prices ("CRSP"). The daily records in the CRSP data set begin on January 1, 1963 and are currently updated to December 31, 2000. As such, we chose to collect daily stock returns data from January 1, 1963 to December 31, 2000 rather than for the past seventy plus years.

Additionally, we had only partial access to the CRSP database (access was provided through a web-enabled interface only) and thus we had limited capabilities in performing customized database-wide searches. Given this limitation, we screened for the 500 largest common stock issues based on the market capitalization of all companies on the last trading day of each calendar year rather than on every trading day of the thirty-eight year window. This screen included only ordinary common shares (that is, all American Depository Receipts, closed-end funds, foreign-domiciled funds, Primes and Scores, and real estate investment trusts were excluded).

Finally, as explained later in the Methodology section of this paper, we guaranteed that significant single-day losses had the potential to be preceded by 250 days of trading observations by beginning our search on January 1, 1964. Also, to allow for at least potentially 12 months of post-event trading activity, we ended our search on December 31, 1999. These two restrictions resulted in a final data set that spanned thirty-six years.

In the interest of analyzing our data set for potential biases, we performed a variety of simple analyses discussed further in this section of the paper. Below is a histogram of single day returns on all (approximately) 4.5 million trading days screened (500 stocks per year * 250 trading days per year * 36 years).

Figure I – Distribution of Returns



The histogram shows what we would expect based on the central limit theorem; for a large number of independent observations (with finite variance), the distribution approaches that of a normal distribution. This assumption will be relied upon and further discussed later in the paper.

Screening Data for Events

Our data set included single-day simple returns on shares of a company's common stock. These returns were taken as provided by CRSP and include re-investment adjustments for any cash or share dividends. In addition, our data set included the daily returns on the CRSP value-weighted index, the CRSP equally-weighted index, and the S&P 500 index (all index returns were also calculated as if dividends were re-invested).

To screen for events, we needed to choose a threshold cut-off criteria for single-day losses. We set this threshold at a single-day, simple return of less than or equal to -20%. The specific choice of -20% was arbitrary, but the intent was to look at what our sponsor considered significant single-day losses in shareholder value. Given the apparently normal distribution of [Figure I], we doubt that our results would have changed significantly given a change in threshold of +/- 5%.

Once an event threshold was chosen, the data set was screened to find any single day occurrences of the following events: a loss of 20% or greater on an individual common stock, a loss of 20% or greater on an individual common stock less the return on the CRSP value-weighted index, a loss of 20% or greater on an individual common stock less the return on the CRSP equally-weighted index, or a loss of 20% or greater on an individual common stock less the return on the S&P 500 index. The results of this screen are presented below in [Table 1]:

Table I – Data Summary

	Events (20% or Greater Drops)			
	Stock Return	Stock Return - Value Return	Stock Return - Equal Return	Stock Return - S&P 500 Return
Observations	455	282	295	300
Average	-26.7%	-27.1%	-26.9%	-27.0%
Median	-24.6%	-24.9%	-24.6%	-24.9%
Stdev	6.3%	7.0%	7.0%	6.9%
Min	-62.8%	-62.8%	-63.1%	-62.7%
Max	-20.1%	-20.0%	-20.0%	-20.0%

By looking at [Table 1] it is obvious that screening for unadjusted stock returns yields the most observations. However, there are two major issues with using this definition of an event. First, it doesn't seem to address the spirit of the problem proposed by our sponsor. Recall that our analysis is an attempt to deal with (in general) idiosyncratic or company-specific losses. Of the 455 observations that came as result of stock return losses alone, 163 of them took place on October 19th, 1987. The losses on this date are primarily related to a systematic event. Our opinion is that prescriptions for buy / hold / sell actions when there are significant losses for the stock market as a whole is a question beyond the scope of this paper. Secondly, as MacKinlay (1997) discusses, there are a variety of ways in which clustering of observations hinder traditional event study statistical analyses. MacKinlay does suggest possible methods to overcome such clustering, but we found the depth of research in dealing with clustering relatively limited compared to well-studied traditional methods of analyzing event study data.

As a result, we analyzed events defined as a single day loss of 20% or greater after subtracting the market return on that day. We chose the return on the CRSP value-weighted index as our proxy for the return on the market portfolio (the reason for this choice is discussed later in the methodology section of this paper). However, we believe, based on the summary data in [Table I] and our cursory analysis of the detailed observations data, that our results would not have been appreciably different if we were to have defined an event using the CRSP equally-weighted index or the S&P 500 as our proxy for the market portfolio.

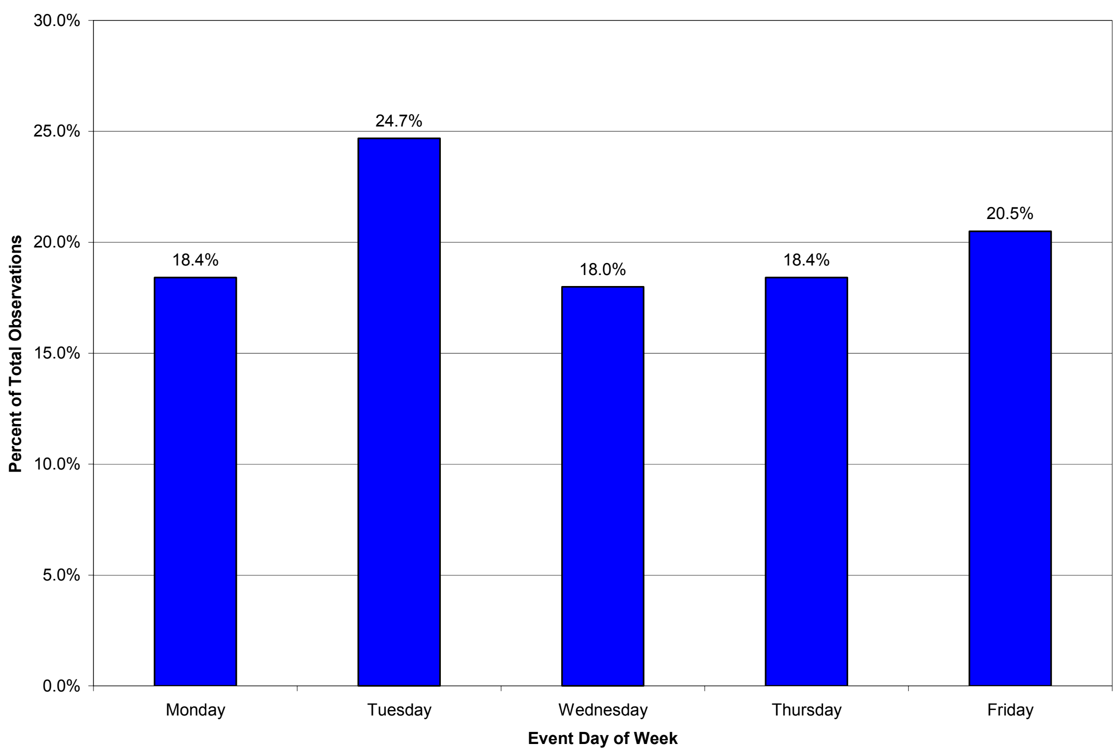
Description of Events Analyzed

As reported in [Table 1], our definition of an event yielded 282 observations during the thirty-six years analyzed. Upon closer inspection of these observations, many came as repeat events for a single company in the same calendar year. In the spirit of our study, we chose to look only at the first event a company experienced in a given calendar year. This further screening reduced the total number of events to 239 observations. As a side note, event date clustering was greatly reduced by defining events as losses of 20% or greater after adjusting for the return on the market. The greatest event date clustering was still associated with the October 1987 market crash, but only nine of our 239 observations occurred on that date.

Data Set Analysis:

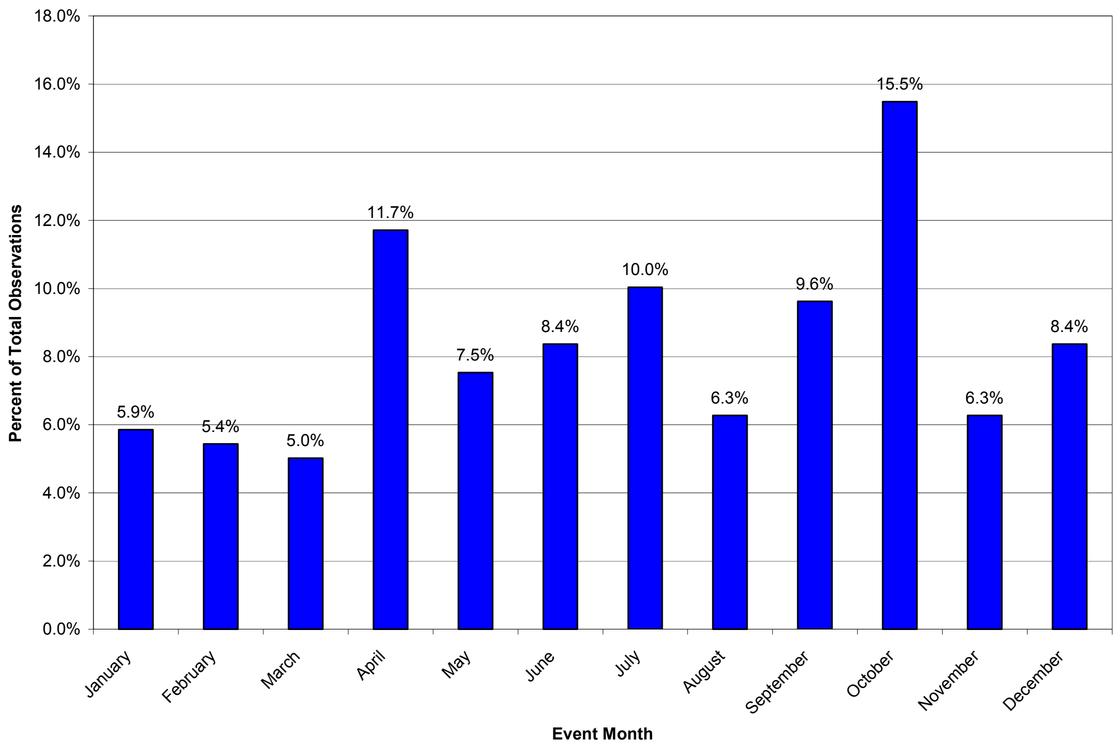
The final 239 events were sorted into several categories to investigate any abnormalities concerning the drops themselves. The first test was categorizing the events by the day of the week that the drop occurred. As seen in [Figure II], the drops occur fairly evenly throughout the week. A chi-squared test showed that we could not reject the null hypothesis that the observations are evenly distributed by day of week (using a two-tailed 95% confidence interval).

Figure II – Event Occurrence by Day of Week



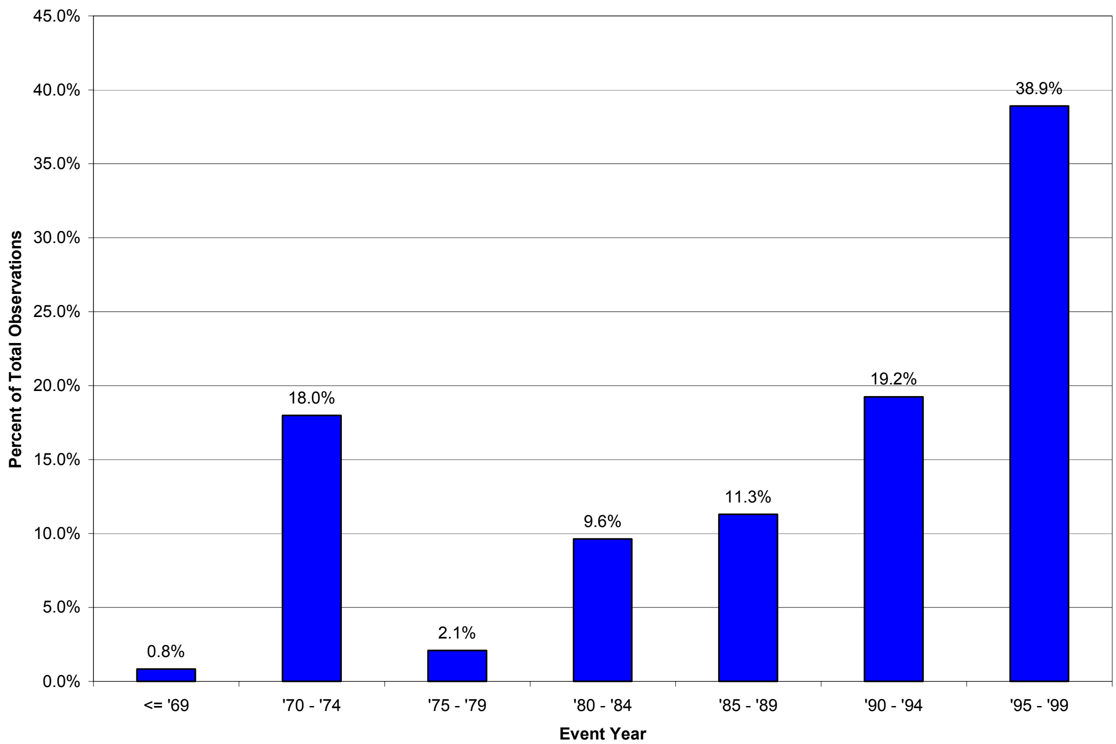
The events were also sorted by the month in which they occurred. A chi-squared test showed that we could reject the null hypothesis that events were evenly distributed by month (using a two-tailed 95% confidence interval). A possible explanation for this is that most events are earnings news related and that these events occur just after the end of the most popular corporate fiscal quarters. This would suggest that the monthly frequency of events would be biased.

Figure III – Event Occurrence by Month



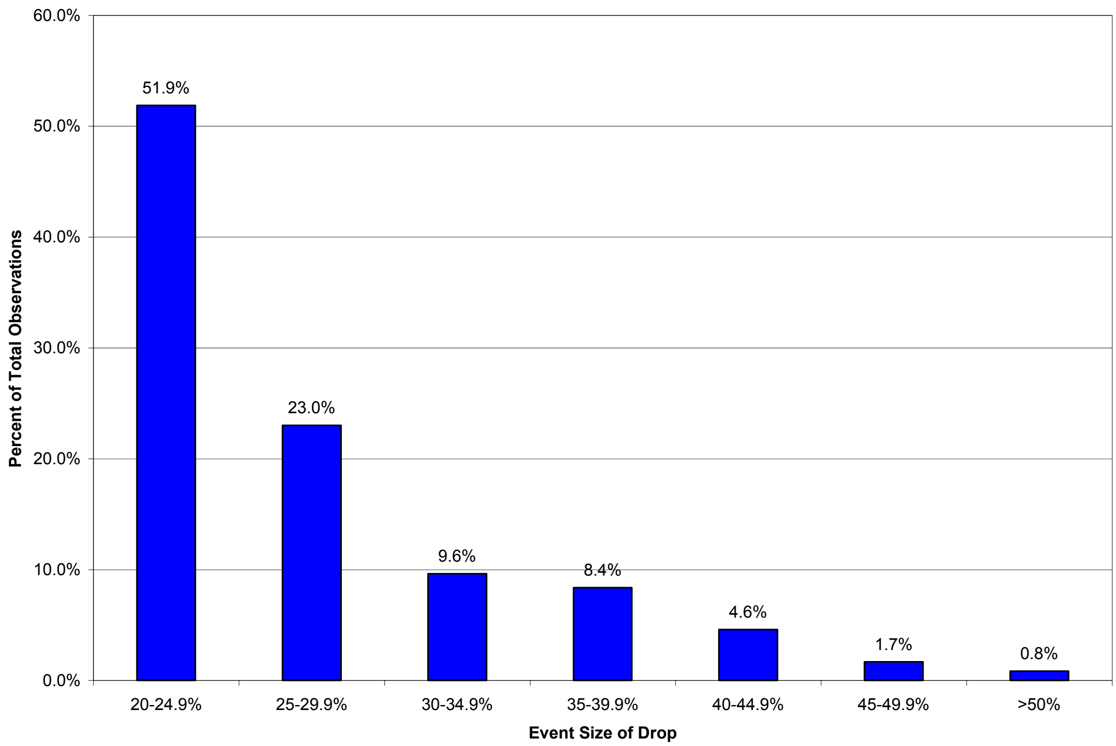
We also grouped the events by the 5-year period in which they occurred. Again we could reject the null hypothesis that the events occurred evenly throughout the past thirty-six years (using a 95% confidence interval). Possible explanations include different economic climates during the various periods, more/less efficient markets affecting the volatility of security returns, and different management practices. One of the most intriguing explanations for this observation is supported by research done by Campbell, Lettau, Malkiel, and Xu (2000). These authors suggest that while systematic risk has not changed significantly over the past forty years, idiosyncratic risk has increased. This would indeed explain the increase in the number of events we observed over the time period of our study.

Figure IV - Event Occurrence by Year



The size of the drop was also plotted via a histogram. As expected, the histogram resembles the tail of a normal distribution.

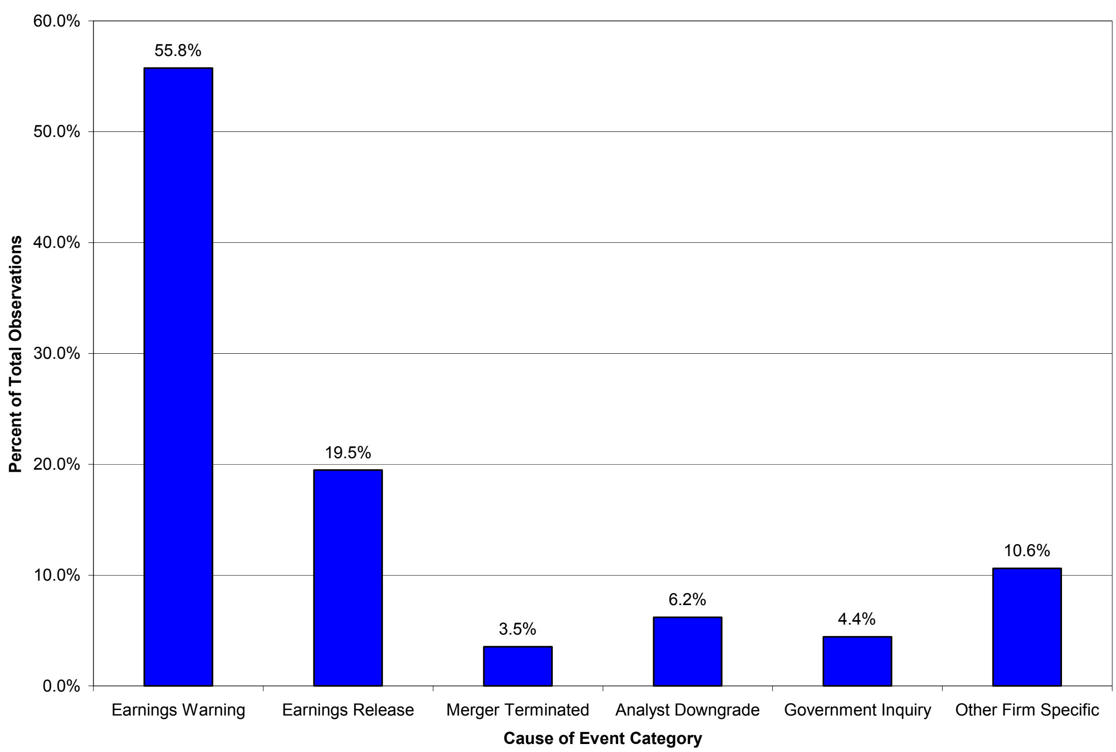
Figure V – Event Occurrence by Size of Percentage Drop



Lastly, a little more than half of the events were researched to determine the cause of the drop. The reasons varied immensely and ranged from: termination of a merger agreement, launch of a SEC investigation over accounting practices, missing Wall Street expectations by a few pennies, to warning a firm would miss expectation significantly in the remaining fiscal year. In all 110 events were researched and the events were sorted into six broad categories: merger terminated, government investigation, analyst downgrade, earning release, earnings warning by management, and other firm specific events (i.e. change in senior management, specific product news).

Often analyst downgrade accompanied one of the other categories or an earning warning was announced with an earnings release. In these circumstances, the first reported explanation of the event was used to categorize the event.

Figure VI –Event Occurrence by Cause of Event



METHODOLOGY

Introduction to Our Abnormal Returns Analysis

As described in the Event Studies Overview section of this paper, the purpose of an event study is to test whether or not empirical observations of stock price behavior conform to the behavior predicted by one of a number of predictive models conditional on a pre-specified event having taken place. Thus Brown and Warner (1980) point out, an event study must clearly define what "abnormal" performance is. In our analysis, we looked at several commonly used methods of defining abnormal performance. Generally, abnormal returns for all the models used in our event study can be summarized using notation similar to MacKinlay's (1997):

$$AR_{iT} = R_{iT} - E(R_{iT}) \qquad \text{Equation 7}$$

Where:

AR_{iT} is the abnormal return for firm *i* over time interval *T*

R_{iT} is the actual return for firm *i* over time interval *T*

$E(R_{iT})$ is the expected / predicted return for firm *i* over time interval *T*

However, as Fama (1998) emphasizes, all models of expected performance are just that, models. And, of the myriad of stock price behavioral models proposed to date by economists, none are robust predictors of the systematic patterns in average stock price returns over any window of time we consider in our event study. Fama concludes, "In short, bad-model problems are unavoidable, and they are more serious in tests on long-term returns."

While we agree with Fama's caveat, the results of even imperfect models are informative and are used frequently in all fields of science. It is simply worth remembering the limitations and biases of any inferences gained by using imperfect predictive models. Our discussion of the models we chose is facilitated by first considering the case of daily abnormal returns, followed by a look at monthly abnormal return models.

Models Used in the Analysis of Daily Abnormal Returns

To analyze post-event daily abnormal returns we employed two common models of stock price behavior. The first model we will refer to as the Market Adjusted Model (see Brown and Warner (1985) and Kothari and Warner (1997) for examples). This simple model employs the same method to calculate abnormal returns that we originally used to define our event dates in the Screening Data for Events section of this paper. The model defines abnormal returns as the excess return on a security, adjusted for the return on the CRSP value-weighted index over the same period of time. The equation for Market Adjusted Abnormal Returns ("MAAR") is:

$$MAAR_{it} = R_{it} - R_{mt}$$ Equation 8

Where:

- $MAAR_{it}$ is the Market Adjusted Abnormal Return on security *i* over time *t*
- R_{it} is the time *t* arithmetic return (including dividends) on security *i*
- R_{mt} is the time *t* arithmetic return on the CRSP value-weighted index (including dividends)

The Market Adjusted Model is an obvious first choice of models in our analysis because of its simplicity in implementation and interpretation. It assumes nothing more than that the expected return on a given security for a given period of time is predicted by the return on the entire market for that same period of time. Put differently, as Brown and Warner (1980) claim, the Market Adjusted Model assumes that each security has the same systematic risk as the entire market.

The second model we used to analyze post-event daily abnormal returns, the Market Model, makes a simple adjustment to the straightforward assumption of the Market Adjusted Model; it estimates each security's systematic risk relative to the market portfolio. Brown and Warner (1985) describe the Market Model as both well specified and relatively powerful under a wide variety of conditions. MacKinlay (1997) also notes that there are limited gains from employing more sophisticated multi-factor derivations of the Market Model because the additional explanatory power provided by these more complicated models is empirically rather small. The equation for Market Model Abnormal Returns ("MMAR") is given by:

$$MMAR_{it} = R_{it} - \alpha_i - \beta_i R_{mt}$$ Equation 9

Where:

- $MAAR_{it}$ is the Market Adjusted Abnormal Return on security *i* over time *t*
- R_{it} is the time *t* arithmetic return (including dividends) on security *i*
- R_{mt} is the time *t* arithmetic return on the CRSP value-weighted index (including dividends)
- α_i & β_i are the ordinary least square ("OLS") parameters estimated for security *i* over the 250 trading day pre-event time window

The length of the pre-event estimation window is similar to that prescribed by MacKinlay (1997) and Brown and Warner (1985). The length of the estimation window is motivated by an attempt to lessen the sampling error in estimating both α_i and β_i. As a side note, we dropped three events from our data set in the analysis of daily returns because they were missing multiple daily return data just prior to their respective event dates.

At this point, it is important to re-acknowledge our use of the CRSP value-weighted index as a proxy for market returns. This assumption is maintained throughout the paper, but there are obvious alternatives for market proxies. Brown and Warner (1980) go into significant detail regarding a choice of a market index. As they summarize, a value-weighted index more accurately reflects the underlying assumption of the Market Model; the model relies on an "an *ex ante* relationship between security expected returns and systematic risk measured with respect to the value-weighted index." However, Brown and Warner find that the CRSP value-weighted index is more likely to cause a Type I error (falsely reject the null hypothesis) than the CRSP equally-weighted index when using the Market Model. They document that this result is linked to the fact that the CRSP value-weighted index systematically overestimates the average Market Model beta coefficient on a randomly selected set of securities (while the CRSP equally-weighted index does not). The cause of this overestimation appears to be related to the fact that event studies equally weight abnormal returns (and implicitly betas) thus under-weighting the betas of large firms in the average. Our particular study, given that we look at only large companies, would seem to be somewhat immune from this potential bias. In addition, a more recent academic study using benchmark portfolios (discussed in the Models Used in the Analysis of Monthly Abnormal Returns section of this paper) by Cowan and Sergeant (2001) found value-weighted portfolios yield the most promising test results (in terms of avoiding biases and misspecifications). In summary, most of the academic literature we surveyed suggested that there are advantages and disadvantages to different choices of market proxies, but for the sake of simplicity and consistency we chose to use the CRSP value-weighted index throughout our analysis.

To conclude our discussion of the models we used to estimate daily abnormal returns, it is worth summarizing several weaknesses of looking at daily abnormal returns rather than monthly returns. To begin with, Brown and Warner (1985) note prior research demonstrating that daily stock returns depart more from normality than do monthly returns (the importance of which is discussed later in the Testing Abnormal Returns for Significance section of this paper). Brown and Warner also comment that non-synchronous trading affects the reliability of any OLS regressions and may induce serial dependence. Finally, Brown and Warner also point to evidence that pre-event variance may increase before certain types of events which would complicate any historical measures of variance used to test for post-event abnormal returns.

Models Used in the Analysis of Monthly Abnormal Returns

There are a variety of methods employed to analyze monthly abnormal returns. We chose to use three of the most common methods: the CAPM, the Fama-French Multi-factor Model, and benchmark portfolio tests. The first of these methods, discussed earlier in the Capital Asset Pricing Model Overview section of this paper, predicts abnormal returns as:

$$CAPMAR_{it} = R_{it} - R_{ft} - \beta_i [R_{mt} - R_{ft}] \qquad \text{Equation 10}$$

Where:

- $CAPMAR_{it}$ is the CAPM Abnormal Return ("CAPMAR") on security *i* over time *t*
- R_{it} is the time *t* arithmetic return (including dividends) on security *i*
- R_{mt} is the time *t* arithmetic return on the CRSP value-weighted index (including dividends)
- R_{ft} is the CRSP 30 day treasury return over time *t*; a proxy for the monthly risk free rate
- β_i is the OLS coefficient estimated for security *i* over the 60 month pre-event time window

If monthly stock returns were not available for the full 60 months of pre-event estimation, the months available were used to calculate the β_i coefficient as long as there were 24 months of pre-event data. Requiring at least 24 months of pre-event data necessitated dropping nineteen of our 239 observations, leaving us with a total of 220 monthly observations. Kothari and Warner (1997) find that requiring prior return data (pre-event survival) can cause estimated post-event abnormal returns to be systematically positive in random samples. However, even their study enforced this limiting requirement on the data set because having fewer than 24 months of pre-event data provides for poor estimates of the β_i coefficient. Brown and Warner (1980) use a similar pre-event estimation window of 89 months. One will notice that the economic interpretation of the model behind CAPMARs is very similar to that of the MMARs used to estimate daily abnormal returns. We did not use the CAPMARs to estimate daily abnormal returns because we assume that the daily return on a risk free security is close to zero and adjusting for it would not add meaningful explanatory power to the daily model.

MacKinlay (1997) notes that the use of the CAPM as an event study model has subsided since the validity of the model has been the subject of popular attack in more recent academic research. However, we include the model in this paper as it is perhaps the most widely understood asset pricing model, and despite its flaws, it serves as a reasonableness check against our results from more recently introduced yet less-tested models of abnormal returns.

The research behind our second monthly abnormal returns model, the Fama-French Multi-factor Model, is discussed earlier in the Fama-French Multi-factor Model Overview section of this paper. The abnormal returns predicted by this model are given by:

$$FFMAR_{it} = R_{it} - R_{ft} - \beta_{i1}[R_{mt} - R_{ft}] - \beta_{i2}HML_t - \beta_{i3}SMB_t \qquad \underline{\text{Equation 11}}$$

Where:

$FFMAR_{it}$	is the CAPM Abnormal Return ("CAPMAR") on security *i* over time *t*
R_{it}	is the time *t* arithmetic return (including dividends) on security *i*
R_{mt}	is the time *t* arithmetic return on the CRSP value-weighted index (including dividends)
R_{ft}	is the CRSP 30 day treasury return over time *t*; a proxy for the monthly risk free rate
HML_t	is the time *t* return for the book to market equity factor discussed earlier in this paper
SMB_t	is the time *t* return for the size factor discussed earlier in this paper
$\beta_{i1},\ \beta_{i2}$, and β_{i3}	are the OLS coefficients estimated for security *i* over the 60 month pre-event time window

Again, we used 60 months (or at least 24 months) of pre-event data to estimate the OLS regression coefficients β_{i1}, β_{i2}, and β_{i3} for each security *i*. Returns for the size and book to market equity factors were taken from Professor French's website at http://web.mit.edu/kfrench/www/data_library.html.

We did not apply the FFMAR model to daily events because the size and book to market equity factors were not readily available on a daily basis. However, we can think of no theoretical reason why this model of abnormal returns couldn't be used to estimate daily abnormal returns if data were available. Also, it is reasonable to assume, as many authors have noted, that to the extent other factors increase the explanatory power of this model, they could be added as well (for example, a coefficient to account for prior return performance).

Our third method of measuring monthly abnormal returns, benchmark portfolios, appears to be the most frequently utilized model in the recent academic literature. In its simplest form, the economic intuition behind the benchmark portfolio method of measuring abnormal returns is similar to that of the Market Adjusted Model described earlier. Abnormal performance is measured by taking the difference between the return on a portfolio and the return on a corresponding index. There are multiple complications to consider in choosing a corresponding index. In our analysis we consider three methods of matching monthly portfolios: (1) matched on size, (2) matched on a book value of equity to market value of equity multiple ("BE/ME"), and (3) matched on a combination of size and BE/ME. The intent on matching returns using these three portfolios is a basic extension of Fama and French's research described in the Fama-French Multi-factor Model Overview section of this paper.

To construct the portfolios we first retrieved data from the COMPUSTAT database on the book value of common equity reported on a firm's balance sheet (data item #60) at the end of December before the event year. We also collected each firm's market value of equity at the end of December before the event year. If firms did not have data on the book value of common equity or if that value was negative, they were dropped from the BE/ME matched data set and the size and BE/ME matched data set. In total, there were thirty-five observations dropped because of lack of book value data. Next, firms were ranked into BE/ME deciles and size deciles based on the decile categories provided on Professor French's web-site. Finally, the return on the benchmark portfolio for the appropriate decile (or in the case of the size and BE/ME matched portfolio there were 100 possible matching portfolios – a 10 by 10 matrix of size and BE/ME deciles) was matched to the return on the individual security. An advantage to using the benchmark portfolio method to calculate abnormal returns is that it does not place any requirements on the existence of pre-event return data. However, it does limit the data set in the BE/ME case because it requires the book value of common equity to be positive and historically attainable.

One issue that has been recently documented is that using reference portfolios to calculate long-term abnormal returns can result in biased test statistics based on our methodology. Barber and Lyon (1997) document that a new listing bias (new firms enter the reference portfolio each year), rebalancing bias (reference portfolios returns are usually calculated assuming periodic rebalancing), and skewness bias (long-run abnormal returns are positively skewed) all exist in such portfolios. One way to correct for this that was beyond our capabilities, given our access level to the CRSP database, would be to (as Barber and Lyon attempted) create a reference portfolio for each event just prior to the event date. Then, one would prevent both rebalancing and new firm entry into that reference portfolio. Cowan and Sargeant (2001) repeat this exercise, but find that it still does not completely free the investigator from misspecified test statistics.

As mentioned, reference portfolios seem to be the model of choice in recent event studies. However, Fama (1997) points out that previous event studies have shown that matching on size can produce much different abnormal returns than matching on size and BE/ME. In addition, size and BE/ME matching captures only a piece of relevant cross-firm variation (and not much more than the two regression models described earlier in this section) in average returns. Thus we agree with Fama, "In short, the matching approach is not a panacea for bad-model problems in studies of long-term abnormal returns."

In summary, the models employed in our analysis, while frequently used, are subject to a host of empirical difficulties. At the very least, all the models are somewhat retrospective: they all use historical data (in one way or another) to predict the reasonableness of future returns. For the benchmark portfolios, we must worry about inaccuracies as a result of size and BE/ME drift as reported by Cowan and Sergeant (2001). For the regression models, we must worry about how the regression coefficients might change over time. Finally, for many types of corporate events, long periods of unusual pre-event returns are common as discussed by Fama (1997). Indeed, our data set is composed of (on average) prior winners by definition (e.g., a stock can move up into the top 500 firms, but it cannot move down into the top 500 firms). The empirical investigation of our data set bears this out, and while we do not report detailed results of this investigation (because it is an obvious point), we believe it is worth keeping in mind when considering the biases that might influence our results.

Methods of Measuring Abnormal Returns

We considered three primary metrics to measure daily and monthly abnormal returns. These metrics were: average abnormal returns, cumulative abnormal returns, and buy and hold abnormal returns. As we discuss these metrics, we will present equations based on the Market Adjusted Model described in the Models Used in the Analysis of Daily Abnormal Returns section of this paper. These equations can be adjusted by simple substitution to represent all of the different abnormal return models we have already discussed.

Average abnormal returns ("AARs") are simply:

$$MAAR_{pt} = \frac{1}{N_t}\sum_{i=1}^{N_t} MAAR_{it}$$ Equation 12

Where:

$MAAR_{pt}$ is the average Market Adjusted Abnormal Return on a portfolio of *N* events over time *t*

As Fama (1998) discusses, one drawback of looking at AARs in an event study is that they do not realistically reflect the return realized by actual investors.

Cumulative abnormal returns ("CARs") are an extension of the AAR equation:

$$CAR_{pT} = \sum_{t=T1}^{T2} MAAR_{pt}$$ Equation 13

Where:

CAR_{pt} is the cumulative Market Adjusted Abnormal Return on a portfolio of *N* events over time period *T*1 to *T*2

Finally buy and hold abnormal returns ("BHARs") measure the difference between the compounded actual return and the compound predicted return:

$$BHAR_{it} = \prod_{t=0}^{T}\left[1 + R_{it}\right] - \prod_{t=0}^{T}\left[1 + R_{mt}\right] \quad \text{Equation 14}$$

Where:

R_{it} is the time t arithmetic return (including dividends) on security i

R_{mt} is the time t arithmetic return on the CRSP value-weighted index (including dividends)

Buy and hold returns are frequently used in modern event studies, but Fama (1997) cautions that "bad-model problems are most acute with long-term BHARs" due to the fact that such returns compound any model's inability to accurately describe short term returns. He continues with a lengthy explanation of the shortcomings of using BHARs, primarily relating to the fact that BHARs can lead to long-term statistically significant abnormal performance even when none is present due to short-term influences. Kothari and Warner (1997) also find that long-horizon buy and hold abnormal returns are significantly right-skewed, although cumulative returns are not. Thus, the chief advantage of looking at BHARs is that, of our abnormal performance measures, they most accurately simulate the effect of an event on an investor's portfolio (due to compounding). However, AARs and CARs help avoid the problems of extreme skewness introduced by BHARs and therefore are helpful in double-checking any conclusions presented by BHARs results.

A final note on our methods of measuring abnormal returns should be that we had considerable difficulty in settling upon how to adjust for missing returns on individual securities. This issue is discussed as a side topic in several papers, but we did not uncover any particularly in-depth research on the topic. Barber and Lyon (1997) briefly highlight the fact that long-horizon tests are sensitive to how missing event returns are handled. Lyon, Barber, and Tsai (1999) fill in missing data first with the CRSP delisting return where available and then with the predicted return on the security. Kothari and Warner (1997), Cowan and Sargeant (2001), and Barber and Lyon (1997) seem to have used a similar method to deal with missing returns data. In the spirit of mimicking the methods utilized in the most recent academic literature, we also filled in missing data first with the CRSP delisting return where available and then with the predicted return on the security. Using the CRSP delisting return is itself not without biases, as Shumway (1997) concludes in an entire paper on the subject. His findings are that correct delisting returns are not available for most stocks that have been delisted for negative reasons. Nearly 10% of our 239 observations are delisted at some point during the 48-month post-event observation window.

Testing Abnormal Returns for Significance

Based on the efficient market hypothesis, as described earlier in this paper, all of our tests for statistical significance are tests of the null hypothesis that abnormal returns are zero over any event window. As in the preceding section of this paper, the equations we will discuss in this section are based on the Market Adjusted Model, but could be easily modified to work for the other models (except where noted).

To begin, we made use of the common parametric *t*-test / *z*-test as a test of the null hypothesis that the post-event observations are not influenced (their return and their variance) by the fact that a major stock price drop occurred. As Brown and Warner (1985) state, "The Central Limit Theorem guarantees that if the excess returns in the cross-section of securities are independent and identically distributed drawings from finite variance distributions, the distribution of the sample mean excess return converges to normality as the number of securities increases." Thus, assuming a large number of observations, independent returns, and identically distributed and finite variances we can state that:

$$MAAR_{pt} \sim N\left(0, \sigma^2\left(MAAR_{it}\right)\right) \qquad \text{Equation 15}$$

Or that the average Market Adjusted Abnormal Return for time t is normally distributed with mean zero and a variance as discussed in the following paragraphs.

The variance of the abnormal return can be measured in several ways. The first of the two most common ways are to assume that the predicted variance of the post-event abnormal return is given by the observed variance of the pre-event time window. In this case, variance is given by:

$$\sigma^2\left(MAAR_{pt}\right) = \sum_{t=-x}^{-1}\left(MAAR_{pt} - Avg(MAAR_{pt})\right)^2 \Big/ (x-1) \qquad \text{Equation 16}$$

Where:

x is the number of observations (days or months) in the pre-event estimation window

And

$$Avg(MAAR_{pt}) = \frac{1}{x}\sum_{t=-x}^{-1} MAAR_{pt} \qquad \text{Equation 17}$$

We refer to this method of calculating variance as the time series method. Barber and Lyon (1997) remind us that time series standard deviations cannot be used when calculating a test statistic for BHARs as the variance of BHARs is naturally expected to change over time. For an example of the time series method for calculating variance in use see Brown and Warner (1985).

We can also calculate a cross-sectional estimate of variance. Under this method the variance of the abnormal return is given by:

$$\sigma^2\left(MAAR_{pt}\right) = \frac{1}{N^2}\sum_{i=1}^{N}\left(MAAR_{it} - MAAR_{pt}\right)^2 \qquad \text{Equation 18}$$

Where the variables are as defined as before. Given our assumptions of distribution and mean we can calculate the a test statistic based on the following measure:

$$test \cdot statistic = MAAR_{pt} / \sigma\left(MAAR_{pt}\right) \qquad \text{Equation 19}$$

Depending on the number of observations we can use the test statistic to test the null hypothesis assuming a unit normal distribution or a student *t* distribution. To calculate a similar statistic for average CARs using the time series variance, all one needs to do is adjust the variance for the accumulation of time:

$$test \cdot statistic = CAR_{pt} / \sigma\left(MAAR_{pt}\right) * T^{1/2} \qquad \text{Equation 20}$$

Where:

T is the total number of event time observations used to calculated CAR_{pt}

To calculate a similar test statistic for average CARs and average BHARs, using cross sectional variance, all one needs to do is adjust the variance used in the equation to measure the cross sectional variance of the average CAR or average BHAR.

Once empowered with these test statistics we can accept or reject our null hypothesis. However, we must use caution in interpreting the validity of our results. Brav (1998) reports, "Statistical inference in many long-horizon event studies has been hampered by the fact that abnormal returns are neither normally distributed nor independent." Kothari and Warner (1997) also report that some of the most common event-study methods systematically underestimate the true variance of abnormal returns. In short, they suggest, "For a variety of reasons, the test statistics do not conform to standard parametric assumptions and over-reject the null hypothesis of no abnormal performance."

One possible solution to the seemingly non-parametric nature of abnormal returns is to use a sign test similar to the method Brown and Warner (1980). The sign test is a simple non-parametric test that can be use to test the null hypothesis that AARs and CARs are half-positive and half-negative. There are obvious flaws with this assumption, but to check for robustness we included this test in our results. The equation for the test statistic is as follows:

$$test \cdot statistic = \left[\frac{N^{+}}{N} - .5 \right] \cdot \frac{\sqrt{N}}{0.5}$$ Equation 21

Where:

N^{+} is the number of positive AAR or CAR observations for a given estimation window

N is the total number of observations in that estimation window

There are several other options to adjust for the apparent non-parametric nature of abnormal returns. One method used by Cowan and Sargeant (2001) is relatively straightforward and easy to implement. This method winsorizes abnormal returns before estimating a test statistic. Winsorization refers to the practice of removing outliers from a population sample by constraining all observations to be within a certain number of standard deviations from the mean sample observation (outliers are not literally removed, but "moved" to a certain number of standard deviations from the sample mean). In their study, Cowan and Sargeant chose a three standard deviation interval for winsorization and we replicate this choice. In the case of abnormal returns, winsorization effectively lessens the positive skew noted by many authors; empirically it is usually only positive observations that lie outside of the three standard deviation threshold.

Cowan and Sargeant also use another method to improve the validity of inferences provided by statistical results. Instead of using a paired difference test statistic (that is one that assumes the actual return and the predicted return are pair-wise dependent), the authors suggest using a two-groups test statistic. The authors argue that the two-group test aids in avoiding the cross-sectional dependence that occurs from overlapping event windows. While in our description of our data set we noted that no observation date dominated the data set, as post-event window estimates of CARs and BHARs increase, cross-sectional dependence also increases. Cowen and Sargeant note, "For example, there can be only nine completely distinct three-year holding periods between 1965 and 1992." While a two-groups test will be less powerful than a paired difference test, the authors suggest using the following statistic as a crude adjustment for cross-sectional dependence:

$$two \cdot group \cdot test \cdot statistic = \frac{CAR_{pT}}{\left(\hat{\sigma}^2 AverageR_{iT} / N + \hat{\sigma}^2 AverageR_{mT} / N \right)^{5}}$$ Equation 22

Of course, a final caveat to our attempts to improve the robustness of our study is echoed by Sutton (1993): "The signed test… and winsorization…can be used to accurately perform a test about the mean of a symmetric distribution… [but] it is important to keep in mind that all of the just-discussed nonparametric and robust procedures for tests about the mean have a requirement of symmetry and that a large sample size does not rectify matters if that assumption is violated in a significant way. In fact, for asymmetric distributions, both the sign and the signed-ranked test become less accurate with an increase in sample size." Sutton suggest the use of a bootstrapped, skewness adjusted *t* statistic for one-sided tests about the mean of a skewed distribution. Lyon, Barber, and Tsai (1999) use this method to calculate the significance of abnormal and find improved test statistic specification. We attempted to implement this statistic, but it was both computationally time consuming and initial results did not prove significantly different than those already provided by simpler measures of statistical significance. There obviously exists room for improvement on different models and statistical tests used in event studies. However, one such recent attempt we surveyed in Brav (1998) was so complicated that any results the method provided would be difficult to interpret let alone implement. We conclude our statistical overview by agreeing with Lyon, Barber, and Tsai (1999) when they say "analysis of long-run abnormal returns is treacherous", but we also believe our results still worth consideration despite the possible model and statistical biases they may contain.

DISCUSSION OF RESULTS

Daily Results

Our finding is that there is strong evidence to support rejection of the null hypothesis that there is no daily abnormal return for the 5, 10, 15, 20, and 30 day post-event observation windows. Detailed results tables and graphs can be found in Appendix A of this paper. Below is a summary table of where we observed two-tailed statistical significance at the 95% confidence interval:

Table II – Summary Daily Statistical Significance

	Days Post Event						
	1	5	10	15	20	30	45
Market Adjusted Model							
• Time series CAR	–	Yes	Yes	Yes	Yes	Yes	–
• Cross sectional CAR	–	Yes	Yes	Yes	Yes	Yes	–
• Cross sectional BHAR	–	Yes	Yes	Yes	Yes	Yes	Yes
Market Model							
• Time series CAR	–	Yes	Yes	Yes	Yes	Yes	–
• Cross sectional CAR	–	–	Yes	Yes	Yes	–	–
• Cross sectional BHAR	–	Yes	Yes	Yes	Yes	Yes	Yes

The Market Adjusted Model suggests short-term horizon daily abnormal returns exist, utilizing any of the different statistical tests at the 5% two-tail significance level; all the drops are significant except for the 1-day and the 45-day measurement periods. On average, the significance levels for the BHARs are higher then those for the CARs. For the 1-day period, none of the statistical tests show 5% significance while for the 45-day period, only the BHARs are significantly different from zero. The higher significance levels are found at the 10, 15 and 20 days post event periods. Skewness is positive for all daily periods except for the 15-day period and decreases over time. Kurtosis is also positive for all periods and decreases over time for the CARs. The mean CARs and BHARs are negative for all periods. At 20 days post-event, the measurement period with strongest statistical significance, the CAR is –3.3% and the BHAR is –3.8%.

The Market Model daily results are consistent with the Market Adjusted Model daily results. A difference arises when comparing the CARs for the 5 and 30 day post-event periods. The CARs cross sectional test statistics are insignificant for the 5 and 30 days post-event periods, although the winsorized cross sectional statistic is significant for the 5-day post-event period. Skewness is again highest in the shorter post-event windows and kurtosis remains low but positive indicating a peaked distribution relative to the normal distribution.

For our daily analysis, we started with the same set of events that were used in the CAPM and Fama and French Multi-factor Model monthly analysis. Recall from our earlier discussion that we narrowed our 239 original events to 220 events for these two monthly models because of our requirement of at least 24 months of pre-event return observations. Also recall that we dropped three events from use in our daily dataset because they lacked frequent (five or more days) daily return observations just before the event date. As our result, our daily analysis includes 217 events; only one of these events had stopped trading by the end of the 45-day post-event observation period.

A summary of daily returns analysis is perhaps easiest to obtain by looking at the graphs in Appendix A. These graphs suggest that the market does, on average, underreact to significant bad news for at least the first 20 days post-event. Although the size of the underreaction varies across different statistical methodology, all underreaction is significant at the 5% level. Therefore, our findings are consistent with strategy of immediately selling the security that drops by 20% or more and refraining from repurchasing it for at least 20 days. There are transactions costs, tax consequences, and non-synchronous trading that would obviously diminish this strategy's returns. Given more time, we believe it would have also been informative to repeat our study and test results for different magnitudes of drops (even smaller drops than 20%).

Monthly Results

For all of the models, monthly abnormal negative returns follow a similar pattern: a significant marked drop for up to twelve months post-event. Given that our results are largely statistically insignificant after the twelve-month period, we are unable to corroborate or refute the return reversals documented by Jegadeesh and Titman (1999) and the various behavioral models discussed earlier in this paper. Notably, in our investigation of BHARs using the CAPM, we obtain statistically significant results until the fourth year but no evidence of significant return reversal is found. Again, more detailed results can be found in Appendix A, but the table on the following page summarizes the statistical significance of our monthly findings:

Table III – Summary Monthly Statistical Significance

	Months Post Event						
	1	3	6	12	24	36	48
CAPM							
• Time series CAR	–	–	Yes	Yes	–	–	–
• Cross sectional CAR	–	–	Yes	Yes	–	–	–
• Cross sectional BHAR	–	Yes	Yes	Yes	Yes	Yes	–
Fama & French Multi-factor Model							
• Time series CAR	–	–	Yes	–	–	–	–
• Cross sectional CAR	–	–	Yes	Yes	–	–	–
• Cross sectional BHAR	–	–	Yes	Yes	–	–	–
Size and BE/ME Matched Portfolio							
• Cross sectional CAR	–	–	Yes	Yes	–	–	–
• Cross sectional BHAR	–	Yes	Yes	Yes	–	–	–

The most negative returns were found in what are considered to be the best-specified models: the CAPM, the Fama-French Multi-factor Model, and the combination size-matched and BE/ME matched portfolio model (the "combination model"). Negative CARs for these models range from –7.5% to –10.2% for the twelve month post-event observation period while negative BHARs for these models range from –9.6% to –12.6% for the twelve month post-event observation window.

Underreaction or delayed overreaction may help explain why the most negative, significant results are found after a time lag of three to twelve months. Since an "earnings warning" is the single most common cause of a large stock drop in our sample, investors may underreact by not selling the stock enough, given its bleaker prospects in upcoming quarters. Or, alternatively, contrarian investors are buying the stock too early, following negative firm-specific news.

The continuing decline in stock returns in the three to twelve month window support the Jegadeesh and Titman (1993, 1999) findings. In addition, we observe that the magnitude of the abnormal returns is similar to that of the abnormal returns observed by Jegadeesh and Titman (1993) in their three to twelve month holding period. Similarly, the continuing decline in stock returns – over the post-event twelve-month period – corroborates behavioral models such as the conservatism bias of Barberis, Schleifer and Vishny (1998) and two-investor group model of Hong and Stein (1998). Since "earnings warnings", again the single most common cause of a large stock drop in our sample, represent "public information," the behavioral model advocated by Daniel, Hirshleifer and Subrahmanyam (1998) that incorporates investor overconfidence about the precision of private information does not appear to be supported.

As alluded to earlier, we do not observe complete or close to complete reversal in returns over the four-year time horizon examined. This does not support the return reversals found by Jegadeesh and Titman (1999). Nor does the evidence completely support the behavioral models that suggest a return to fundamental values once investors have reconciled their biases or once full information is incorporated into the prices.

The number of event observations varies between 220 and 203 for month one, and from 135 to 123 for month forty-eight, although this drop-off in event observations would have been even more extreme if we had not filled in missing data points with predicted returns (as mentioned earlier in the Methodology section of this paper). Another reason for the drop-off in event observations after four years is the fact that nearly 40% of events occurred in the last five year time period studied, 1995 to 1999.

All of the models exhibited notable kurtosis in BHARs, for which we were not able to find an adequate explanation in the literature. Brown and Warner (1985) mention that high kurtosis can arise in smaller samples, but our sample is larger than their threshold level, so their comment does seem to apply to our case. Predictably, BHARs are all increasingly right-skewed with time. CARs exhibited neither systematic skew nor kurtosis in any of the models used.

Results by Cause of Event

In addition to the aggregate results of event observations reported above, the abnormal returns of each of our event categories (e.g. "earnings warning") were contrasted with the abnormal returns of the total sample for which we had categorized events (110 events) to determine if a category could help predict future returns and thereby aid in the buy, sell, or hold decision. The results, including the mean, standard deviation, sample size, t-statistic, and significance level for monthly returns can be found at the end of Appendix A. Abnormal returns were calculated using the CAPM.

To test results for significance, we tested for a difference in the mean of each sub-category with that of the total sample. The number of observations we had to work with declined from 110 (at month one) to 39(at month forty-eight). CARs and BHARs for the entire sample of 110 events follow a similar pattern to that of the CAPM model for all 220-event observations, with the exception of month 48, (but this may be due to the small sample size at that point). T-statistics for a difference in mean remain low throughout the tests (not significant), but are the highest for six and twelve months in each sub-sample. As a result, there are no strong conclusions to be drawn from these tests.

CONCLUSION

We analyzed thirty-six years of daily data to screen for large stocks that had a return of –20% or worse, even when adjusted for the market return on the same trading day. While our analysis does not attempt to incorporate the effects of transactions costs, taxes, and portfolio diversification strategies, it does lead us to a general recommendation: sell. However, as noted throughout the paper, statistical inferences based on imperfect models of abnormal returns should be regarded with caution. The efforts we undertook in the collection of our data set and its analysis reinforced the fact that significant obstacles must be overcome to protect the integrity of the results, even in seemingly straightforward event studies. Furthermore, in our studies of sub-samples sorted by cause of drop, we found no significant results, suggesting that the "reason for drop" is not a useful predictor of subsequent abnormal returns.

As we were concluding our research, one of our Kellogg professors asked us about our project. When she heard that we were basing our recommendation entirely on technical analysis she laughed, "Didn't we teach you the value of looking at fundamentals here?" We place this comment here, at the conclusion of our paper, to encourage our reader to consider the context in which our results are meaningful and actionable.

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APPENDIX A – RESULTS: TABLES AND GRAPHS

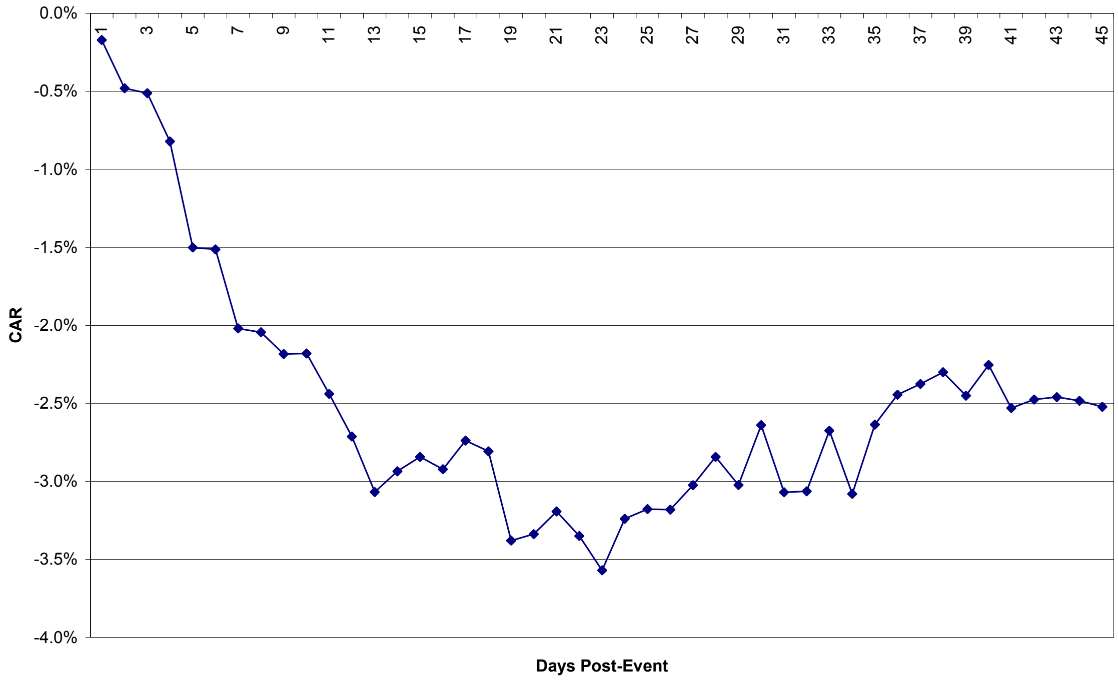
Market Adjusted Model Daily Abnormal Returns

Market Adjusted Model Daily Abnormal Returns

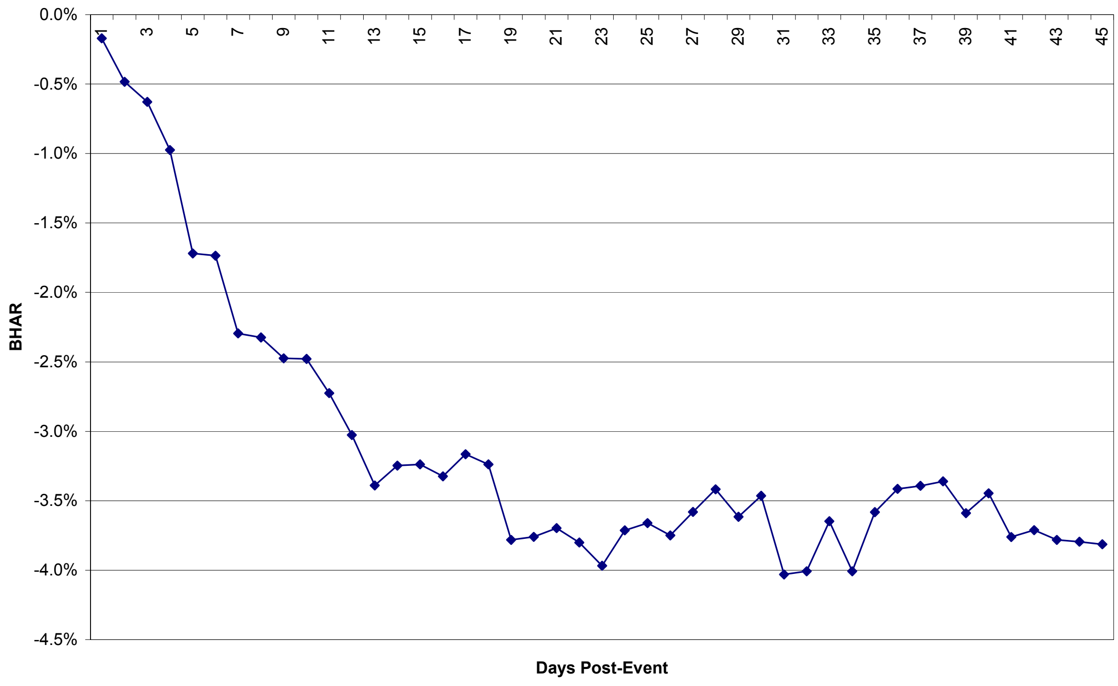
	Post-Event Time (days)						
	1	5	10	15	20	30	45
Number of observations	217	217	217	217	217	217	216
Cumulative Abnormal Returns (CAR)							
Mean	-0.2%	-1.5%	-2.2%	-2.8%	-3.3%	-2.6%	-2.5%
Standard deviation	7.9%	10.6%	12.6%	14.9%	16.6%	19.2%	21.4%
Skewness	0.70	0.21	0.37	(0.03)	0.04	0.01	0.07
Kurtosis	3.37	2.35	0.30	1.21	1.03	1.57	0.58
CAR test statistics							
Time series	NMF	NMF	NMF	NMF	NMF	NMF	NMF
Cross sectional	(0.32)	(2.08) *	(2.54) *	(2.81) *	(2.96) *	(2.03) *	(1.74)
Winsorized cross sectional	(0.48)	(2.18) *	(2.59) *	(2.79) *	(2.98) *	(2.10) *	(1.77)
Sign test	(1.02)	(2.78) *	(2.92) *	(2.92) *	(3.19) *	(2.51) *	(1.15)
Buy and Hold Abnormal Returns (BHAR)							
Mean	-0.2%	-1.7%	-2.5%	-3.2%	-3.8%	-3.5%	-3.8%
Standard deviation	7.9%	10.2%	12.3%	14.3%	16.2%	18.9%	21.4%
Skewness	0.70	0.29	0.50	0.25	0.42	0.57	0.60
Kurtosis	3.37	1.47	0.40	0.79	0.98	2.04	1.39
BHAR test statistics							
Cross sectional	(0.32)	(2.48) *	(2.97) *	(3.32) *	(3.42) *	(2.70) *	(2.62) *
Winsorized cross sectional (paired)	(0.48)	(2.55) *	(3.01) *	(3.33) *	(3.49) *	(2.93) *	(2.80) *
Winsorized cross sectional (two groups)	(0.42)	(2.37) *	(2.69) *	(2.97) *	(3.09) *	(2.48) *	(2.35) *

(*) Indicates two-tail statistical significance at the 5.0% level.

Market Adjusted Model Daily CAR



Market Adjusted Model Daily BHAR



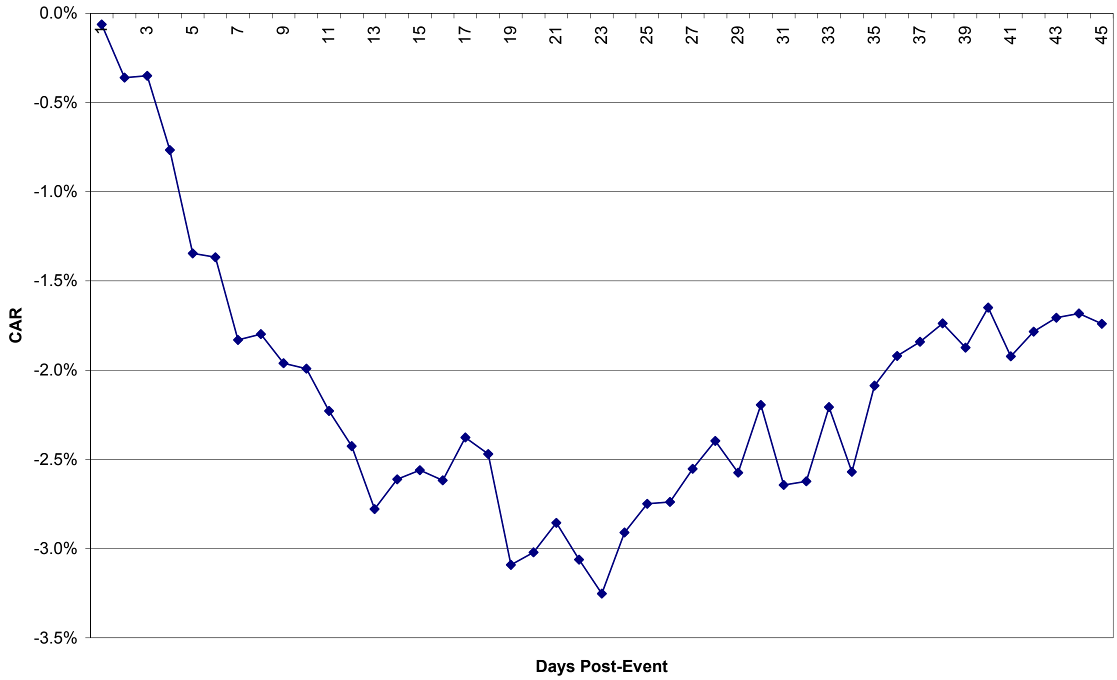
Market Model Daily Abnormal Returns

Market Model Daily Abnormal Returns

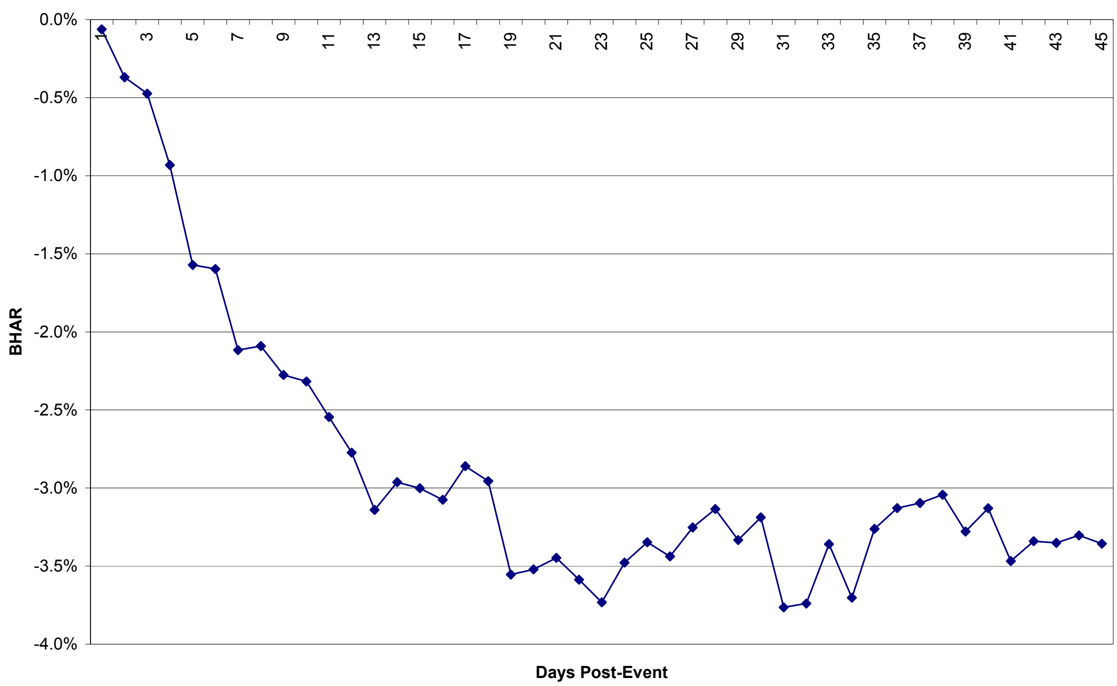
	Post-Event Time (days)						
	1	5	10	15	20	30	45
Number of observations	217	217	217	217	217	217	216
Cumulative Abnormal Returns (CAR)							
Mean	-0.1%	-1.3%	-2.0%	-2.6%	-3.0%	-2.2%	-1.7%
Standard deviation	8.0%	10.6%	12.5%	15.2%	16.8%	19.5%	22.2%
Skewness	0.68	0.28	0.29	(0.06)	0.08	0.06	0.08
Kurtosis	3.08	2.23	0.06	1.09	1.15	2.17	0.89
CAR test statistics							
Time series	(0.35)	(3.37) *	(3.53) *	(3.70) *	(3.78) *	(2.24) *	(1.45)
Cross sectional	(0.11)	(1.88)	(2.34) *	(2.48) *	(2.64) *	(1.66)	(1.16)
Winsorized cross sectional	(0.26)	(1.98) *	(2.35) *	(2.46) *	(2.68) *	(1.78)	(1.22)
Sign test	(0.75)	(2.51) *	(2.24) *	(2.51) *	(2.65) *	(2.10) *	(1.29)
Buy and Hold Abnormal Returns (BHAR)							
Mean	-0.1%	-1.6%	-2.3%	-3.0%	-3.5%	-3.2%	-3.4%
Standard deviation	8.0%	10.2%	12.2%	14.6%	16.5%	19.3%	22.2%
Skewness	0.68	0.35	0.42	0.21	0.47	0.64	0.54
Kurtosis	3.08	1.42	0.15	0.75	1.21	2.89	1.59
BHAR test statistics							
Cross sectional	(0.11)	(2.28) *	(2.80) *	(3.02) *	(3.14) *	(2.44) *	(2.23) *
Winsorized cross sectional (paired)	(0.26)	(2.36) *	(2.81) *	(3.04) *	(3.25) *	(2.74) *	(2.42) *
Winsorized cross sectional (two groups)	(0.23)	(2.15) *	(2.42) *	(2.66) *	(2.78) *	(2.19) *	(1.92)

(*) Indicates two-tail statistical significance at the 5.0% level.

Market Model Daily CAR



Market Model Daily BHAR

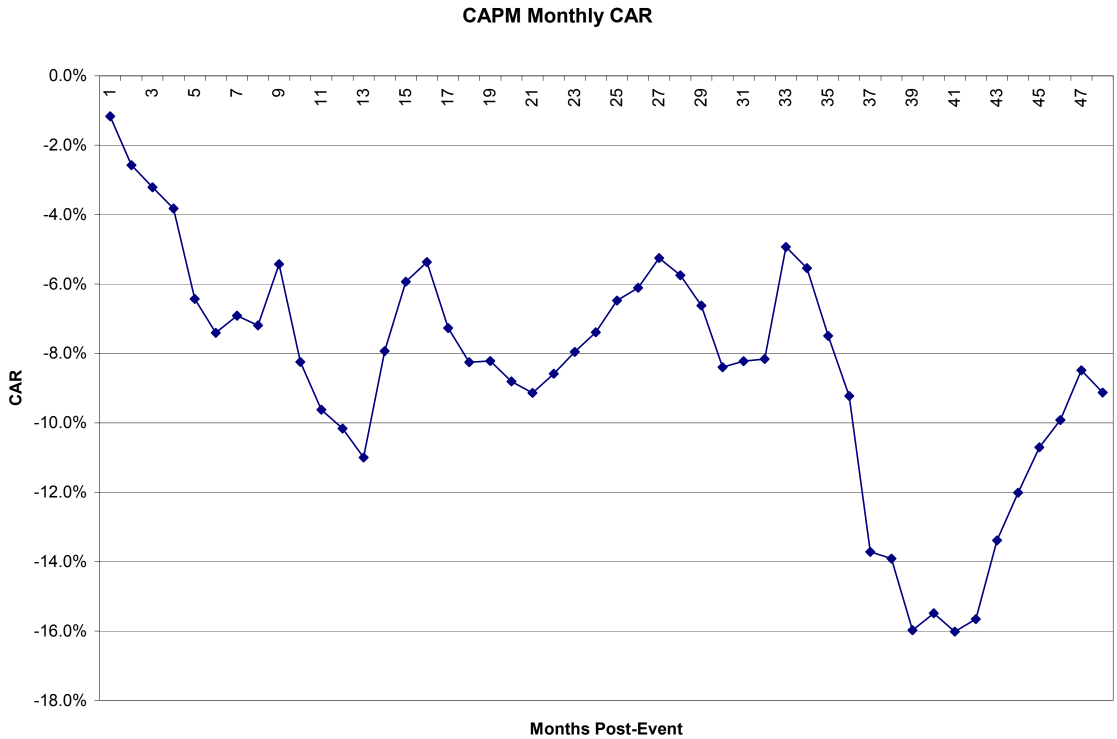


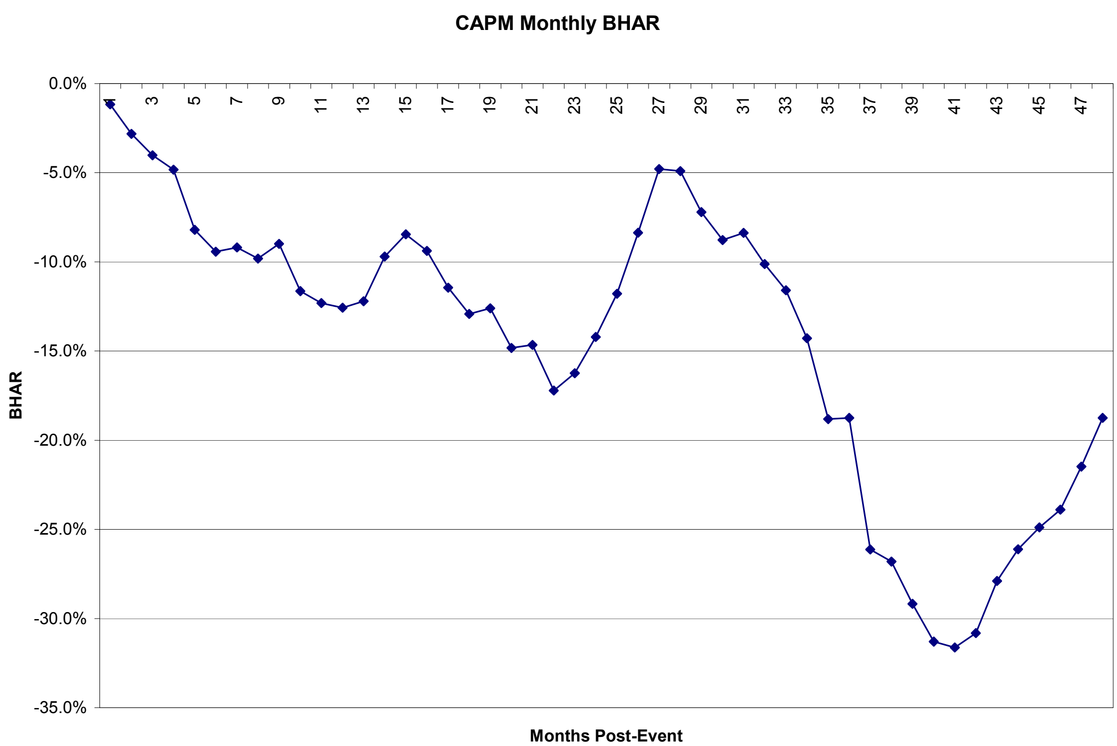
CAPM Monthly Abnormal Returns

CAPM Monthly Abnormal Returns

	Post-Event Time (months)						
	1	3	6	12	24	36	48
Number of observations	220	216	210	192	174	148	123
Cumulative Abnormal Returns (CAR)							
Mean	-1.2%	-3.2%	-7.4%	-10.2%	-7.4%	-9.2%	-9.1%
Standard deviation	17.5%	25.6%	34.1%	52.4%	69.7%	82.7%	87.2%
Skewness	1.30	0.52	0.00	(0.28)	(0.41)	(0.58)	(0.52)
Kurtosis	8.59	2.35	0.21	1.34	2.69	1.53	0.80
CAR test statistics							
Time series	(0.87)	(1.39)	(2.26) *	(2.19) *	(1.13)	(1.15)	(0.98)
Cross sectional	(0.99)	(1.86)	(3.23) *	(2.81) *	(1.47)	(1.45)	(1.27)
Winsorized cross sectional	(1.47)	(2.05) *	(3.24) *	(2.95) *	(1.40)	(1.38)	(1.23)
Sign test	(4.18) *	(4.72) *	(4.72) *	(3.04) *	(2.45) *	(1.99) *	(0.82)
Buy and Hold Abnormal Returns (BHAR)							
Mean	-1.2%	-4.0%	-9.4%	-12.6%	-14.2%	-18.7%	-18.7%
Standard deviation	17.5%	25.9%	34.7%	58.9%	96.9%	119.1%	185.3%
Skewness	1.30	0.83	0.60	2.55	2.26	1.28	4.25
Kurtosis	8.59	3.15	0.51	17.41	12.40	6.58	36.08
BHAR test statistics							
Cross sectional	(0.99)	(2.30) *	(4.03) *	(3.10) *	(2.03) *	(2.05) *	(1.23)
Winsorized cross sectional (paired)	(1.47)	(2.55) *	(4.08) *	(4.04) *	(2.82) *	(2.47) *	(2.25) *
Winsorized cross sectional (two groups)	(1.13)	(2.06) *	(3.39) *	(3.11) *	(2.27) *	(2.12) *	(1.48)

(*) Indicates two-tail statistical significance at the 5.0% level.


CAPM Monthly CAR
CAR
Months Post-Event
0.0%
-2.0%
-4.0%
-6.0%
-8.0%
-10.0%
-12.0%
-14.0%
-16.0%
-18.0%


CAPM Monthly BHAR
BHAR
Months Post-Event
0.0%
-5.0%
-10.0%
-15.0%
-20.0%
-25.0%
-30.0%
-35.0%

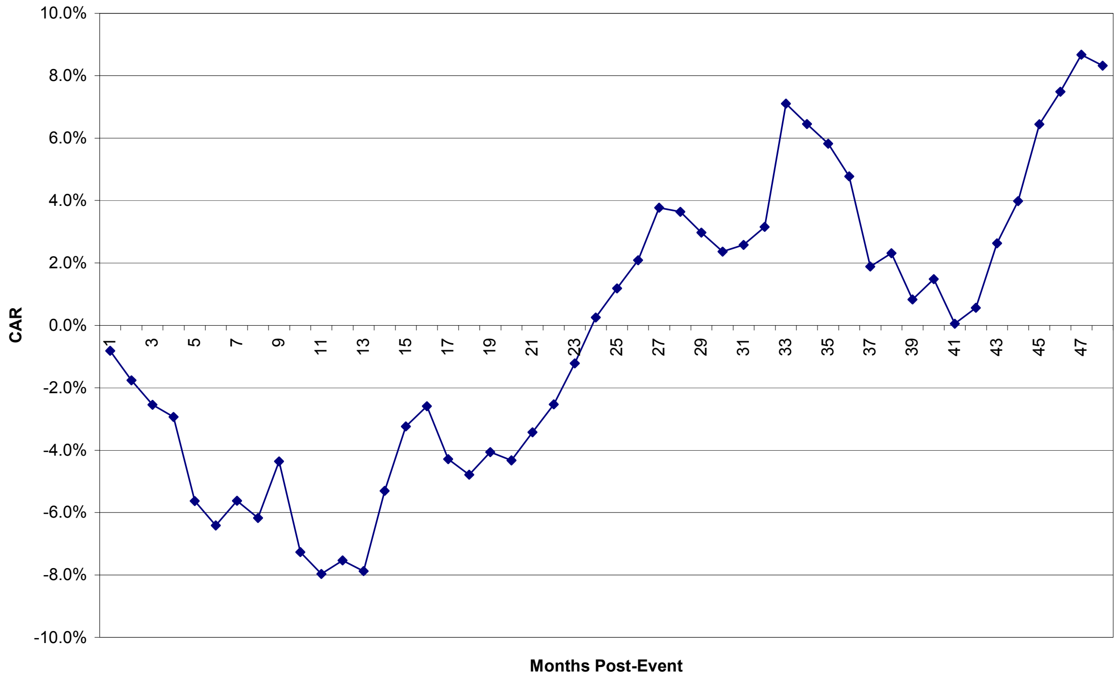
Fama and French Multi-factor Model Monthly Abnormal Returns

Fama and French Multifactor Model Monthly Abnormal Returns

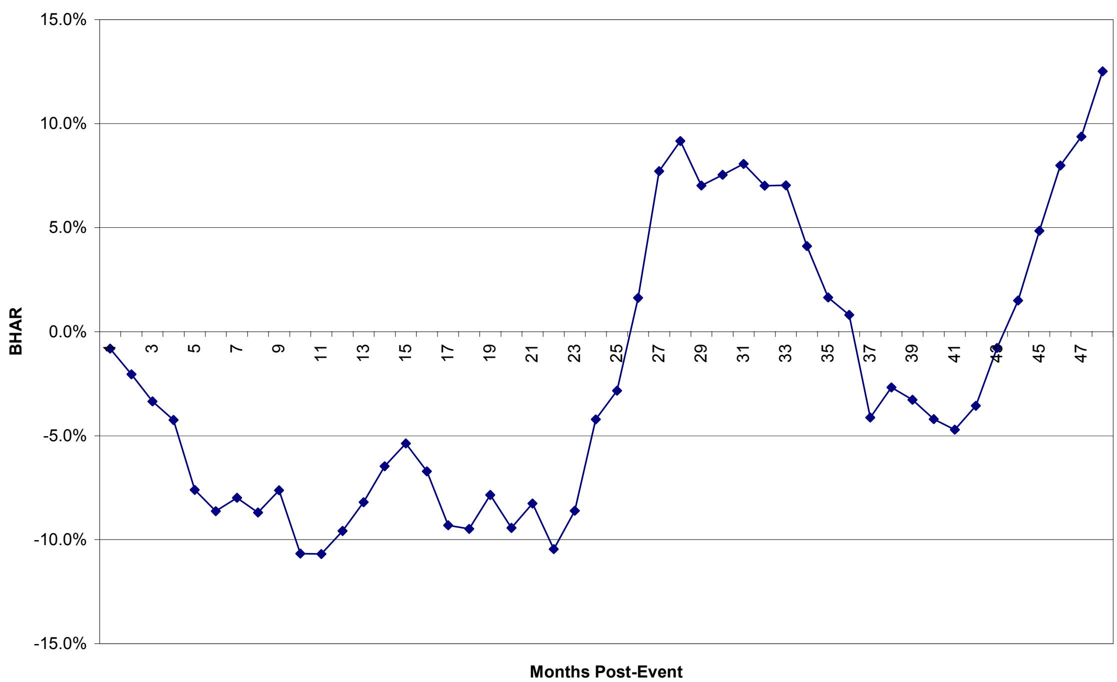
	Post-Event Time (months)						
	1	3	6	12	24	36	48
Number of observations	220	216	210	192	174	148	123
Cumulative Abnormal Returns (CAR)							
Mean	-0.8%	-2.5%	-6.4%	-7.5%	0.3%	4.8%	8.3%
Standard deviation	16.7%	25.3%	33.6%	49.4%	65.4%	78.3%	85.4%
Skewness	1.45	0.44	0.01	(0.39)	(0.40)	(0.46)	(0.25)
Kurtosis	8.86	1.93	0.16	0.81	2.84	2.08	1.56
CAR test statistics							
Time series	(0.68)	(1.23)	(2.19) *	(1.82)	0.04	0.67	1.01
Cross sectional	(0.72)	(1.49)	(2.83) *	(2.21) *	0.05	0.80	1.19
Winsorized cross sectional	(1.22)	(1.64)	(2.83) *	(2.24) *	0.15	0.87	1.24
Sign test	(3.91) *	(4.85) *	(4.58) *	(2.35) *	(1.73)	(0.15)	0.49
Buy and Hold Abnormal Returns (BHAR)							
Mean	-0.8%	-3.4%	-8.6%	-9.6%	-4.2%	0.8%	12.5%
Standard deviation	16.7%	25.8%	35.6%	55.9%	89.7%	114.9%	184.4%
Skewness	1.45	0.69	0.32	1.82	2.44	1.26	5.00
Kurtosis	8.86	2.49	1.02	10.83	13.82	7.91	42.96
BHAR test statistics							
Cross sectional	(0.72)	(1.92)	(3.60) *	(2.48) *	(0.65)	0.09	0.83
Winsorized cross sectional (paired)	(1.22)	(2.13) *	(3.59) *	(3.12) *	(1.28)	(0.15)	0.46
Winsorized cross sectional (two groups)	(0.88)	(1.66)	(2.80) *	(2.24) *	(0.91)	(0.12)	0.29

(*) Indicates two-tail statistical significance at the 5.0% level.

Fama and French Multifactor Model Monthly CAR



Fama and French Multifactor Model Monthly BHAR



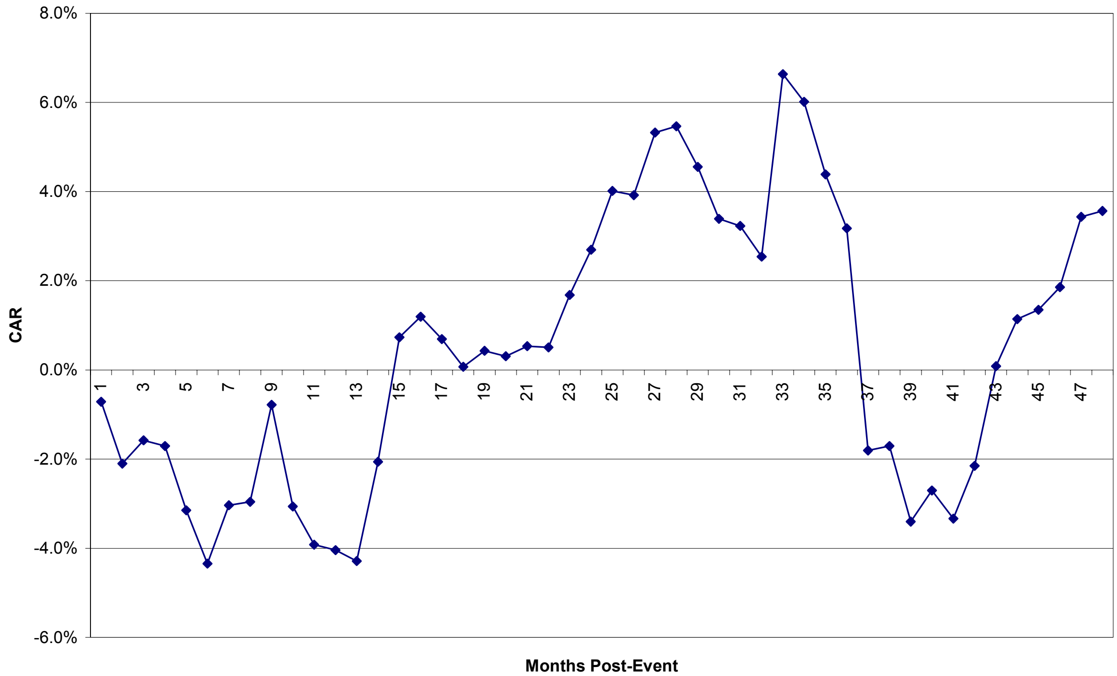
Size Matched Monthly Abnormal Returns

Size Matched Monthly Abnormal Returns

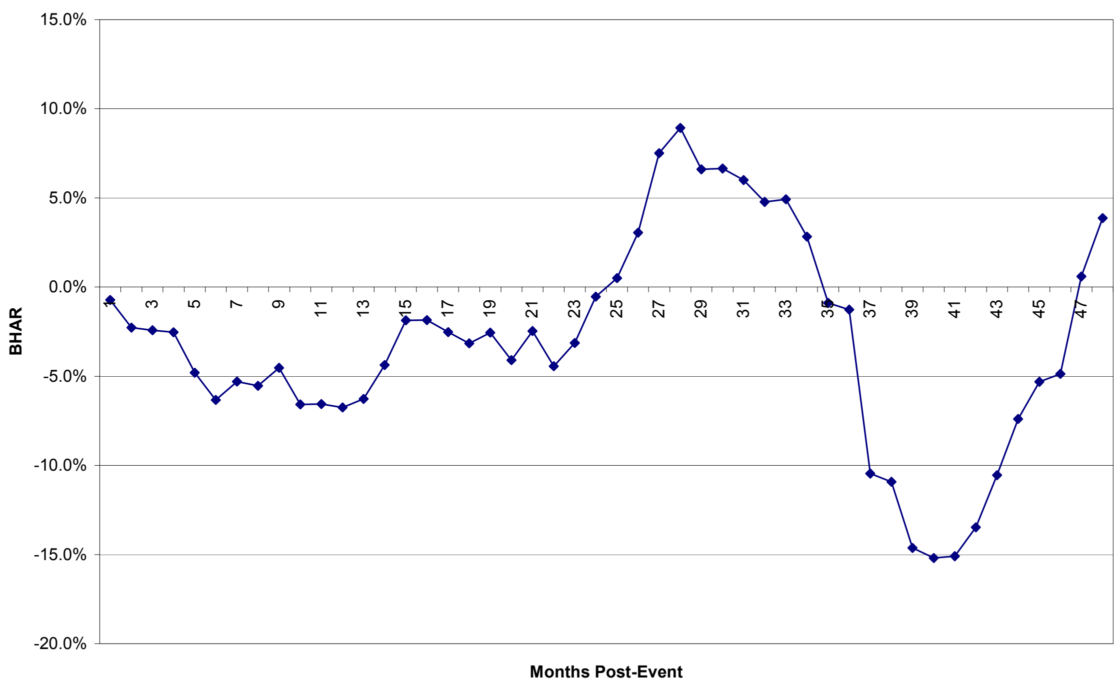
	Post-Event Time (months)						
	1	3	6	12	24	36	48
Number of observations	211	211	211	202	184	163	142
Cumulative Abnormal Returns (CAR)							
Mean	-0.7%	-1.6%	-4.3%	-4.0%	2.7%	3.2%	3.6%
Standard deviation	15.2%	22.6%	31.3%	48.1%	61.7%	69.3%	79.4%
Skewness	0.72	0.19	(0.10)	(0.16)	(0.10)	(0.14)	(0.20)
Kurtosis	3.38	0.42	0.21	2.36	2.20	1.25	1.14
CAR test statistics							
Time series	NMF	NMF	NMF	NMF	NMF	NMF	NMF
Cross sectional	(0.68)	(1.02)	(2.02) *	(1.19)	0.59	0.58	0.54
Winsorized cross sectional	(0.92)	(1.02)	(2.02) *	(1.28)	0.62	0.54	0.49
Sign test	(4.61) *	(4.20) *	(4.34) *	(2.53) *	(2.95) *	(1.80)	0.67
Buy and Hold Abnormal Returns (BHAR)							
Mean	-0.7%	-2.4%	-6.3%	-6.7%	-0.5%	-1.3%	3.9%
Standard deviation	15.2%	22.6%	32.0%	56.9%	89.6%	106.7%	177.6%
Skewness	0.72	0.53	0.68	3.13	2.89	2.55	6.09
Kurtosis	3.38	0.54	0.58	23.12	14.79	11.29	54.96
BHAR test statistics							
Cross sectional	(0.68)	(1.56)	(2.88) *	(1.69)	(0.08)	(0.15)	0.26
Winsorized cross sectional (paired)	(0.92)	(1.60)	(2.90) *	(2.50) *	(0.66)	(0.65)	(0.42)
Winsorized cross sectional (two groups)	(0.75)	(1.27)	(2.36) *	(1.89)	(0.51)	(0.51)	(0.26)

(*) Indicates two-tail statistical significance at the 5.0% level.

Size Matched Monthly CAR



Size Matched Monthly BHAR



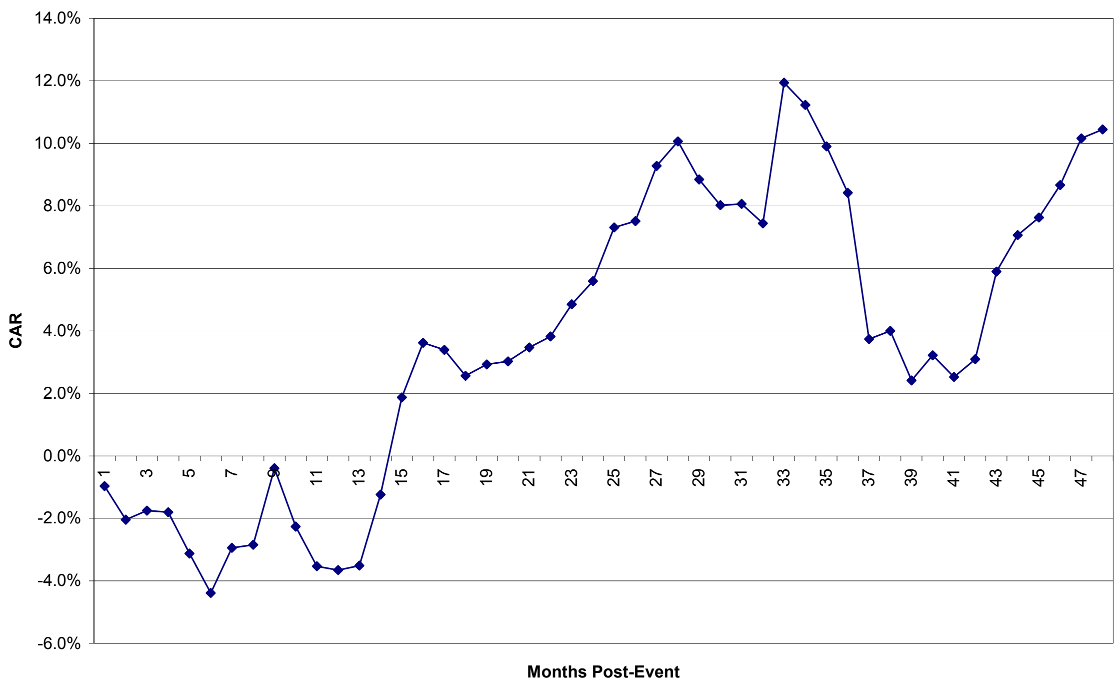
Be to ME Matched Monthly Abnormal Returns

BE to ME Matched Monthly Abnormal Returns

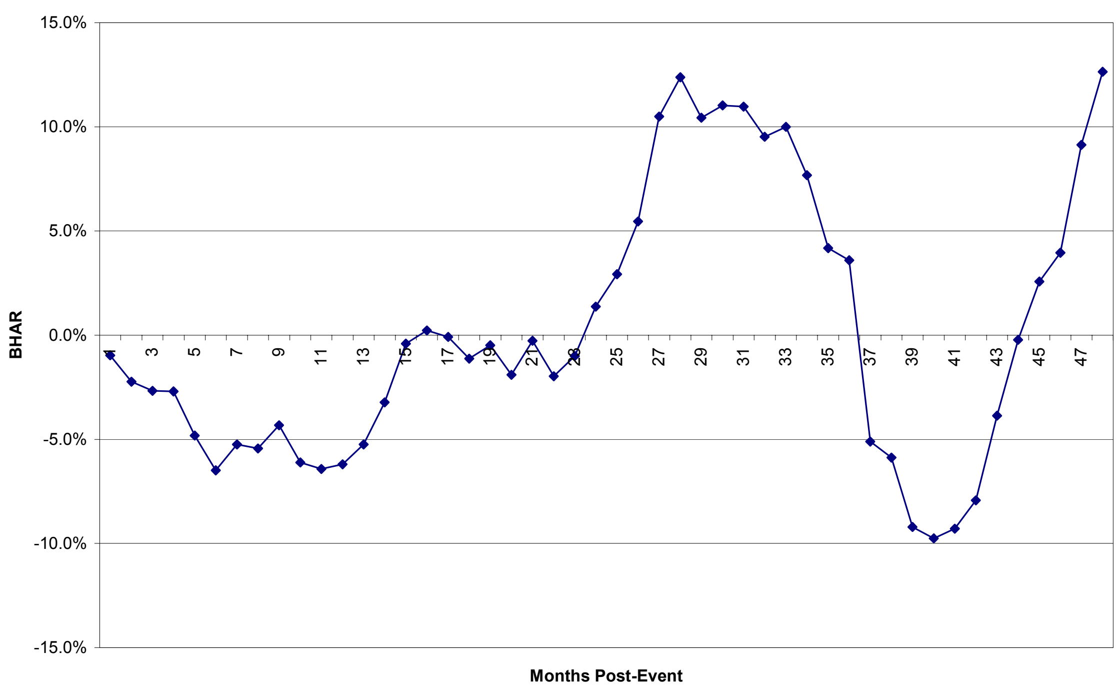
	Post-Event Time (months)						
	1	3	6	12	24	36	48
Number of observations	204	204	204	196	177	156	135
Cumulative Abnormal Returns (CAR)							
Mean	-1.0%	-1.8%	-4.4%	-3.7%	5.6%	8.4%	10.4%
Standard deviation	15.2%	23.2%	31.8%	48.4%	59.0%	68.2%	78.9%
Skewness	0.76	0.25	(0.12)	(0.32)	(0.11)	(0.17)	(0.21)
Kurtosis	3.71	0.82	0.27	2.18	2.14	1.16	0.98
CAR test statistics							
Time series	NMF	NMF	NMF	NMF	NMF	NMF	NMF
Cross sectional	(0.91)	(1.08)	(1.97)	(1.06)	1.26	1.54	1.54
Winsorized cross sectional	(1.17)	(1.06)	(1.96)	(1.12)	1.30	1.48	1.51
Sign test	(4.76) *	(4.62) *	(3.64) *	(2.57) *	(2.48) *	(0.64)	2.15 *
Buy and Hold Abnormal Returns (BHAR)							
Mean	-1.0%	-2.7%	-6.5%	-6.2%	1.4%	3.6%	12.6%
Standard deviation	15.2%	23.2%	32.6%	56.7%	88.2%	106.1%	180.6%
Skewness	0.76	0.62	0.69	2.99	2.75	2.23	5.87
Kurtosis	3.71	1.07	0.70	21.88	14.15	9.36	51.26
BHAR test statistics							
Cross sectional	(0.91)	(1.64)	(2.84) *	(1.53)	0.21	0.42	0.81
Winsorized cross sectional (paired)	(1.17)	(1.74)	(2.87) *	(2.29) *	(0.31)	0.08	0.42
Winsorized cross sectional (two groups)	(0.95)	(1.41)	(2.37) *	(1.71)	(0.23)	0.06	0.26

(*) Indicates two-tail statistical significance at the 5.0% level.

BE to ME Matched Monthly CAR



BE to ME Matched Monthly BHAR



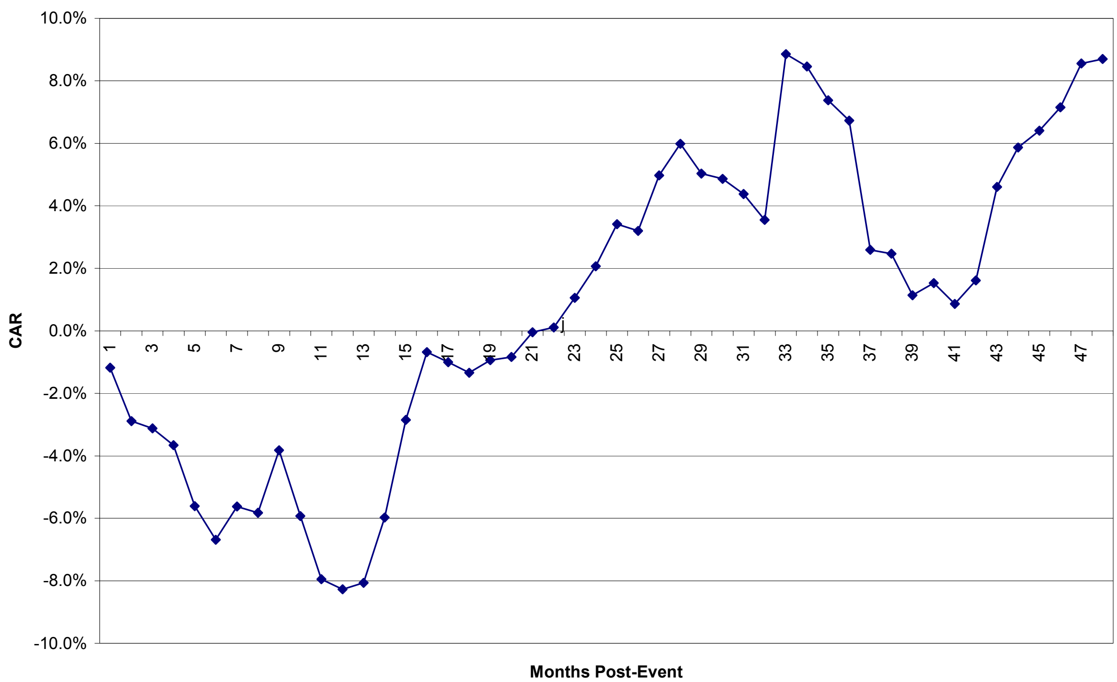
Size and BE to ME Matched Monthly Abnormal Returns

Size and BE to ME Matched Monthly Abnormal Returns

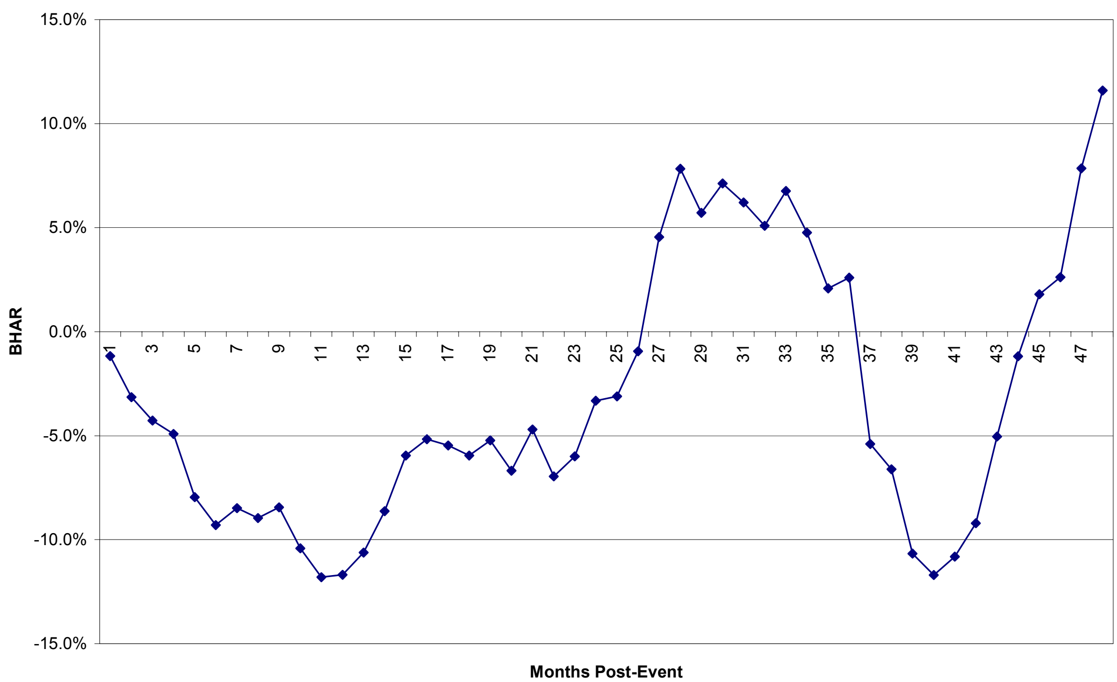
	Post-Event Time (months)						
	1	3	6	12	24	36	48
Number of observations	203	203	203	195	176	155	135
Cumulative Abnormal Returns (CAR)							
Mean	-1.2%	-3.1%	-6.7%	-8.3%	2.1%	6.7%	8.7%
Standard deviation	14.8%	23.1%	32.2%	49.7%	60.9%	65.0%	75.3%
Skewness	0.68	0.18	(0.02)	(0.30)	(0.17)	(0.12)	(0.13)
Kurtosis	3.62	0.45	0.04	2.46	2.97	1.28	1.36
CAR test statistics							
Time series	NMF	NMF	NMF	NMF	NMF	NMF	NMF
Cross sectional	(1.13)	(1.92)	(2.96) *	(2.32) *	0.45	1.29	1.34
Winsorized cross sectional	(1.39)	(1.92)	(2.96) *	(2.48) *	0.53	1.25	1.29
Sign test	(4.28) *	(4.42) *	(4.42) *	(3.22) *	(2.26) *	(1.69)	1.12
Buy and Hold Abnormal Returns (BHAR)							
Mean	-1.2%	-4.3%	-9.3%	-11.7%	-3.3%	2.6%	11.6%
Standard deviation	14.8%	23.4%	34.4%	59.1%	91.6%	110.3%	177.1%
Skewness	0.68	0.38	0.42	2.75	2.57	2.76	6.48
Kurtosis	3.62	0.78	0.96	21.25	13.38	13.24	58.70
BHAR test statistics							
Cross sectional	(1.13)	(2.60) *	(3.85) *	(2.76) *	(0.48)	0.29	0.76
Winsorized cross sectional (paired)	(1.39)	(2.65) *	(3.86) *	(3.76) *	(1.10)	(0.20)	0.32
Winsorized cross sectional (two groups)	(1.08)	(2.09) *	(3.14) *	(2.79) *	(0.83)	(0.14)	0.19

(*) Indicates two-tail statistical significance at the 5.0% level.

Size and BE to ME Matched Monthly CAR



Size and BE to ME Matched Monthly BHAR



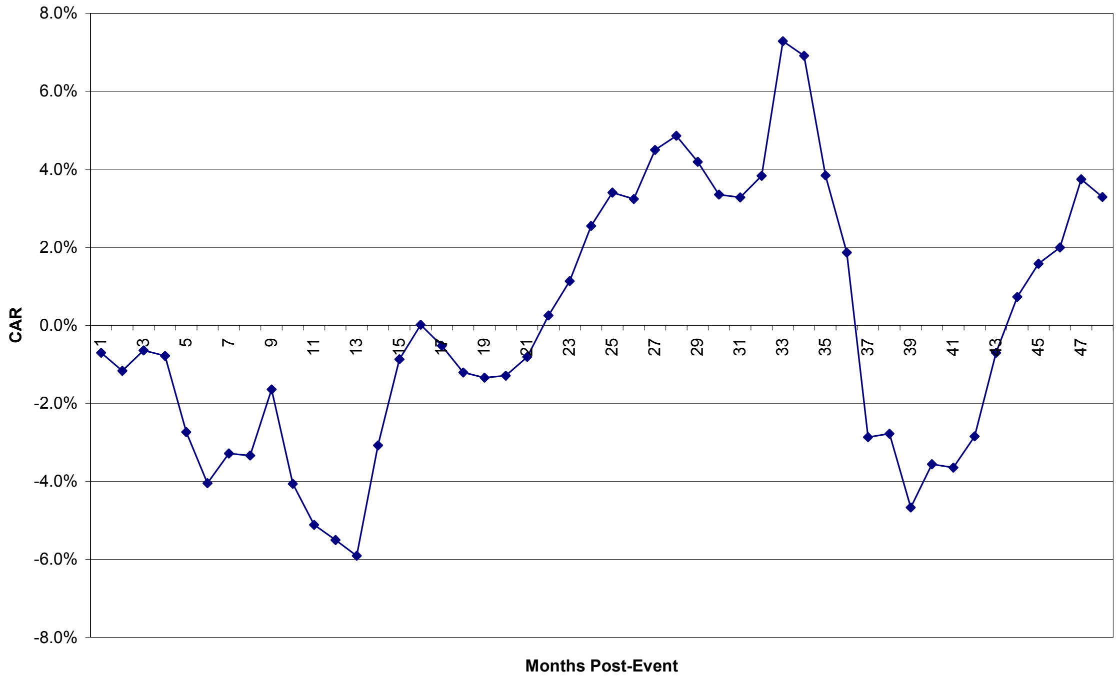
Market Adjusted Model Monthly Abnormal Returns

Market Adjusted Model Monthly Abnormal Returns

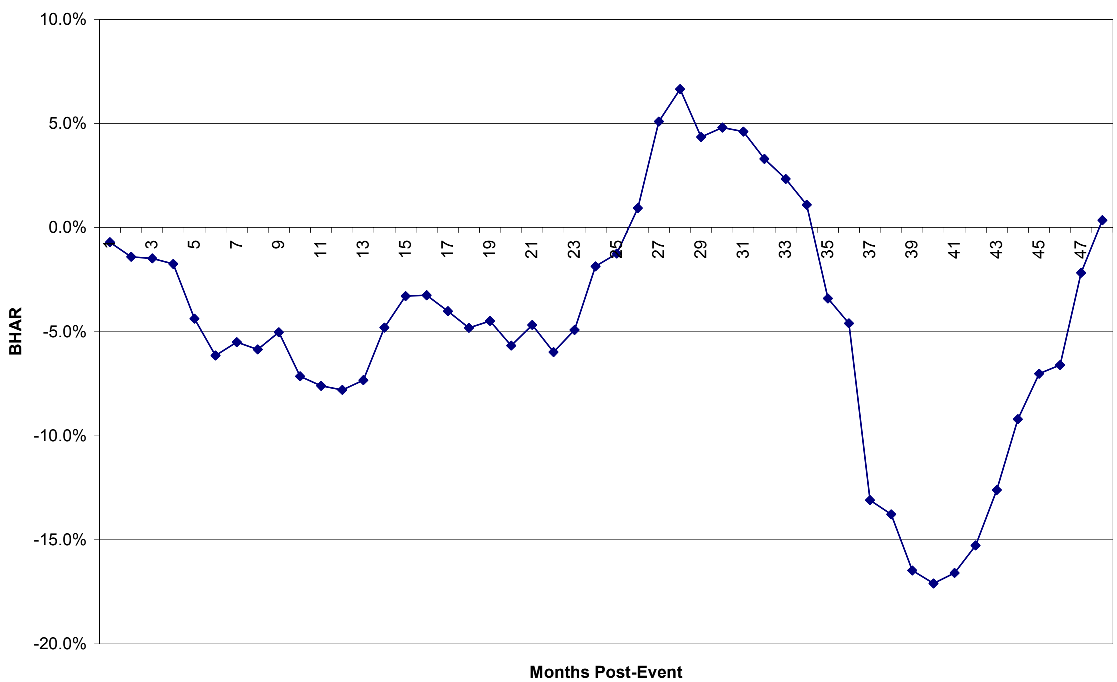
	Post-Event Time (months)						
	1	3	6	12	24	36	48
Number of observations	239	239	239	229	210	187	163
Cumulative Abnormal Returns (CAR)							
Mean	-0.7%	-0.6%	-4.0%	-5.5%	2.6%	1.9%	3.3%
Standard deviation	17.4%	24.8%	33.2%	50.6%	65.2%	75.0%	82.0%
Skewness	1.23	0.59	(0.01)	(0.38)	0.08	(0.32)	(0.25)
Kurtosis	7.48	2.64	0.62	1.80	2.04	0.92	0.67
CAR test statistics							
Time series	NMF	NMF	NMF	NMF	NMF	NMF	NMF
Cross sectional	(0.63)	(0.40)	(1.89)	(1.65)	0.57	0.34	0.51
Winsorized cross sectional	(1.01)	(0.55)	(1.93)	(1.73)	0.52	0.32	0.48
Sign test	(4.98) *	(4.33) *	(3.95) *	(3.11) *	(1.79)	(2.12) *	0.70
Buy and Hold Abnormal Returns (BHAR)							
Mean	-0.7%	-1.5%	-6.1%	-7.8%	-1.9%	-4.6%	0.4%
Standard deviation	17.4%	25.1%	33.3%	56.2%	89.7%	106.4%	173.5%
Skewness	1.23	1.01	0.71	2.83	2.70	2.07	5.68
Kurtosis	7.48	3.58	0.75	20.41	13.81	8.85	52.02
BHAR test statistics							
Cross sectional	(0.63)	(0.92)	(2.85) *	(2.10) *	(0.30)	(0.59)	0.03
Winsorized cross sectional (paired)	(1.01)	(1.15)	(2.89) *	(2.91) *	(0.87)	(1.03)	(0.71)
Winsorized cross sectional (two groups)	(0.83)	(0.96)	(2.51) *	(2.27) *	(0.70)	(0.88)	(0.47)

(*) Indicates two-tail statistical significance at the 5.0% level.

Market Adjusted Model Monthly CAR



Market Ajdusted Model Monthly BHAR



Abnormal Returns by Cause of Event

All Events Researched

Period (months)	1	3	6	12	24	36	48
N	110	110	110	108	69	48	39
CAR Post Event -->	-1.9%	-3.9%	-9.0%	-9.9%	-3.3%	-12.5%	-21.5%
Sample STDEV -->	14.0%	24.0%	33.6%	52.9%	72.7%	84.9%	92.5%

Earnings Release

Period (months)	1	3	6	12	24	36	48
N	22	22	22	22	17	13	10
CAR Post Event -->	-2.1%	1.8%	-3.1%	9.3%	21.6%	2.7%	-10.6%
Sample STDEV -->	11.8%	23.7%	32.3%	60.7%	94.2%	107.7%	123.6%
t-statistic	0.08	-1.00	-0.77	-1.35	-0.99	-0.45	-0.25
significance	0.07	0.68	0.56	0.82	0.68	0.35	0.20

Firm Specific (Other)

Period (months)	1	3	6	12	24	36	48
N	12	12	12	12	7	6	6
CAR Post Event -->	-2.6%	-1.0%	16.4%	15.4%	21.7%	16.1%	1.5%
Sample STDEV -->	12.8%	18.0%	36.3%	61.2%	69.2%	57.3%	49.0%
t-statistic	0.17	-0.49	-2.23	-1.32	-0.85	-1.00	-0.87
significance	0.14	0.38	0.97	0.81	0.60	0.68	0.61

Earnings Warning

Period (months)	1	3	6	12	24	36	48
N	60	60	60	59	34	23	17
CAR Post Event -->	-1.3%	-6.2%	-15.9%	-21.4%	-16.3%	-15.2%	-16.8%
Sample STDEV -->	12.9%	24.3%	32.1%	49.1%	64.9%	79.1%	79.1%
t-statistic	-0.26	0.60	1.30	1.40	0.91	0.13	-0.19
significance	0.20	0.45	0.80	0.84	0.63	0.10	0.15

Analyst Downgrade

Period (months)	1	3	6	12	24	36	48
N	7	7	7	7	6	3	3
CAR Post Event -->	-12.2%	-8.9%	-17.2%	-19.9%	-22.1%	-84.5%	-71.1%
Sample STDEV -->	26.6%	32.0%	38.4%	35.2%	68.4%	87.3%	120.4%
t-statistic	0.94	0.38	0.51	0.66	0.59	1.14	0.57
significance	0.65	0.29	0.39	0.49	0.44	0.74	0.43

Merger Plans Terminated

Period (months)	1	3	6	12	24	36	48
N	4	4	4	3	2	1	1
CAR Post Event -->	6.1%	-0.9%	-2.9%	-12.6%	-5.0%	-44.9%	-36.2%
Sample STDEV -->	16.2%	27.0%	9.3%	21.1%	34.4%		
t-statistic	-0.85	-0.19	-0.98	0.17	0.05		
significance	0.60	0.15	0.67	0.14	0.04		

Government Investigation

Period (months)	1	3	6	12	24	36	48
N	5	5	5	5	3	2	2
CAR Post Event -->	2.2%	-3.0%	-7.8%	-2.6%	-17.3%	-41.9%	-103.7%
Sample STDEV -->	12.3%	27.9%	35.4%	44.5%	26.8%	61.1%	144.1%
t-statistic	-0.65	-0.06	-0.07	-0.32	0.67	0.47	0.57
significance	0.48	0.05	0.06	0.25	0.49	0.36	0.43

APPENDIX B – VISUAL BASIC CODE

An extensive amount of visual basic code was required to extract data from the CRSP database. Future students who are using the CRSP database and would like a copy of this code can email Andrew Grinstead @: agrinstead2001@kellogg.nwu.edu