Reconciling Daily and Weekly Return Behavior Following Positive and Negative Events

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Abstract

Stocks returns following large price changes provide a conflicting picture when events are measured weekly or daily. We use a new methodology to identify event thresholds and study post-event daily stock return behavior over a period of 20 days. After negative events, we find strong reversal in the short-term followed by continuing reversal up to four weeks, with the reversal being proportional to the price decline. After positive events, the results are mixed in aggregate, but there is strong evidence of overreaction in the short- and longer-term following extremely large gains. We further use a regression based model to help explain these conflicting results.

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1. Introduction

Stock returns show a decisive pattern of continuation in semi-annual and annual holding periods while there is evidence of reversal over three to five years.[1] This has led to development of behavioral models by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) to gain an understanding of these alternating patterns of continuation and reversal. Over a weekly horizon, Lehmann (1990) follows a long-short strategy to demonstrate contrarian profits but subsequent studies attribute his profits to cross-autocorrelation in large and small stocks and bid-ask bounce (e.g., Lo and MacKinlay, 1990; Conrad, Gultekin, and Kaul, 1997). Conditioning on volume, Campbell, Grossman and Wang (1993) and Conrad, Hameed and Niden (1994), among others, demonstrate reversals following periods of high volume. Cooper (1999) shows reliable evidence of unconditional market overreaction up to a year following large positive and negative weekly returns, with low volume stocks exhibiting greater reversal.

However, the evidence is decidedly mixed when daily winners and losers are considered. Atkins and Dyl (1990) and Bremer and Sweeney (1991) present evidence of overreaction, while Brown, Harlow, and Tinic (1988) show predictable variation. When the portfolios are unconditionally formed based on large daily declines and/or gains (also referred to as an event), a correction for bid-asked bounce considerably weakens or reverses short-term (up to three or four days) overreaction [e.g., Cox and Peterson, 1994; Park, 1995; Pritamani and Singal, 2001). In the

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[1] Some of the papers in this area include Jegadeesh and Titman (1993), DeBondt and Thaler (1985, 1987), Fama and French (1988), Poterba and Summers (1988), Chan, Jegadeesh, and Lakonishok (1996), Chopra, Lakonishok, and Ritter (1992), and Lakonishok, Shleifer, and Vishny (1994).

longer-term (three or four days beyond a negative event), there appears to be a general tendency towards continuation. Cox and Peterson (1994), Park (1995), Pritamnani and Singal (2001), and Larson and Madura (2003) find some continuation from day four/five to day twenty after a negative event. By contrast, after a positive event, Park (1995) shows no systematic longer-term variation, while Larson and Madura (2003) find a decline up to 20 days and Pritamani and Singal (2001) show a gain.

The contrast between the post-event performance of daily versus weekly event horizons is puzzling, as large daily returns should also coincide with large weekly returns as average daily returns are quite small.[2] As a result, if overreaction is found in weekly returns, a similar overreaction should be expected after large daily returns. A possible reconciliation of the two conflicting results may be in the hypothesis advanced by Subrahmanyam (2005) that "… reversals are caused, in substantial part, by reversals in beliefs of financial market agents." In a shorter event horizon of a day or intra-day, a change in beliefs may be unlikely, thus resulting in a lack of overreaction. Therefore, stock return behavior following large positive and negative returns warrants further investigation to see if reconciliation between these two streams of literature is possible.

Prior studies have either used fixed thresholds to define events which can yield a sample biased towards high-volatility stocks, or have employed a dispersion-based norm as in Pritamani and Singal (2001) which should be free from such a bias. In this study, the Self-Exciting

[2] Cox and Peterson (1994) condition on more than a 10% loss, Park (1995) on a greater than 10% abnormal gain or loss, and Pritamani and Singal (2001) on a greater than three standard deviation abnormal move from the mean (an approximate 7% average gain or loss). Cooper (1999) shows reliable overreaction with weekly declines/gains as small as 2%. At 6% or greater gain or loss, the overreaction is very strong.

Threshold Auto Regressive (SETAR) time series model endogenously determines positive and negative event thresholds – thus identifying positive, negative, and non event regions – based on security return characteristics. The method optimally searches for return thresholds that best fit three AR(1) models, one for each region. This allows us to detect those thresholds where the post-event day return is best explained by the event day return in each state. The thresholds are allowed to vary asymmetrically for negative and positive events, as well as across securities and time.

We divide the aggregate period (1/1/63-12/31/03) into eight subperiods for threshold estimation to account for changes in volatility, liquidity, and institutional trading.[3] For each subperiod, we estimate the event thresholds using daily returns and analyze several post-event timeframes up to 20 days after the event. We conduct this analysis on a within sample basis and also for a two-year subperiod immediately following each parameter estimation period (to eliminate the look ahead bias inherent in many trading rules).[4] We adopt a model for the analysis of post-event stock return behavior that eliminates the impact of microstructure issues such as bid-ask bounce, non-synchronous trading, and volume related return autocorrelation (as shown by Chordia and Swaminathan, 2000).

We find strong evidence of reversal after a negative event – in the short term (1-3 days). This reversal is pervasive across time and the three markets (NYSE, Amex, and Nasdaq) and is proportional to the degree of decline on the event day. From four days after the event up to twenty days, we find strong evidence of overreaction similar to the weekly return results of Cooper (1999). Our positive event results are mixed as in previous studies, but there is generally evidence

[3] For instance, Cox and Peterson (1994) note differences prior to and following October 1987.

[4] Because our last year available in the CRSP database is 2003, we use four years in our last threshold estimation period to ensure a two-year out of sample test.

of overreaction in the short-term. Over the longer-term, there is a fixed decline effect as well as a conflicting continuation effect that is proportional to the event-day return. Our results are important as they refute prior filter rule studies that explicitly corrected for the bid-ask bounce in daily returns and found no evidence of reversal in the short-term and underreaction in the longer-term. We also show that the commonly used Long/Short portfolio strategy results in a positive return that increases in proportion to the absolute magnitude of the positive and negative events.

The organization of the paper is as follows. In Section 2 we introduce the SETAR model. In Section 3 we describe our data and present the results. Finally we conclude in Section 4.

2. Research method

First, we subdivide the security returns from 1963 to 2001 into eight estimation subperiods (with the last being only four years). Second, we identify the parameters of the SETAR model for every security that has a sufficient number of returns available in the subperiod for model identification. Third, armed with the estimated thresholds we identify negative event, positive event, and non-event days for every security, both on a within-sample and out-of-sample basis. Our out-of-sample periods are essentially two years (less if the security stops trading) following every non-overlapping, five-year parameter estimation interval.[5] These events are then used for further, in-depth, post-event analysis.

The SETAR model is ideally suited for distinguishing significant events, as its autoregressive feature is contingent on the state of the process. Thus unlike other models, we endogenously estimate the thresholds and the AR process for each region. This allows us to capture the subtle interplay between the previous day's return and the AR process of stock returns

[5] Although we do not examine every available year in our out-of-sample study, the strong agreement of the out-of-sample results to the within-sample results allows us to save on computational effort.

the next day. We do not simply concentrate on the days of extreme price change, unlike a large number of prior studies. Instead, we focus on those days where a relatively large price change occurred and simultaneously there was also an accompanying change in the autoregressive model of security returns. This statistical procedure allows us to not only identify the AR(1) models in each state, but it also estimates the thresholds that delineate the regions. As long as the autoregression in security returns varies across regions, the model will properly identify.

2.1 SETAR estimation and threshold identification

Threshold Auto Regressive (TAR) models are a class of non-linear time series models that were first introduced by Tong (1978).[6] The essential idea underlying the class of threshold autoregressive models is the piece-wise linearization of non-linear models over the state space by the introduction of thresholds. A threshold autoregressive process can be modeled as:

$$r_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i r_{t-i} + \sum_{j=1}^{n} \left[\beta_{oj} + \sum_{i=1}^{k} \beta_{ij} r_{t-i} \right] I_j(\gamma_t) + \varepsilon_t \tag{1}$$

where k is the order of the autoregressive process, n is the number of regions, and $I_j(\gamma_t)$ is an indicator function such that $I(a) = 1$ if a is true, else $I(a) = 0$. The n-1 thresholds divide the state space into n regions and an autoregressive model is estimated for each region j with k_j number of lags. The state of the process (i.e. the region in which it is at time t) is determined by the value of

[6] For a detailed account of the TAR model and its motivation see Tong (1983). SETAR models have been successfully applied to various popular nonlinear time series including sunspot data (Tong and Lim, 1980), and Canadian lynx data (Tsay, 1989). Applications to financial data include exchange rates (Kräger and Kugler, 1993; Clements and Smith, 2001), stock indices (Dufrénot, Guégan, and Péguin-Feissolle, 2005) and GNP (Tiao and Tsay, 1994).

the threshold variable. This threshold variable can be a lagged value (r_{t-d}) of the variable at lag *d*, as would be relevant in our model.[7]

Our specification of the SETAR model contains three states/regions separated by two threshold values, r_l and r_h with a lag *d*=1 as shown below.

$$\left\{ \begin{array}{c} low \;\; state\,,\; if \;\; r_{t-1} < r_l \\ normal \;\;\; state\,,\; if \;\; r_l \le r_{t-1} \le r_h \\ high \;\; state\,,\; if \;\; r_{t-1} > r_h \end{array} \right\} \qquad (2)$$

The above two-threshold case is appropriate for us as we intend to study the return behavior after large declines and gains, yielding positive, negative and non-event regions. We use an autoregression with a maximum lag of one within each region. Thus, in some cases, the identified model can be intercept-only.

Assuming frequent trading and a single price, thus avoiding non-synchronous trading and bid-ask bounce – the next-day return should have no correlation with the present day return in any of the three states, leading to arbitrary threshold selection and similar AR models across regions with insignificant lagged coefficients. However, bid-ask bounce and non-synchronous trading both alter this picture. On a non-event day, the security will randomly close at the bid (or ask) price inducing a positive (or negative) bid-ask bounce in the next day return. This manifests itself as negative correlation in transactional returns between the non-event day and the next day.[8] Non-synchronous trading will also induce a negative correlation. Thus, for the non-event

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[7] For the special case where γ_t is replaced with a lagged value of the time series, the model is denoted as a Self-Exciting Threshold Auto Regressive (SETAR) model of order (n;k_1, k_2,... k_n). The SETAR model is a natural generalization of the linear Auto Regressive Moving Average (ARMA) process and can also accommodate nonlinearities as observed by Scheinkman and LeBaron (1989), fat tails, and non-normality.

[8] See, for example, Kaul and Nimalendran (1990).

region, we should expect a negative AR1 coefficient, the magnitude of which will generally be larger for small stocks – owing to a larger bid-ask bounce and a higher probability of non-trading. The intercept term should be positive, reflecting the average nominal periodic return for the security.

In the negative (positive) region, altered return characteristics will exist because the security will *systematically* close at the bid (ask) price in the face of selling (buying) pressure. Because of the non-random nature of this process, the resulting positive (negative) bid-ask bounce in the next day return will be captured in the intercept term, strengthening (counteracting) the average nominal return mentioned previously. Also, it is safe to assume that non-synchronous trading is not an issue for negative or positive event days, where one will encounter generally heavy trading. Therefore, for the negative event region, we expect a positive intercept and for the positive event region, we expect a generally lower or negative intercept, as the negative bid-ask bounce will reduce the fitted intercept. In both regions, the AR(1) coefficient should equal zero unless one assumes liquidity pressures, changing expected returns or some form of market inefficiency.[9] Thus, the SETAR model is ideally suited for actual security return characteristics, and is capable of generating non-arbitrary, meaningful thresholds delineating the positive, negative, and non-event regions.

To estimate the model, we start by choosing a large number of points on both sides of the mean return as potential thresholds based on the return variability. More precisely, we choose potential thresholds from 1 to 2.5 standard deviations away from the mean in either direction. Next, one potential threshold from either side of the mean is selected and the state space (to wit, the security return data) is delineated into three regions, leading to three subsamples based on the

[9] Cox and Peterson (1994) were the first to use similar motivation to study overreaction.

event day return (r_{t-1}). For each subsample, a separate AR model is estimated with a maximum of one lag and the overall Akaike Information Criterion (AIC) for the set of three models is computed. This step is repeated for *all* possible pairs of thresholds. The optimal model is selected based on the overall AIC criteria from all candidate models above. It should be noted that the choice of thresholds is not simply based on the dispersion measure, but rather the thresholds are optimally chosen in an iterative process to yield the best-fit family of three AR(1) models.

2.2 Event identification and post-event return analysis

Once the thresholds have been identified for a security in a given period, we scan through the security returns over the next two years after the parameter estimation period to identify the days when the returns cross one of the two thresholds.[10] This provides us with an out-of-sample set of positive and negative event days. We often have more than one security registering a negative (positive) event for each day and given the high cross-sectional correlation of returns, it would be inappropriate to count the same day occurrences as separate events. So the securities that register an event each day are combined into an equally weighted portfolio – essentially a short-term analog of the Mitchell and Stafford (2000) approach.[11] Cooper (1999) implements a similar

[10] We also perform the same analysis on a within-sample basis with strong results but do not report the results to conserve space. The out-of-sample method provides a more stringent test of the hypotheses.

[11] Cox and Peterson (1994) use the first stock that appears in an alphabetical sort of all stocks registering an event for each day. We believe that this approach effectively discards valuable information. In addition, the first stock approach suffers from serious sampling issues in that a single stock could be sampled on numerous days. In fact, we find that as few as five (5) stocks can represent as high as 46% of the observations within a subperiod. In numerous instances, a single company is sampled for over ten% of the

approach with weekly returns. The event portfolio return variance automatically subsumes the cross-sectional covariances and provides the most efficient use of the information.[12] Forming a portfolio usually induces positive autocorrelation in portfolio returns both due to nonsynchronous trading and volume leadership as suggested by Chordia and Swaminathan (2000). This bias can lead one to wrongly conclude post-event continuation while there is actually none; however for reversal, the bias actually makes the tests less likely to reject the null hypothesis. Still, with our sample of high volume, event registering securities, we expect this issue to be irrelevant.

We analyze the post-event day returns by first examining abnormal returns, where the market model parameters are computed using a pre-event window of –6 through –105 days.[13] As abnormal returns contain the bid-ask bounce and the averages could be quite susceptible to outliers, we perform further analysis by regressing post-event abnormal returns on the event day abnormal returns.[14] The regression model is specified below.

$$PEDAR_i = \alpha + \beta_1 EDAR_i + \beta_2 Dec_i + \beta_3 D_{Amex,i} + \beta_4 D_{Nasdaq,i} + \varepsilon_i \qquad (3)$$

where

total observations. Therefore, in our view, this approach is too heavily weighted on a few individual companies to yield representative results.

[12] Counting only one observation per day and subdividing the entire period into subperiods also greatly reduces the sample size associated with each test statistic. Lindley's Paradox – that standard errors decline in sample size – would have limited impact on our test statistics.

[13] We report results using the combined CRSP NYSE/Amex/Nasdaq index as the proxy for the market index, however we also computed abnormal returns using exchange-specific, value-weighted market index proxies, exchange-specific equally weighted index proxies, and post-event betas. All of these additional robustness tests provide essentially the same conclusion.

[14] This regression equation is similar to the approach of Cox and Peterson (1994).

$PEDAR_i$ = the post-event day abnormal return for equally weighted portfolio *i*,

$EDAR_i$ = the event day abnormal return for equally weighted portfolio *i*,

Dec_i = the decile size ranking for equally weighted portfolio *i*,

$D_{Amex,i}$ = a dummy variable equal to 1 if portfolio *i* is Amex, and equal to 0 otherwise,

$D_{Nasdaq,i}$ = a dummy variable equal to 1 if portfolio *i* is Nasdaq, and equal to 0 otherwise,

All estimations employ White's (1980) heteroskedasticity-consistent covariance matrix. We incorporate dummies for the markets, so our sample of all events for all securities is first separated into three subsamples by market. After the equally weighted event portfolios are created for each market, they are then pooled to run the regression. In the regression equation, the size variable is obtained by taking the average of the CRSP decile rankings of all negative (positive) event-registering securities by market for each day.

The dependent variable takes on one of two specifications — cumulative days 1-3, and cumulative days 4-20. Under the null hypothesis of market efficiency, time-invariant expected returns, and no difference across the three markets, all parameter estimates, except the intercept, should be equal to zero across the two specifications of the dependent variable. As the average abnormal return is expected to be zero, the intercept should essentially be the bid-ask bounce whenever the dependent variable includes the day 1 return but should be zero otherwise.[15]

3. Data and results

[15] The regression intercept should not be confused with the SETAR model intercept where we expected generally positive coefficients to reflect average returns for each security.

Daily observations for all securities in the Center for Research in Security Prices (CRSP) database were obtained for the sample period from January 1, 1963 to December 31, 2003. We construct daily transactional returns file for NYSE and Amex securities for the entire period. For Nasdaq, transactional prices are unavailable for National Market securities prior to November 1, 1982 and for Small Cap securities prior to June 15, 1992. Hence, in the sample period between December 14, 1972 and November 1, 1982, all prices are actually closing bid-ask averages.[16]

We choose to keep all securities – stocks, REITs, close-ended funds, ADRs *et cetera*. Two restrictions reduce the size of our sample. First, as we are modeling infrequent events, we eliminate any security with fewer than 1,000 daily returns in each subperiod to ensure that we have enough variation in the data to identify a realistic model. Also, at least two percent of the observations must be present in the positive and negative event regions to ensure adequate degrees of freedom for estimation.[17] Although intuition suggests that a majority of observations must fall in the non-event region, we imposed a much weaker restriction that identified models must have at least 1/3 of the total observations in the non-event region.[18] Finally we also impose a reasonable restriction that the lower (upper) thresholds be negative (positive).

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[16] Therefore the Nasdaq inferences for the first two subperiods are virtually free of the bid-ask bounce.

[17] We checked the number of observations in the negative and positive event regions and found that the mean value for negative events runs from 65 to 83 over the first seven subperiods of five years each. This equates to an event occurring every 3.5 weeks in the first case and every three weeks in the second case. The incidence of positive events occurs approximately every 2.5 weeks in subperiod one to every three weeks in subperiod five. These numbers do not seem unreasonable given typical market conditions.

[18] Not only does this assumption formalize the intuition of a normal (or a fat tailed) distribution for stock returns, it also has another beneficial effect in terms of making the algorithm far more efficient. It is an important issue, as we have to individually identify the model for every qualifying stock in each subperiod.

3.1 Summary statistics for the SETAR models

In Table 1 we present summary statistics related to the SETAR model parameters across the eight subperiods and three markets (NYSE, Amex, and Nasdaq).

(Place Table 1 approximately here)

Average lower and upper thresholds are the smallest for the NYSE securities in the first subperiod (1963-1967) and display a tendency to rise in magnitude through time to the most recent subperiod. Thus the bandwidth of the non-event region increases from 5.12% to 7.46%. These changing thresholds are consistent with the fact that market volatility has generally risen over time, thus requiring securities to move more before registering an event. For Amex securities, thresholds and bandwidths once again vary across subperiods and the bandwidths are clearly larger than NYSE for each subperiod, consistent with the fact that Amex securities are generally more volatile than NYSE securities. The Nasdaq thresholds and bandwidths also show a clear tendency to rise in magnitude with time. In the last four subperiods, the Nasdaq also produces the widest average bandwidths of the three markets under study, consistent with the conventional view that it trades the most volatile securities among the three markets. The minimum and maximum values of the two thresholds for each market and subperiod show a wide variation. In magnitude, the highest negative threshold is –56.41% whereas the lowest negative threshold is only about –0.27%.[19] It therefore is quite clear that fixed thresholds (such as a 10% movement) can potentially give rise to samples with omitted events and false events.

[19] It could be argued that a drop of 0.27% is too low to be called a negative event. On the other hand, it could actually be considered a bad sign for a stock with positive momentum. We chose not to impose our beliefs on how bad it has to be before it starts being bad. Thus the negative (positive) thresholds could be *any* negative (positive) number.

The largest *average* negative threshold of –6.90% occurs for Nasdaq in the most recent period. For other subperiods and markets, the average thresholds are frequently much lower in magnitude. In comparison to our model, previous studies have focused on much larger gains and declines. We on the other hand focus on the level of decline/gain (i.e. events) that changes the return generating process – generally a more moderate price change based on averages. Thus our post-event performance could be different from the previous studies. Average positive and negative thresholds are fairly close to being symmetric in magnitude, although positive thresholds are slightly larger than negative thresholds. Although, we do not present this information in the table, our number of events far surpasses those in previous studies. For example, in the first subperiod, we identify 176,425 positive events and 143,074 negative events, counting each security-day as an event. The largest event counts are in the seventh subperiod with 527,135 positive and 502,343 negative events. The last period is shorter than the others and naturally does not show the highest counts. Since we are using the SETAR model primarily for the estimation of threshold values, we do not report statistics concerning intercept and AR coefficients for the three regions. Instead, we conduct positive and negative event analysis through regression models to make our results directly comparable to previous studies. Table 1 also presents the variance of the non-event, positive event, and negative event region returns – essentially the variance of the error term from the AR model for each region. The event variances (positive and negative) are at least twice as high as the non-event region variances, and in many cases they are much higher, indicating a higher perception of risk on the next day. Finally, the first column also presents the number of securities for each market and subperiod and clearly shows that our sample is quite large, despite the fact that we do not include securities with less than 1000 returns in any subperiod.

3.2 Post-event nominal returns

Table 2 presents averages of event and post-event day security returns by market over the two-year out-of-sample period following threshold parameter estimation. For comparison, we also present the average of the event day NYSE/Amex/Nasdaq value weighted index (market) return and the average two-year exchange-specific security return. Day 4-20 return is presented as an average daily return to facilitate comparison with other days. These returns are comparable to Cooper (1999) in that they are raw returns. The event day average returns (day 0) are predictably large in magnitude for positive and negative events.

(Place Table 2 approximately here)

The average event day decline never exceeds 6% (9%, 10%) for the NYSE (Amex, Nasdaq). These average declines are below the customary 10% used in many prior studies and underscore the fact that we have a fundamentally different and more comprehensive sample. Consistent with the SETAR model thresholds shown in Table 1, the average increase on the positive event day is always higher than the magnitude of decline on negative event days. Event day average declines and increases are significantly larger in magnitude compared to the same-day market return, indicating that most are company-specific or sector-specific, not market-wide.

Post-negative event, day 1 average returns are at least four times the average daily returns for the NYSE, barring one exception. Similar averages for the Amex are higher than the NYSE averages and are at least ten times the average Amex return. The Nasdaq shows a similar pattern of high day 1 average return, except for the 1983-84 subperiod. Thus day 1 returns are clearly quite high after a negative event. In all cases, post-negative event day 2 and 3 returns are also clearly larger than the average returns on the NYSE/Amex/Nasdaq – despite no systematic bid-ask bounce that generally contaminates day 1 returns. Thus, the day 2 and 3 returns cast doubt on the spread-based explanation of the post-event performance and are supportive of Cooper (1999) where skip-day weekly returns on losers are similarly high. For positive events, the NYSE/Amex/Nasdaq securities generally have low or negative day 1 returns. With few exceptions, day 2 and 3 returns after a positive event are either negative or clearly lower than the corresponding negative event returns – thus indicating a stronger performance following a negative event and a weaker performance after a positive event. These results indicate that a Long/Short strategy similar to Lehmann (1990) and others would show positive returns at least on a before-transaction cost basis.

The post-negative event returns for days 4-20 are mostly higher than the average exchange-specific. Also, day 4-20 returns show a pattern of underperformance after a positive event relative to the performance after a negative event, in a manner similar to Cooper (1999). This once again provides strong evidence of outperformance after a negative event with mixed results after a positive event. The nominal return based evidence so far does not provide support to Cox and Peterson (1994), Park (1995), Pritamani and Singal (2001), and Larson and Madura (2003) where some continuation is found after a negative return. Instead, nominal returns show a tendency to be higher after a negative event.

3.3 Post-event abnormal returns

Table 3 presents two-year out-of-sample post-event abnormal returns for the three markets.

(Place Table 3 approximately here)

After a negative event, days 1, 2, and 3 returns are almost always positive and significant with a vast majority being significantly different than zero at the 0.1% level. This suggests that security returns revert in the days following a large decline and is generally consistent with the CARs presented by Cox and Peterson, Bremer and Sweeny, and Park for days 1-3 (i.e. in the short-term).

As day 2 and day 3 returns are not affected by the bid/ask bounce, our results strongly indicate reversal after a negative event. Similar to nominal returns, in most cases, abnormal returns show a clear tendency of reversal in the longer-term (day 4-20) in all three markets. Our in-sample abnormal returns, though not presented here, are quite similar to the out-of-sample results. Overall, there appears to be a reversal after a negative event for the next 20 days.[20]

Following positive events in NYSE/Amex securities, we still see strong reversal in a large majority of cases from days 1 through 3 with 40 negative daily returns out of a total of 48 across the subperiods and the two markets which corroborate our intuition from nominal returns. For day 4-20, NYSE/Amex stocks demonstrate reversal in half of the subperiods. This is consistent with the mixed evidence of prior studies after positive events in the longer-term.

For Nasdaq positive events, the evidence is inconclusive. However, on a pair-wise comparison, the abnormal returns in days 1 through 3 after a positive event are mostly lower than those after a negative event with the last two periods yielding clearly negative returns. The pair-wise comparison over days 4-20 returns are always lower after a positive event than after a negative event, allowing a successful Long/Short portfolio strategy.

The evidence so far appears to suggest reversals for stocks after negative events over the next 20 days, with weaker short-term evidence of reversals following positive events. This extends the results of Cooper (1999) where he finds reversal in weekly returns for the largest 300 stocks in the NYSE and the Amex. We demonstrate that reversals continue beyond the first week across all

[20] To gauge the economic significance of our results, we consider transactions cost estimates from two sources – Barber and Odean (2000) and Plexus Group. Our conclusion is that the average investor would not be able to profit based on our evidence. However, economic profits are possible for institutional traders to the extent that they can avoid commission costs.

stocks for the negative event. This result is different from the evidence of continuation shown in prior daily event based research.

3.4 Tests of proportionality

So far the results clearly show a strong tendency of reversal for twenty days after a negative event. For positive events, there is reversal in the short-term but in the longer-term there is mixed evidence of reversal in some subperiods and markets with continuation in others. The evidence is aggregate across all events and thus could hide interesting dynamics with respect to the degree of price change, and could also have strong susceptibility to outliers. To investigate further, we regress post-event abnormal returns on the event-day abnormal returns per Equation 3, and present the results in Table 4 for negative and positive events. If the bid-ask bounce is the main culprit for day 1 returns, there should not be a proportionate relation between the strength of reversal and the event day decline (or rise). The bounce should be mostly subsumed in the intercept of the regression.

In Table 4 (Panel A), the post negative event results are once again generally unanimous and strong.

(Place Table 4 approximately here)

The coefficient on the event date abnormal return (*EDAR*, hereafter also referred to as the slope) is significantly negative for day 1-3 across all subperiods. For day 4-20 returns where the bid-ask bounce is not relevant, we still find the slope to be significantly negative at the conventional level of 5% barring one subperiod. Thus, the degree of reversal is pervasively proportionate to the level of decline, both in the short and longer term and across subperiods.[21] These negative slope

[21] It may appear that the post-event performance that we see is a direct outcome of the SETAR model estimation; however, we only use the day 1 return for SETAR modeling, not days 2 through 20.

coefficients are indeed remarkable in light of the fact that we are studying the autoregression in the returns of a portfolio which could potentially have a positive slope bias for two reasons – non-synchronous trading induced autocorrelation well as volume leadership induced autocorrelation as noted by Chordia and Swaminathan (2000). Day 1-3 intercepts are large and positive in five out of eight subperiods though generally not significant, which appears to corroborate our conjecture that the bid-ask bounce will be captured in the intercept.

The size coefficient is negative and significant for day 1-3 in five out of eight subperiods indicating that larger stocks revert less. In the longer term for day 4-20, the size coefficient is mostly positive suggesting that large stocks bounce back more on a proportionate basis. Counter-intuitively, the Amex and Nasdaq dummies are generally negative for day 1-3 indicating lower overrreaction for Amex/Nasdaq securities while these dummies are inconclusive in the longer run.

In Table 4 (Panel B), following positive events, slope coefficients are generally negative for day 1-3, but only three of the eight are significant, suggesting weak reversal. The intercept is negative in six subperiods with large magnitudes for day 1-3 returns with five significances, once again supporting the conjecture that the intercept captures the bid-ask bounce. By contrast, day 4-20 returns show strong continuation as the slope is positive and significant in six subperiods. Surprisingly, the intercept term is almost always significantly negative at 0.1% and would likely dominate the proportionate continuation effect, suggesting a constant longer-term decline after a positive event.

The coefficient on the size variable is often positive with five significances for day 1-3, and all but one are significant for day 4-20. Thus, securities in higher deciles generally gain more in the longer-term as well as in the short-term, after a positive event. The Amex and Nasdaq dummies are generally positive with some significance suggesting that Amex and Nasdaq securities show stronger continuation after a positive event.

The analyses thus far strongly indicate that after a negative event, securities revert in the short term as well as in the longer term, with smaller securities reverting more in the short term and larger securities gaining more in the longer-term. After a positive event, longer-term results indicate a proportionate (slope effect) continuation but a constant (intercept effect) reversal with further gains for larger securities as well as gains for Amex/Nasdaq stocks in some subperiods. This could help explain why other studies have found conflicting results across different return filters, stock sizes, and markets. In the short-term, the post-positive event performance generally indicates reversal. In addition to the out-of-sample tests reported in the paper, we also conducted in-sample tests using the five years' data of each estimation period. Both sets of results were quite similar and the in-sample results are available from the authors.

3.5 Comparison with previous studies

In this section, we compare our results with two of the more recent studies, Cooper (1999) and Pritamani and Singal (2001) to provide further evidence on overreaction. This is not an attempt to replicate the previous studies as each one, including ours, has its own unique technique of defining events. In addition, Cooper (1999) uses weekly transactional returns while Pritamani and Singal (2001) employ daily returns based on bid-ask average prices.

Table 5 presents results for four weeks after positive and negative events for various subsamples. The first set in Panel A is the subsample of top 300 NYSE/Amex stocks, analogous to Cooper (1999). The results are strongly indicative of a reversal that continues over the next four weeks after a negative event. Similar to Cooper's skip-day next week result, Panel A shows a positive return that increases in magnitude as the event return becomes increasingly more negative.

In addition, a slowly decaying pattern of positive returns in weeks 2-4 suggests that the reversal extends well beyond the first week, even for the most liquid stocks. The overreaction following negative events is robust to the choice of the event period (weekly or daily), the technique of selecting the event, and extends beyond Cooper's sample period of 1962-1993. The fact that our post-event returns are lower than his, however, could be an indication that the overreaction effect has been diminished over the 1994 to 2002 period due to a substantially improved trading process in terms of bid-asked spread, speed of execution, and trading volumes.

For positive events, as the magnitude increases, the skip-day, next week return decreases and eventually becomes negative, indicative of overreaction. Whereas our result shows a negative return starting in the (+4 to +6) event filter, Cooper's reversal first appears in the (+6 to +8) event filter. Although the reversals are mitigated over the remaining three weeks, the overall 4-week holding period return still remains negative for the two largest event categories. Again, a Long/Short portfolio strategy would show positive returns, with the magnitude increasing as the strategy moves from small events to large events.

When we change our sample in Panel B to include all NYSE/Amex securities similar to Pritamani and Singal (2001) with no distinction as to event magnitude, our results again indicate significantly higher returns after negative events, continuing through week 4. This pattern of overreaction is different from the continuation result found by Pritamani and Singal and further supports Cooper's findings. Following positive events, there is weak evidence of overreaction with a small negative return in the first week. Despite the fact that the second week return is positive, it still represents less than a 9% annualized return, suggesting further underperformance. Our week 3 and week 4 returns are significantly positive, similar to Pritamani and Singal's raw return results, but are clearly smaller than the corresponding return for negative events, allowing a successful Long/Short portfolio strategy.[22] In Panel C, Nasdaq securities appear to show reversal for four weeks after a negative event; however after a positive event, weekly returns are found to be quite large, suggesting a lack of reversal. This is consistent with our Nasdaq results in Tables 2 and 3. Finally, in a more direct comparison to the sample period of Pritamani and Singal, we use returns from January 1, 1990 through December 2, 1992 in Panel D and obtain positive event results that are similar to theirs, but still find reversal after negative events.

4. Conclusions

When analyzing stock price overreactions and underreactions to events, there is a surprising lack of agreement between daily and weekly return horizons. We help reconcile the conflict by studying stock return behavior after large price changes, with negative and positive events identified through the use of the Self-Exciting Threshold Autoregressive model. Our technique permits estimation of thresholds directly from the data and allows the event definition to vary across securities and subperiods.

Following negative events, our results strongly indicate overreaction with reversal in the short term (days 1-3) and in the longer term (days 4-20). The evidence is pervasive for all sizes, markets, subperiods, and post-event holding periods including and excluding day 1 returns. Our daily return outcomes support the weekly return results of Cooper (1999) and are different from the continuation evidence of other daily return studies.

After positive events, the results are mixed although there is generally evidence of overreaction in the short-term. We support Cooper's (1999) weekly overreaction result in the short-term and long-term for the largest stocks with high magnitude positive events. However, when smaller stocks are included, our long term results over week 3 and week 4 bear some

[22] These individual stock results are not directly comparable to the regressions in Table 4 where portfolio returns are used.

resemblance to Pritimani and Singal (2001), as well as others. However, when both negative and positive events are considered overall, our daily return based study strongly supports the weekly return results of Cooper.

Additionally, our regression model helps explain the conflicting findings of prior studies. In the longer term following a positive event, there is a fixed decline accompanied by a proportional continuation of event day performance. This clearly demonstrates that the result depends upon the magnitude of the filters. In conclusion, we show that a commonly used Long/Short portfolio strategy results in a positive return that increases in proportion to the absolute magnitude of the positive and negative events.

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Table 1

SETAR model for CRSP securities using raw returns

Descriptive statistics are reported for the thresholds of each stock and for the variances of each region for each stock. Returns are times 10^2.

	Number of Companies	Average Lower Threshold	Maximum Lower Threshold	Minimum Lower Threshold	Average Upper Threshold	Maximum Upper Threshold	Minimum Upper Threshold	Average Threshold Band Width	Average Non-Event Variance	Average Negative Event Variance	Average Positive Event Variance
NYSE											
1/1/63–12/31/67	1084	-2.501	-0.781	-8.885	2.620	12.022	0.753	5.121	0.030	0.063	0.069
1/1/68–12/31/72	1127	-3.038	-0.437	-9.039	3.182	8.910	0.479	6.220	0.042	0.089	0.092
1/1/73–12/31/77	1412	-3.578	-0.769	-15.774	3.696	16.337	1.123	7.274	0.063	0.146	0.160
1/1/78–12/31/82	1331	-3.220	-0.851	-11.504	3.388	15.779	0.978	6.608	0.049	0.109	0.116
1/1/83–12/31/87	1248	-3.559	-0.927	-14.982	3.652	14.796	1.014	7.211	0.049	0.245	0.141
1/1/88–12/31/92	1381	-3.289	-0.572	-26.973	3.615	36.469	0.475	6.904	0.068	0.248	0.236
1/1/93–12/31/97	1990	-2.731	-0.675	-16.451	2.987	19.535	0.813	5.718	0.040	0.104	0.098
1/1/98–12/31/01	1982	-3.554	-0.490	-14.323	3.908	17.481	0.503	7.462	0.037	0.196	0.185
Amex											
1/1/63–12/31/67	767	-4.436	-0.422	-30.117	4.952	47.615	0.484	9.388	0.110	0.220	0.285
1/1/68–12/31/72	869	-4.664	-0.569	-12.035	4.736	14.629	0.584	9.400	0.101	0.207	0.233
1/1/73–12/31/77	1018	-5.479	-0.981	-17.867	5.764	23.739	1.163	11.243	0.147	0.372	0.388
1/1/78–12/31/82	738	-4.660	-0.944	-15.963	5.097	17.085	1.182	9.758	0.104	0.262	0.322
1/1/83–12/31/87	591	-4.649	-1.132	-19.252	4.941	24.739	0.947	9.591	0.098	0.423	0.298
1/1/88–12/31/92	710	-5.261	-0.553	-31.840	5.850	58.389	0.825	11.112	0.166	0.794	0.579
1/1/93–12/31/97	642	-4.298	-0.746	-24.735	4.915	31.803	0.747	9.213	0.110	0.349	0.351
1/1/98–12/31/01	492	-5.304	-0.665	-19.328	5.977	32.390	0.696	11.281	0.186	0.589	0.571
Nasdaq											
1/1/63–12/31/67	-	-	-	-	-	-	-	-	-	-	-
1/1/68–12/31/72	-	-	-	-	-	-	-	-	-	-	-
1/1/73–12/31/77	2303	-4.535	-0.468	-18.206	4.551	18.749	0.549	9.086	0.083	0.240	0.284
1/1/78–12/31/82	2022	-3.940	-0.323	-15.722	4.033	21.454	0.448	7.974	0.071	0.201	0.254
1/1/83–12/31/87	2716	-5.076	-0.270	-19.510	5.048	20.771	0.358	10.124	0.109	0.462	0.407
1/1/88–12/31/92	3152	-6.576	-0.732	-36.149	7.145	49.839	0.825	13.721	0.201	0.934	0.702
1/1/93–12/31/97	3382	-6.366	-1.004	-56.408	7.257	94.469	1.179	13.623	0.221	0.692	0.559
1/1/98–12/31/01	2783	-6.904	-1.211	-27.826	7.794	31.414	1.389	14.698	0.259	0.800	0.807

Table 2
Out-of-sample nominal post-event returns for an equally weighted portfolio

Average returns for the equally weighted portfolio of all stocks are shown for event days as well as the three days following both negative and positive events across eight subperiods for NYSE and Amex and six subperiods for Nasdaq securities. Day 4-20 return is the average daily return (not the cumulative seventeen-day return) to facilitate comparison. Value-weighted NYSE/Amex/Nasdaq market returns on the event day are shown as well as the average return for an equally weighted exchange specific portfolio of all securities over the subperiod.

	1/1/68-12/31/69		**1/1/73-12/31/74**		**1/1/78-12/31/79**		**1/1/83-12/31/84**		**1/1/88-12/31/89**		**1/1/93-12/31/94**		**1/1/98-12/31/99**		**1/1/02-12/31/03**	
	Neg	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**
NYSE																
Day 0 return	-3.073	3.596	-4.390	4.828	-3.974	5.027	-3.859	4.421	-5.643	5.997	-4.099	4.768	-4.025	4.719	-4.843	5.187
Day 1 return	0.168	0.154	0.307	-0.209	0.577	0.103	0.227	0.211	1.028	-0.424	0.643	-0.239	0.211	0.034	0.256	0.068
Day 2 return	0.142	-0.086	0.104	-0.173	0.239	-0.034	0.217	0.019	0.204	-0.002	0.217	-0.012	0.085	-0.023	0.149	0.071
Day 3 return	0.107	-0.088	0.071	-0.182	0.195	-0.015	0.188	-0.021	0.177	-0.011	0.162	0.004	0.062	-0.012	0.179	0.034
Day 4-20 return	0.025	-0.014	-0.028	-0.073	0.115	0.087	0.097	0.050	0.072	0.039	0.074	0.052	0.038	0.011	0.094	0.087
Day 0 market return	0.006	0.006	-0.100	-0.100	0.062	0.062	0.049	0.049	0.085	0.085	0.022	0.022	0.092	0.092	0.012	0.012
NYSE Average return	0.015		-0.109		0.095		0.065		0.082		0.038		0.011		0.059	
Amex																
Day 0 return	-4.687	6.363	-7.340	8.139	-6.203	7.729	-6.029	6.935	-7.839	8.679	-6.668	8.167	-6.651	8.459	-8.272	10.445
Day 1 return	0.497	0.362	1.786	-1.250	1.593	-0.107	1.127	-0.077	2.509	-1.023	1.730	-0.396	1.630	-0.645	2.216	-0.614
Day 2 return	0.302	-0.223	0.352	-0.216	0.451	-0.008	0.356	0.038	0.481	0.137	0.409	0.042	0.349	0.065	0.580	0.191
Day 3 return	0.194	-0.208	0.232	-0.086	0.316	0.012	0.258	-0.062	0.275	0.125	0.280	0.079	0.319	-0.025	0.510	0.140
Day 4-20 return	0.039	-0.012	0.062	-0.034	0.207	0.130	0.115	0.055	0.224	0.147	0.178	0.119	0.188	0.153	0.381	0.262
Day 0 market return	0.006	0.006	-0.100	-0.100	0.062	0.062	0.049	0.049	0.085	0.085	0.022	0.022	0.092	0.092	0.012	0.012
Amex average return	0.035		-0.101		0.158		0.074		0.107		0.089		0.062		0.124	
Nasdaq																
Day 0 return	-	-	-	-	-5.907	7.087	-5.382	6.284	-7.208	7.980	-8.892	10.720	-8.331	10.665	-9.332	11.485
Day 1 return	-	-	-	-	0.310	0.784	-0.015	0.747	2.398	-1.401	4.175	-2.557	2.229	-0.957	2.311	-0.856
Day 2 return	-	-	-	-	0.297	0.239	0.075	0.322	0.213	0.240	0.490	0.335	0.469	0.000	0.494	0.049
Day 3 return	-	-	-	-	0.229	0.142	0.148	0.101	0.177	0.177	0.398	0.370	0.344	0.104	0.347	0.058
Day 4-20 return	-	-	-	-	0.181	0.101	0.087	0.021	0.164	0.127	0.363	0.326	0.248	0.183	0.244	0.194
Day 0 market return	-	-	-	-	0.062	0.062	0.049	0.049	0.085	0.085	0.022	0.022	0.092	0.092	0.012	0.012
Nasdaq average return	-		-		0.132		0.033		0.088		0.165		0.167		0.111	

Table 3
Out of sample abnormal post-event returns for an equally weighted portfolio

Average transactional price abnormal returns for the equally weighted portfolio of all stocks are shown for the three days following both negative and positive events across eight subperiods for NYSE and Amex and six subperiods for Nasdaq securities. Cumulative abnormal returns for days 4 through 20 are also shown.

	1/1/68-12/31/69		**1/1/73-12/31/74**		**1/1/78-12/31/79**		**1/1/83-12/31/84**		**1/1/88-12/31/89**		**1/1/93-12/31/94**		**1/1/98-12/31/99**		**1/1/02 12/31/03**	
	Neg	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**	**Neg**	**Pos**
NYSE																
Day 1	0.155[c]	0.098[c]	0.462[c]	-0.136[c]	0.494[c]	-0.036	0.182[c]	0.143[c]	0.995[c]	-0.472[c]	0.604[c]	-0.297[c]	0.219[c]	0.022	0.211[c]	0.036
Day 2	0.105[c]	-0.122[c]	0.230[c]	-0.068[a]	0.139[c]	-0.158[c]	0.167[c]	-0.037[a]	0.177[c]	-0.054	0.167[c]	-0.058[b]	0.090[b]	-0.030	0.120[c]	0.037
Day 3	0.075[c]	-0.123[c]	0.194[c]	-0.074[b]	0.082[c]	-0.136[c]	0.140[c]	-0.078[c]	0.147[b]	-0.052	0.111[c]	-0.040[a]	0.062[a]	-0.009	0.144[c]	-0.007
Days 4-20	-0.003	-0.040[c]	0.085[c]	0.032[b]	-0.008	-0.051[c]	0.039[c]	-0.006	0.046[c]	-0.003	0.026[c]	0.004	0.037[c]	0.006	0.047[c]	0.039[c]
Amex																
Day 1	0.429[c]	0.218[c]	1.881[c]	-1.201[c]	1.427[c]	-0.300[c]	1.057[c]	-0.159[b]	2.393[c]	-1.125[c]	1.610[c]	-0.522[c]	1.559[c]	-0.722[c]	2.002[c]	-0.824[c]
Day 2	0.215[c]	-0.329[c]	0.430[c]	-0.150[b]	0.270[c]	-0.190[c]	0.288[c]	-0.043	0.366[c]	0.038	0.284[c]	-0.083	0.272[c]	-0.004	0.382[c]	-0.026
Day 3	0.108[b]	-0.313[c]	0.301[c]	-0.017	0.130[b]	-0.171[c]	0.184[c]	-0.141[b]	0.178[b]	0.018	0.146[b]	-0.048	0.247[c]	-0.093	0.289[b]	-0.073
Days 4-20	-0.045[c]	-0.105[c]	0.132[c]	0.031	0.012	-0.063[c]	0.039[b]	-0.026[a]	0.120[c]	0.044[c]	0.053[c]	-0.003	0.110[c]	0.082[c]	0.169[c]	0.042[a]
Nasdaq																
Day 1	-	-	-	-	0.178[c]	0.624[c]	-0.076[a]	0.673[c]	2.307[c]	-1.489[c]	3.902[c]	-2.845[c]	2.126[c]	-1.073[c]	2.177[c]	-1.001[c]
Day 2	-	-	-	-	0.146[c]	0.097[b]	0.004	0.251[c]	0.122[c]	0.156[c]	0.209[c]	0.047	0.368[c]	-0.113[b]	0.358[c]	-0.089
Day 3	-	-	-	-	0.073[a]	0.003	0.079[b]	0.035	0.088[b]	0.094[c]	0.115[c]	0.084[a]	0.240[c]	-0.000	0.217[c]	-0.076
Days 4-20	-	-	-	-	0.017	-0.054[c]	0.015	-0.045[c]	0.074[c]	0.042[c]	0.083[c]	0.041[c]	0.141[c]	0.074[c]	0.104[c]	0.050[c]

[c] Indicates statistical significance at the 0.001 level
[b] Indicates statistical significance at the 0.01 level
[a] Indicates statistical significance at the 0.05 level

Table 4
Out of sample regression explaining cumulative abnormal returns following events

A regression model is run on a pooled sample of transactional price returns for an equally weighted portfolio of securities from the three markets as follows:

$$PEDAR_i = \alpha + \beta_1 EDAR_i + \beta_2 Dec_i + \beta_3 D_{Amex,i} + \beta_4 D_{Nasdaq,i} + \varepsilon_I$$

The regression is run for two specifications of the dependent variable Cumulative Days 1-3, and Cumulative Days 4-20. The independent variables are the event day return for each security, a decile ranking for each security, and dummy variables for Amex and Nasdaq.

Time Period	Intercept	EDAR	Dec	D_{Amex}	D_{Nasdaq}	F Value	R^2
Panel A: Negative Events							
Days 1-3							
1/1/68 – 12/31/69	-0.0064	-0.3345[c]	-0.0001	-0.0019	-	19.42	0.0579
1/1/73 – 12/31/74	0.0531[a]	-0.4771[c]	-0.0076[b]	-0.0305[c]	-	136.58	0.2894
1/1/78 – 12/31/79	0.0343[c]	-0.2698[c]	-0.0047[c]	-0.0136[c]	-0.0267[c]	96.20	0.2031
1/1/83 – 12/31/84	-0.0267	-0.5272[c]	0.0013	0.0030	-0.0089[a]	107.50	0.2213
1/1/88 – 12/31/89	-0.0330[a]	-0.5795[c]	0.0018	0.0088[a]	0.0074[a]	89.20	0.1911
1/1/93 – 12/31/94	0.0279[b]	-0.4691[c]	-0.0049[c]	-0.0183[c]	-0.0080[b]	529.28	0.5837
1/1/98 – 12/31/99	0.0147	-0.5016[c]	-0.0038[b]	-0.0121[b]	-0.0115[c]	177.84	0.3207
1/1/02 – 12/31/03	0.0047	-0.4489[c]	-0.0029[b]	-0.0068	-0.0061[a]	118.72	0.2471
Days 4-20							
1/1/68 – 12/31/69	-0.0034	-0.0274[a]	0.0003	0.0005	-	6.41	0.0199
1/1/73 – 12/31/74	-0.0064	-0.0884[c]	0.0004	-0.0003	-	24.59	0.0683
1/1/78 – 12/31/79	0.0075[c]	0.0128	-0.0009[c]	-0.0029[c]	-0.0028[c]	8.13	0.0211
1/1/83 – 12/31/84	-0.0079[c]	-0.0569[c]	0.0007[c]	0.0013[a]	0.0013[a]	17.28	0.0437
1/1/88 – 12/31/89	-0.0017	-0.0344[c]	0.0000	0.0001	-0.0002	15.47	0.0394
1/1/93 – 12/31/94	0.0005	-0.0177[a]	-0.0001	-0.0006	-0.0008	10.69	0.0275
1/1/98 – 12/31/99	-0.0110[c]	-0.1032[c]	0.0009[c]	0.0015[a]	-0.0006	38.21	0.0921
1/1/02 – 12/31/03	-0.0022	-0.0426[c]	0.0001	-0.0000	-0.0011[a]	14.45	0.0384
Panel B: Positive Events							
Days 1-3							
1/1/68 – 12/31/69	0.0079	0.1279	-0.0019	-0.0140[b]	-	8.64	0.0266
1/1/73 – 12/31/74	-0.0627[b]	-0.1578	0.0082[c]	0.0296[c]	-	52.96	0.1364
1/1/78 – 12/31/79	-0.0097	-0.0811	0.0013	0.0036	0.0172[c]	70.09	0.1566
1/1/83 – 12/31/84	0.0195[a]	-0.1467[b]	-0.0015	-0.0053	0.0074[b]	73.32	0.1624
1/1/88 – 12/31/89	-0.0383[c]	-0.0779[a]	0.0047[c]	0.0128[c]	0.0083[b]	30.72	0.0752
1/1/93 – 12/31/94	-0.0427[c]	-0.0752	0.0054[c]	0.0195[c]	0.0009	282.85	0.4283
1/1/98 – 12/31/99	-0.0601[c]	0.0954	0.0068[c]	0.0164[c]	0.0048	41.36	0.0989
1/1/02 – 12/31/03	-0.0312[c]	-0.0749[a]	0.0050[c]	0.0137[c]	0.0059[a]	41.10	0.1020
Days 4-20							
1/1/68 – 12/31/69	-0.0036[a]	0.0012	0.0004[a]	0.0011	-	11.11	0.0340
1/1/73 – 12/31/74	-0.0237[c]	0.0966[c]	0.0023[c]	0.0069[c]	-	33.95	0.0919
1/1/78 – 12/31/79	-0.0014	-0.0085	0.0002	0.0007	0.0007	1.64	0.0043
1/1/83 – 12/31/84	-0.0115[c]	0.0542[c]	0.0011[c]	0.0022[c]	0.0021[c]	28.47	0.0700
1/1/88 – 12/31/89	-0.0063[c]	0.0278[c]	0.0006[c]	0.0017[c]	0.0016[c]	15.15	0.0386
1/1/93 – 12/31/94	-0.0032[b]	0.0192[b]	0.0003[a]	0.0004	0.0004	10.37	0.0267
1/1/98 – 12/31/99	-0.0154[c]	0.0670[c]	0.0015[c]	0.0045[c]	0.0017[b]	48.07	0.1132
1/1/02 – 12/31/03	-0.0058[c]	0.0196[a]	0.0007[c]	0.0019[c]	0.0008	9.88	0.0266

[c] Indicates statistical significance at the 0.001 level
[b] Indicates statistical significance at the 0.01 level
[a] Indicates statistical significance at the 0.05 level

Table 5
Average weekly holding period returns following negative and positive events

Sample period includes 1/1/1963 – 12/31/2002 and returns are expressed in percent.

	0 to –2	**–2 to –4**	**–4 to –6**	**–6 to –8**	**–8 to –10**	**< –10**	**0 to +2**	**+2 to +4**	**+4 to +6**	**+6 to +8**	**+8 to +10**	**> +10**
Panel A: Top 300 (NYSE/Amex)												
Day 0	-1.58[c]	-2.84[c]	-4.75[c]	-6.80[c]	-8.82[c]	-14.30[c]	1.61[c]	2.89[c]	4.78[c]	6.81[c]	8.82[c]	13.74[c]
Day 1	0.12[c]	0.10[c]	0.20[c]	0.44[c]	1.17[c]	2.08[c]	0.03[c]	0.15[c]	0.16[c]	0.13[c]	0.20[c]	-0.06
Skip-day, Week 1	0.28[c]	0.45[c]	0.51[c]	0.62[c]	0.82[c]	1.09[c]	0.21[c]	0.01	-0.15[c]	-0.15[b]	-0.41[c]	-0.52[c]
Week 2	0.36[c]	0.36[c]	0.28[c]	0.17[a]	0.32[c]	0.25[a]	0.20[c]	0.15[c]	0.13[b]	0.05	0.07	-0.04
Week 3	0.31[c]	0.29[c]	0.25[c]	0.07	0.21[a]	0.25[a]	0.21[c]	0.23[c]	0.22[c]	0.21[c]	0.18[b]	0.20[a]
Week 4	0.31[c]	0.26[c]	0.32[c]	0.17[a]	0.26[b]	0.37[c]	0.24[c]	0.20[c]	0.16[c]	0.23[c]	0.12	0.14

	Negative	**Positive**
Panel B: All Stocks (NYSE/Amex)		
Day 0	-4.81[c]	5.65[c]
Day 1	0.84[c]	0.01
Skip-day, Week 1	0.76[c]	-0.04
Week 2	0.53[c]	0.16[b]
Week 3	0.44[c]	0.27[c]
Week 4	0.41[c]	0.29[c]
Panel C: All Stocks (Nasdaq)		
Day 0	-7.52[c]	8.96[c]
Day 1	1.76[c]	-0.31[c]
Skip-day, Week 1	0.84[c]	0.47[c]
Week 2	0.75[c]	0.35[c]
Week 3	0.62[c]	0.38[c]
Week 4	0.61[c]	0.41[c]
Panel D: NYSE/Amex (1990-92)		
Day 0	-5.65[c]	6.73[c]
Day 1	1.28[c]	-0.31[c]
Skip-day, Week 1	0.85[c]	0.10
Week 2	0.68[c]	0.25[c]
Week 3	0.50[c]	0.30[c]
Week 4	0.47[c]	0.33[c]

[c] Indicates statistical significance at the 0.001 level
[b] Indicates statistical significance at the 0.01 level
[a] Indicates statistical significance at the 0.05 level