# Evaluating Stock Price Behavior after Events: An Application of the Self-Exciting Threshold Autoregressive Model

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*Stocks returns following large price changes provide a conflicting picture when events are measured weekly or daily. This study uses a new methodology to identify event thresholds and to examine post-event daily stock return behavior over a period of 20 days. After negative events, there is 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. A regression-based model helps to further explain these conflicting results.*

## Introduction

After events have occurred, 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] Over a weekly horizon, Lehmann (1990) demonstrates 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

[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).


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Wang (1993) and Conrad, Hameed, and Niden (1994) 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. This weekly reversal is at odds with the daily horizon where results about reversal/continuation have been inconclusive. This research seeks to shed further light on the subject by reexamining events with a daily horizon using a different model—the self-exciting threshold autoregressive model.

With a daily event window, Atkins and Dyl (1990) and Bremer and Sweeney (1991) present evidence of overreaction, while Brown, Harlow, and Tinic (1988) show predictable variation. When portfolios are unconditionally formed based on large daily declines and/or gains (events), 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 longer term (three or four days beyond a negative event), there appears to be a general tendency toward continuation. Cox and Peterson (1994), Park (1995), Pritamani and Singal (2001), and Larson and Madura (2003) find some continuation from day four/five to day 20 after a negative event. By contrast, after a positive event, Park (1995) shows no systematic longer-term variation, 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 performances of daily versus weekly event horizons is puzzling, as large daily returns should coincide with large weekly returns because average daily returns are small. As a result, if overreaction is found in weekly returns, a similar result should be expected after large daily returns. Therefore, stock return behavior following large positive and negative returns warrants further investigation to see if these two streams of literature can be reconciled.

Prior studies have either used fixed thresholds to define events which can yield a sample biased toward high-volatility stocks or have employed a dispersion-based norm that should be free from such a bias.[2] In this study, the self-exciting threshold autoregressive (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 the detection of 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.

[2]Cox and Peterson (1994) condition on more than a 10 percent loss, Park (1995) on a greater than 10 percent abnormal gain or loss, and Cooper (1999) uses return filters at 2 percent intervals between -10 percent and +10 percent with the extremes in two remaining negative and positive categories. Pritamani and Singal (2001) use abnormal moves greater than three standard deviations from the mean (an approximate 7 percent average gain or loss).

The aggregate period (1/1/63—12/31/03) is divided into eight subperiods to account for changes in volatility, liquidity, and institutional trading. For each subperiod, the event thresholds are estimated using daily returns and several post-event timeframes up to 20 days after the event are analyzed. A within-sample analysis is conducted as well as an examination of a two-year subperiod immediately following each parameter estimation period (to eliminate the look-ahead bias inherent in many trading rules). The model used eliminates the impact of microstructure issues such as bid-ask bounce, non-synchronous trading, and volume related return autocorrelation shown by Chordia and Swaminathan (2000).

There is strong evidence of reversal after a negative event in the short term (one to three 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 20 days, the overreaction is similar to the weekly return results of Cooper (1999). The positive event results are mixed as in previous studies, but there is generally evidence 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. These 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. The commonly used long-short portfolio strategy also achieves a positive return that increases in proportion to the absolute magnitude of the positive and negative events.

## Research Method

First, the security returns from 1963 to 2001 are subdivided into eight estimation subperiods.[3] Second, the parameters of the SETAR model are identified for every security that has a sufficient number of returns available in the subperiod for model identification. Third, negative event, positive event, and non-event days are identified for every security using the estimated thresholds, both on a within-sample and out-of-sample basis. The out-of-sample periods are two years (less if the security stops trading) following every non-overlapping, five-year parameter estimation interval.[4] These events then are 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. The thresholds and the AR process for each region are endogenously estimated, thus capturing the subtle interplay between the previous day's return and the AR process of stock returns the

[3]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.

[4]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.

next day. Instead of simply concentrating on the days of extreme price change as in prior studies, the focus is on those days where a relatively large price change occurred accompanied by a simultaneous change in the autoregressive model of security returns. As long as the autoregression in security returns varies across regions, the model will properly identify.

## SETAR Estimation and Threshold Identification

Threshold autoregressive (TAR) models are a class of non-linear time series models that were first introduced by Tong (1978).[5] 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 represented as:

$$r_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i r_{t-i} + \sum_{j=1}^{n} \left[ \beta_{0j} + \sum_{i=1}^{k} \beta_{ij} r_{t-i} \right] I_j(\gamma_t) + \varepsilon_t \tag{1}$$

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 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 this study. For the special case where $\gamma_t$ is replaced with a lagged value of the time series, the model is denoted as a self-exciting threshold autoregressive (SETAR) model of order ($n; k_1, k_2, \ldots k_n$).

The specification of the SETAR model with three regions separated by two threshold values, $r_l$ and $r_h$ with a lag d=1 is shown below.

$$\begin{Bmatrix} \text{low state, if } r_{t-1} < r_l \\ \text{normal state, if } r_l \le r_{t-1} \le r_h \\ \text{high state, if } r_{t-1} > r_h \end{Bmatrix} \tag{2}$$

The two-threshold case is appropriate for the study of return behavior after large declines and gains, yielding positive, negative, and non-event regions. The autoregression has a maximum lag of one within each region. Thus, the identified model can be intercept only in some cases. To give further intuition for using the SETAR model, it is assumed that on a non-event day, the security will *randomly*

[5]For a detailed account of the TAR model and its motivation see Tong (1983). SETAR models have been successfully applied to exchange rates [Kräger and Kugler (1993); Clements and Smith (2001)], stock indices [Dufrénot, Guégan, and Péguin-Feissolle (2005)], and GNP [Tiao and Tsay (1994)].

close at the bid (or ask) price inducing a positive (or negative) bid-ask bounce in the next day return. This bounce, along with non-trading, induce negative correlation in transactional returns between the non-event day and the next day [See Kaul and Nimalendran (1990) and Lo and MacKinlay (1999), for example], leading to an expected AR(1) coefficient that is negative in the non-event region.

In the negative (positive) event region, the security *systematically* closes at the bid (ask) price in the face of selling (buying) pressure. The resulting positive (negative) bid-ask bounce in the next day return will be captured in the intercept term, unlike the case of the non-event region above. Also, non-trading would not be a major issue for negative or positive event days, where heavy trading is encountered. Therefore, for the negative event region, a positive intercept is expected. For the positive event region, the intercept should be generally lower or negative due to negative bid-ask bounce. In both positive and negative event regions (unlike the non-event region), the AR(1) coefficient should be close to zero unless there are liquidity pressures, changing expected returns, or some form of market inefficiency. Given the differences across regions, the SETAR model is ideally suited for our purpose.

To estimate the model, a large number of potential thresholds are chosen on both sides of the mean return based on a variability of one to 2.5 standard deviations. Next, one potential threshold from either side of the mean is selected, and the state space of security returns is delineated into three regions, leading to three subsamples based on the 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. Thus, the choice of thresholds is not simply based on the dispersion measure; rather, the optimal thresholds are chosen in an iterative process to yield the best-fit family of three AR(1) models based on overall AIC criteria from all candidates.

## Event Identification and Post-event Return Analysis

Once the thresholds have been identified for a security in a given period, the returns are scanned over the next two years to identify the days when the returns cross one of the two thresholds. This provides an out-of-sample set of positive and negative event days. [6]

There is often more than one security registering an event for each day. Given the high cross-sectional correlation of returns, it would be inappropriate to count the same day occurrences as separate events.[7] So the securities that register an event

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[6]The same analysis is performed on a within-sample basis with strong results, but only the out-of-sample results are reported because it is a more stringent test of the hypotheses.

[7]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 and could lead to serious sampling issues when a single stock is sampled on

each day are combined into an equally weighted portfolio—essentially a short-term analog of the Mitchell and Stafford (2000) approach. Cooper (1999) implements a similar approach with weekly returns. The event portfolio return variance automatically subsumes the cross-sectional covariances and provides the most efficient use of the information.[8] 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 to incorrectly concluding that post-event continuation exists; however, for reversal, the bias actually makes the test less likely to reject the null hypothesis. Still, with a sample of high volume, event-registering securities, this issue is expected to be irrelevant.

The post-event day returns are analyzed by examining abnormal returns, where the market model parameters are computed using a pre-event window of –6 through –105 days.[9] As abnormal returns contain the bid-ask bounce and the averages could be susceptible to outliers, further analysis is done by regressing post-event abnormal returns on the event day abnormal returns similar to the approach of Cox and Peterson (1994):

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

where:

$PEDAR_i$ = 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 average 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; and
$D_{Nasdaq,i}$ = A dummy variable equal to 1 if portfolio i is Nasdaq and equal to 0 otherwise.

All estimations employ a heteroskedasticity-consistent covariance matrix.

Because market dummy variables are used, the sample of all events for all securities first is separated by market, and equally weighted event portfolios are created. The three subsamples then are pooled to run the regression. The size vari-

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numerous days. We find that as few as five stocks can represent as high as 46 percent of the observations within a subperiod. In numerous instances, a single company is sampled for over ten percent of the total observations. Therefore, this approach is too heavily weighted on a few individual companies to yield representative results.

[8]Counting only one observation per day and subdividing 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 the test statistics.

[9]Results are reported using the combined CRSP NYSE/Amex/Nasdaq index as the proxy for the market. Abnormal returns also were computed 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.

able 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 through 3 and cumulative days 4 through 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 essentially should be the bid-ask bounce whenever the dependent variable includes the day one return, but should be zero otherwise.[10]

## Data

Daily observations for all securities in the Center for Research in Security Prices (CRSP) database are obtained from January 1, 1963 to December 31, 2003. Daily transactional returns are constructed 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 closing bid-ask averages and Nasdaq inferences for the first two subperiods are virtually free of the bid-ask bounce.

Two restrictions reduce the size of the sample. Any security with fewer than 1,000 daily returns in each subperiod is eliminated to ensure that there is enough variation in the data to identify a realistic model of infrequent events. 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.[11] Although intuition suggests that a majority of observations must fall in the non-event region, a much weaker restriction is imposed whereby at least one-third of the total observations are included in the non-event region. 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 more efficient. It is an important issue, as the model must be individually identified for every qualifying stock in each subperiod. The final reasonable restriction is that the lower (upper) thresholds be negative (positive).

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

[11]The estimated thresholds across various subperiods indicate that the negative event frequency is approximately once every 3.5 weeks, while the positive event frequency is around once every 2.5 weeks.

**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 |

## Summary Statistics for the SETAR Models

Table 1 presents summary statistics related to the SETAR model parameters across the eight subperiods and three markets (NYSE, Amex, and Nasdaq). 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. Thus, the bandwidth of the non-event region increases from 5.12 percent to 7.46 percent. These changing thresholds are consistent with the fact that market volatility generally has risen over time, thus requiring securities to move more before registering an event. For Amex securities, thresholds and bandwidths also vary across subperiods. 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 show a clear tendency to rise in magnitude through time as well. In the last four subperiods, the Nasdaq 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 percent, whereas the lowest negative threshold is only about –0.27 percent. It is clear that fixed thresholds (such as a 10 percent movement) potentially can give rise to samples with omitted events and false events. A counter-argument could suggest that a drop of 0.27 percent is too low to be called a negative event. This small drop, however, actually could be a bad sign for a stock with positive momentum. Therefore, no subjective beliefs are imposed, and negative (positive) thresholds can be *any* negative (positive) number.

The largest *average* negative threshold of –6.90 percent occurs for Nasdaq in the most recent period. For other subperiods and markets, the average thresholds are frequently much lower in magnitude. The SETAR model generally produces a more moderate price change based on averages than previous studies. Average positive and negative thresholds are fairly symmetric in magnitude, although positive thresholds are slightly larger than negative thresholds. Although not reported, the number of events far surpasses those in previous studies. For example, there are 176,425 positive events and 143,074 negative events in the first subperiod, counting each security-day as an event. The largest counts are in the seventh subperiod with 527,135 positive and 502,343 negative events.

The variances 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—show that the event variances (positive and negative) are at least twice as high as the non-event region variances. In many cases they are much higher, indicating a higher perception of risk on the next day. Finally, the first column includes the number of securities for each market and subperiod and clearly shows that the sample is large, despite the fact that securities with fewer than 1000 returns in any subperiod are excluded. Because the SETAR model is used primarily for the estimation of threshold values, statistics concerning intercept and AR coefficients for the three regions are not reported. Instead, the positive and negative event analysis is conducted through regression models to make these results directly comparable to previous studies.

## 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, the average of the event day NYSE/Amex/Nasdaq value weighted index (market) return and the average two-year exchange-specific security return are also shown. Day 4-20 return is presented as an average daily return to facilitate comparison with other days. These are raw returns, comparable to Cooper (1999). The

**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 | |
|---|---|---|---|---|---|---|---|---|
| | 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 |
| Day 1 Return | 0.168 | 0.154 | 0.307 | -0.209 | 0.577 | 0.103 | 0.227 | 0.211 |
| Day 2 Return | 0.142 | -0.086 | 0.104 | -0.173 | 0.239 | -0.034 | 0.217 | 0.019 |
| Day 3 Return | 0.107 | -0.088 | 0.071 | -0.182 | 0.195 | -0.015 | 0.188 | -0.021 |
| Day 4-20 Return | 0.025 | -0.014 | -0.028 | -0.073 | 0.115 | 0.087 | 0.097 | 0.050 |
| Day 0 Market Return | 0.006 | 0.006 | -0.100 | -0.100 | 0.062 | 0.062 | 0.049 | 0.049 |
| NYSE Average Return | 0.015 | | -0.109 | | 0.095 | | 0.065 | |
| Amex | | | | | | | | |
| Day 0 Return | -4.687 | 6.363 | -7.340 | 8.139 | -6.203 | 7.729 | -6.029 | 6.935 |
| Day 1 Return | 0.497 | 0.362 | 1.786 | -1.250 | 1.593 | -0.107 | 1.127 | -0.077 |
| Day 2 Return | 0.302 | -0.223 | 0.352 | -0.216 | 0.451 | -0.008 | 0.356 | 0.038 |
| Day 3 Return | 0.194 | -0.208 | 0.232 | -0.086 | 0.316 | 0.012 | 0.258 | -0.062 |
| Day 4-20 Return | 0.039 | -0.012 | 0.062 | -0.034 | 0.207 | 0.130 | 0.115 | 0.055 |
| Day 0 Market Return | 0.006 | 0.006 | -0.100 | -0.100 | 0.062 | 0.062 | 0.049 | 0.049 |
| Amex Average Return | 0.035 | | -0.101 | | 0.158 | | 0.074 | |
| Nasdaq | | | | | | | | |
| Day 0 Return | - | - | - | - | -5.907 | 7.087 | -5.382 | 6.284 |
| Day 1 Return | - | - | - | - | 0.310 | 0.784 | -0.015 | 0.747 |
| Day 2 Return | - | - | - | - | 0.297 | 0.239 | 0.075 | 0.322 |
| Day 3 Return | - | - | - | - | 0.229 | 0.142 | 0.148 | 0.101 |
| Day 4-20 Return | - | - | - | - | 0.181 | 0.101 | 0.087 | 0.021 |
| Day 0 Market Return | - | - | - | - | 0.062 | 0.062 | 0.049 | 0.049 |
| Nasdaq Average Return | - | | - | | 0.132 | | 0.033 | |

**Table 2 (cont.)—Out-of-Sample Nominal Post-event Returns for an Equally Weighted Portfolio**

| | 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 |
| NYSE | | | | | | | | |
| Day 0 Return | -5.643 | 5.997 | -4.099 | 4.768 | -4.025 | 4.719 | -4.843 | 5.187 |
| Day 1 Return | 1.028 | -0.424 | 0.643 | -0.239 | 0.211 | 0.034 | 0.256 | 0.068 |
| Day 2 Return | 0.204 | -0.002 | 0.217 | -0.012 | 0.085 | -0.023 | 0.149 | 0.071 |
| Day 3 Return | 0.177 | -0.011 | 0.162 | 0.004 | 0.062 | -0.012 | 0.179 | 0.034 |
| Day 4-20 Return | 0.072 | 0.039 | 0.074 | 0.052 | 0.038 | 0.011 | 0.094 | 0.087 |
| Day 0 Market Return | 0.085 | 0.085 | 0.022 | 0.022 | 0.092 | 0.092 | 0.012 | 0.012 |
| NYSE Average Return | 0.082 | | 0.038 | | 0.011 | | 0.059 | |
| Amex | | | | | | | | |
| Day 0 Return | -7.839 | 8.679 | -6.668 | 8.167 | -6.651 | 8.459 | -8.272 | 10.445 |
| Day 1 Return | 2.509 | -1.023 | 1.730 | -0.396 | 1.630 | -0.645 | 2.216 | -0.614 |
| Day 2 Return | 0.481 | 0.137 | 0.409 | 0.042 | 0.349 | 0.065 | 0.580 | 0.191 |
| Day 3 Return | 0.275 | 0.125 | 0.280 | 0.079 | 0.319 | -0.025 | 0.510 | 0.140 |
| Day 4-20 Return | 0.224 | 0.147 | 0.178 | 0.119 | 0.188 | 0.153 | 0.381 | 0.262 |
| Day 0 Market Return | 0.085 | 0.085 | 0.022 | 0.022 | 0.092 | 0.092 | 0.012 | 0.012 |
| Amex Average Return | 0.107 | | 0.089 | | 0.062 | | 0.124 | |
| Nasdaq | | | | | | | | |
| Day 0 Return | -7.208 | 7.980 | -8.892 | 10.720 | -8.331 | 10.665 | -9.332 | 11.485 |
| Day 1 Return | 2.398 | -1.401 | 4.175 | -2.557 | 2.229 | -0.957 | 2.311 | -0.856 |
| Day 2 Return | 0.213 | 0.240 | 0.490 | 0.335 | 0.469 | 0.000 | 0.494 | 0.049 |
| Day 3 Return | 0.177 | 0.177 | 0.398 | 0.370 | 0.344 | 0.104 | 0.347 | 0.058 |
| Day 4-20 Return | 0.164 | 0.127 | 0.363 | 0.326 | 0.248 | 0.183 | 0.244 | 0.194 |
| Day 0 Market Return | 0.085 | 0.085 | 0.022 | 0.022 | 0.092 | 0.092 | 0.012 | 0.012 |
| Nasdaq Average Return | 0.088 | | 0.165 | | 0.167 | | 0.111 | |

event day average returns (day 0) are predictably large in magnitude for positive and negative events.

The average event day decline never exceeds 6 percent (9 percent, 10 percent) for the NYSE (Amex, Nasdaq). These average declines are below the customary 10 percent used in many prior studies and underscore the fact that this is a fundamentally different and more comprehensive sample. Consistent with the SETAR model thresholds shown in Table 1, the average increase on positive event days 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 high after a negative event. In all cases, post-negative event day 2 and 3 returns are also 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, and 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 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 used by Lehmann (1990) and others would show positive returns at least on a before-transaction cost basis.

For days 4-20, the post-negative event returns are always higher than the average exchange-specific return, whereas the post-positive event returns are higher in slightly more than one-half of the subperiods. Also, these longer-term 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.

## Post-event Abnormal Returns

Table 3 presents two-year out-of-sample post-event abnormal returns for the three markets. 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 0.001 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 (1994), Bremer and Sweeny (1991), and Park (1995) 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 (days 4-20) in all three markets. Though not presented here, the in-sample abnormal returns are similar to the out-of-sample results. Overall, there appears to be a reversal after a negative event for the next 20 days.[12]

[12]To gauge the economic significance of the results, transactions cost estimates are considered from two sources. Barber and Odean (2000) found round-trip commission costs of 3.03 percent for trades in excess of $1,000 for households using large discount brokerage firms. Investment Technology Group (ITG) estimated that trading costs within the United States in the fourth quarter of 2003 (for combined large and small cap stocks) equaled a combined total of 70 basis points, composed of timing delay costs of 36 basis points, market impact costs of 19 basis points, and commission costs of 14 basis points. Our conclusion is that economic profits are possible only for institutional traders to the extent that they can avoid trading costs.

**Table 3—Out-of-sample Abnormal Post-event Returns for an Equally Weighted Portfolio**

Average 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 | |
|---|---|---|---|---|---|---|---|---|
| | Neg | Pos | Neg | Pos | Neg | Pos | Neg | Pos |
| NYSE | | | | | | | | |
| Day 1 | 0.155*** | 0.098*** | 0.462*** | -0.136*** | 0.494*** | -0.036 | 0.182*** | 0.143*** |
| Day 2 | 0.105*** | -0.122*** | 0.230*** | -0.068* | 0.139*** | -0.158*** | 0.167*** | -0.037* |
| Day 3 | 0.075*** | -0.123*** | 0.194*** | -0.074** | 0.082*** | -0.136*** | 0.140*** | -0.078*** |
| Days 4-20 | -0.003 | -0.040*** | 0.085*** | 0.032** | -0.008 | -0.051*** | 0.039*** | -0.006 |
| Amex | | | | | | | | |
| Day 1 | 0.429*** | 0.218*** | 1.881*** | -1.201*** | 1.427*** | -0.300*** | 1.057*** | -0.159** |
| Day 2 | 0.215*** | -0.329*** | 0.430*** | -0.150** | 0.270*** | -0.190*** | 0.288*** | -0.043 |
| Day 3 | 0.108** | -0.313*** | 0.301*** | -0.017 | 0.130** | -0.171*** | 0.184*** | -0.141** |
| Days 4-20 | -0.045*** | -0.105*** | 0.132*** | 0.031 | 0.012 | -0.063*** | 0.039** | -0.026* |
| Nasdaq | | | | | | | | |
| Day 1 | - | - | - | - | 0.178*** | 0.624*** | -0.076* | 0.673*** |
| Day 2 | - | - | - | - | 0.146*** | 0.097** | 0.004 | 0.251*** |
| Day 3 | - | - | - | - | 0.073* | 0.003 | 0.079** | 0.035 |
| Days 4-20 | - | - | - | - | 0.017 | -0.054*** | 0.015 | -0.045*** |

| | 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 |
| NYSE | | | | | | | | |
| Day 1 | 0.995*** | -0.472*** | 0.604*** | -0.297*** | 0.219*** | 0.022 | 0.211*** | 0.036 |
| Day 2 | 0.177*** | -0.054 | 0.167*** | -0.058** | 0.090** | -0.030 | 0.120*** | 0.037 |
| Day 3 | 0.147** | -0.052 | 0.111*** | -0.040* | 0.062* | -0.009 | 0.144*** | -0.007 |
| Days 4-20 | 0.046*** | -0.003 | 0.026*** | 0.004 | 0.037*** | 0.006 | 0.047*** | 0.039*** |
| Amex | | | | | | | | |
| Day 1 | 2.393*** | -1.125*** | 1.610*** | -0.522*** | 1.559*** | -0.722*** | 2.002*** | -0.824*** |
| Day 2 | 0.366*** | 0.038 | 0.284*** | -0.083 | 0.272*** | -0.004 | 0.382*** | -0.026 |
| Day 3 | 0.178** | 0.018 | 0.146** | -0.048 | 0.247*** | -0.093 | 0.289** | -0.073 |
| Days 4-20 | 0.120*** | 0.044*** | 0.053*** | -0.003 | 0.110*** | 0.082*** | 0.169*** | 0.042* |
| Nasdaq | | | | | | | | |
| Day 1 | 2.307*** | -1.489*** | 3.902*** | -2.845*** | 2.126*** | -1.073*** | 2.177*** | -1.001*** |
| Day 2 | 0.122*** | 0.156*** | 0.209*** | 0.047 | 0.368*** | -0.113** | 0.358*** | -0.089 |
| Day 3 | 0.088** | 0.094*** | 0.115*** | 0.084* | 0.240*** | -0.000 | 0.217*** | -0.076 |
| Days 4-20 | 0.074*** | 0.042*** | 0.083*** | 0.041*** | 0.141*** | 0.074*** | 0.104*** | 0.050*** |

***, **, and * indicate statistical significance at the 0.001, 0.01, and 0.05 level

Following positive events in NYSE/Amex securities, there is still strong reversal in a large majority of cases from days 1 through 3 with 40 negative daily returns of a total of 48 across the subperiods and the two markets, corroborating the intuition from nominal returns. For days 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. On a pair-wise comparison, however, 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 comparisons over days 4-20 are always lower after a positive event than after a negative event, allowing a positive return for a 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 Cooper's (1999) result of reversal in weekly returns for the largest 300 stocks in the NYSE and the Amex. The demonstrated reversals that continue beyond the first week across all stocks for the negative event, however, refute prior daily event based evidence of continuation.

## Are the Reversals Driven by Bid-asked Bounce?

There is a strong tendency of reversal for 20 days after a negative event. For positive events, there is reversal in the short term. In the longer term, however, there is mixed evidence of reversal in some subperiods and markets with continuation in others. Because the results are aggregated across all events, interesting dynamics could be hidden with respect to the degree of price change. A strong susceptibility to outliers is also possible. To investigate further, post-event abnormal returns are regressed on the event-day abnormal returns per equation (3), and the results are presented in Table 4. 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 Panel A, the post negative event results are once again generally unanimous and strong. The coefficient on the event date abnormal return (EDAR, hereafter also referred to as the slope) is significantly negative for days 1 through 3 across all subperiods. For days 4 through 20 where the bid-ask bounce is not relevant, the slope is still significantly negative at the conventional 0.05 level, 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.[13] These negative slope coefficients are remarkable in light of the fact that the autoregression in the returns of a portfolio could potentially have a positive slope bias for two reasons: non-synchronous trading induced autocorrelation as well as volume leadership induced

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

**Table 4—Out-of-sample Regression Explaining Cumulative Abnormal Returns Following Events**

A regression model (Equation 3) is run on a pooled sample of returns for an equally weighted portfolio of securities from the three markets. The regression is run for two specifications of the dependent variable. The independent variables are the average event day return for each portfolio, an average decile ranking for each portfolio, 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*** | -0.0001 | -0.0019 | - | 19.42 | 0.0579 |
| 1/1/73 – 12/31/74 | 0.0531* | -0.4771*** | -0.0076** | -0.0305*** | - | 136.58 | 0.2894 |
| 1/1/78 – 12/31/79 | 0.0343*** | -0.2698*** | -0.0047*** | -0.0136*** | -0.0267*** | 96.20 | 0.2031 |
| 1/1/83 – 12/31/84 | -0.0267 | -0.5272*** | 0.0013 | 0.0030 | -0.0089* | 107.50 | 0.2213 |
| 1/1/88 – 12/31/89 | -0.0330* | -0.5795*** | 0.0018 | 0.0088* | 0.0074* | 89.20 | 0.1911 |
| 1/1/93 – 12/31/94 | 0.0279** | -0.4691*** | -0.0049*** | -0.0183*** | -0.0080** | 529.28 | 0.5837 |
| 1/1/98 – 12/31/99 | 0.0147 | -0.5016*** | -0.0038** | -0.0121** | -0.0115*** | 177.84 | 0.3207 |
| 1/1/02 – 12/31/03 | 0.0047 | -0.4489*** | -0.0029** | -0.0068 | -0.0061* | 118.72 | 0.2471 |
| Days 4-20 | | | | | | | |
| 1/1/68 – 12/31/69 | -0.0034 | -0.0274* | 0.0003 | 0.0005 | - | 6.41 | 0.0199 |
| 1/1/73 – 12/31/74 | -0.0064 | -0.0884*** | 0.0004 | -0.0003 | - | 24.59 | 0.0683 |
| 1/1/78 – 12/31/79 | 0.0075*** | 0.0128 | -0.0009*** | -0.0029*** | -0.0028*** | 8.13 | 0.0211 |
| 1/1/83 – 12/31/84 | -0.0079*** | -0.0569*** | 0.0007*** | 0.0013* | 0.0013* | 17.28 | 0.0437 |
| 1/1/88 – 12/31/89 | -0.0017 | -0.0344*** | 0.0000 | 0.0001 | -0.0002 | 15.47 | 0.0394 |
| 1/1/93 – 12/31/94 | 0.0005 | -0.0177* | -0.0001 | -0.0006 | -0.0008 | 10.69 | 0.0275 |
| 1/1/98 – 12/31/99 | -0.0110*** | -0.1032*** | 0.0009*** | 0.0015* | -0.0006 | 38.21 | 0.0921 |
| 1/1/02 – 12/31/03 | -0.0022 | -0.0426*** | 0.0001 | -0.0000 | -0.0011* | 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** | - | 8.64 | 0.0266 |
| 1/1/73 – 12/31/74 | -0.0627** | -0.1578 | 0.0082*** | 0.0296*** | - | 52.96 | 0.1364 |
| 1/1/78 – 12/31/79 | -0.0097 | -0.0811 | 0.0013 | 0.0036 | 0.0172*** | 70.09 | 0.1566 |
| 1/1/83 – 12/31/84 | 0.0195* | -0.1467** | -0.0015 | -0.0053 | 0.0074** | 73.32 | 0.1624 |
| 1/1/88 – 12/31/89 | -0.0383*** | -0.0779* | 0.0047*** | 0.0128*** | 0.0083** | 30.72 | 0.0752 |
| 1/1/93 – 12/31/94 | -0.0427*** | -0.0752 | 0.0054*** | 0.0195*** | 0.0009 | 282.85 | 0.4283 |
| 1/1/98 – 12/31/99 | -0.0601*** | 0.0954 | 0.0068*** | 0.0164*** | 0.0048 | 41.36 | 0.0989 |
| 1/1/02 – 12/31/03 | -0.0312*** | -0.0749* | 0.0050*** | 0.0137*** | 0.0059* | 41.10 | 0.1020 |
| Days 4-20 | | | | | | | |
| 1/1/68 – 12/31/69 | -0.0036* | 0.0012 | 0.0004* | 0.0011 | - | 11.11 | 0.0340 |
| 1/1/73 – 12/31/74 | -0.0237*** | 0.0966*** | 0.0023*** | 0.0069*** | - | 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*** | 0.0542*** | 0.0011*** | 0.0022*** | 0.0021*** | 28.47 | 0.0700 |
| 1/1/88 – 12/31/89 | -0.0063*** | 0.0278*** | 0.0006*** | 0.0017*** | 0.0016*** | 15.15 | 0.0386 |
| 1/1/93 – 12/31/94 | -0.0032** | 0.0192** | 0.0003* | 0.0004 | 0.0004 | 10.37 | 0.0267 |
| 1/1/98 – 12/31/99 | -0.0154*** | 0.0670*** | 0.0015*** | 0.0045*** | 0.0017** | 48.07 | 0.1132 |
| 1/1/02 – 12/31/03 | -0.0058*** | 0.0196* | 0.0007*** | 0.0019*** | 0.0008 | 9.88 | 0.0266 |

***, **, and * indicate statistical significance at the 0.001, 0.01, and 0.05 level

autocorrelation as noted by Chordia and Swaminathan (2000). Days 1 through 3 intercepts are large and positive in five of eight subperiods though generally not significant, appearing to corroborate that the bid-ask bounce is captured in the intercept.

The size coefficient is negative and significant for days 1 to 3 in five of eight subperiods, indicating that larger stocks revert less. In the longer term for days 4 through 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 days 1 to 3, indicating lower overrreaction for Amex/Nasdaq securities while these dummies are inconclusive in the longer run.

In Panel B following positive events, slope coefficients are generally negative for days 1 to 3, but only three of the eight are significant, suggesting weak reversal. The intercept is negative in six subperiods with large magnitudes for days 1 through 3 returns with five significances, once again supporting the conjecture that the intercept captures the bid-ask bounce. By contrast, days 4 through 20 returns show strong continuation, as the slope is positive and significant in six subperiods. The intercept terms is surprisingly almost always significantly negative at the 0.001 level and would likely dominate the proportionate continuation effect, suggesting a constant longer-term decline.

The coefficient on the size variable is often positive, with five significances for days 1 through 3, and all but one are significant for days 4 to 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 in the short term, the performance generally indicates reversal.[14] The longer-term results show 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 addition to the out-of-sample tests reported here, similar results were found for in-sample tests using the five years' data of each estimation period.

## Comparison with Previous Studies

In this section, the results are compared 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 has its

[14]As another robustness check, we used *bid-asked average returns* for Nasdaq securities and found that reversals still existed, albeit somewhat muted, in the short term after a negative event. After positive events, the results suggested continuation.

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 shows returns 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, there is a positive return that increases in magnitude as the event size becomes more negative. In addition, a slowly decaying pattern of positive returns in weeks 2 through 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 the 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 the post-event return becomes negative starting in the (+4 to +6) 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 four-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 the sample is changed in Panel B to include all NYSE/Amex securities similar to Pritamani and Singal (2001) with no distinction as to event magnitude, the 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 nine percent annualized return, suggesting further underperformance. The week 3 and week 4 returns are significantly positive, similar to Pritamani and Singal's raw return results, but are smaller than the corresponding return for negative events, allowing a successful long-short portfolio strategy.[15] 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 large, suggest-

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

ing a lack of reversal. This is consistent with the Nasdaq results in Tables 2 and 3. Finally, in a more direct comparison to the sample period of Pritamani and Singal, returns from January 1, 1990 through December 2, 1992 are used in Panel D. Positive event results are similar to theirs, but there is still a reversal after negative events.

**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 |
|---|---|---|---|---|---|---|
| Panel A: Top 300 (NYSE/Amex) | | | | | | |
| Day 0 | -1.58*** | -2.84*** | -4.75*** | -6.80*** | -8.82*** | -14.30*** |
| Day 1 | 0.12*** | 0.10*** | 0.20*** | 0.44*** | 1.17*** | 2.08*** |
| Skip-day, Week 1 | 0.28*** | 0.45*** | 0.51*** | 0.62*** | 0.82*** | 1.09*** |
| Week 2 | 0.36*** | 0.36*** | 0.28*** | 0.17* | 0.32*** | 0.25* |
| Week 3 | 0.31*** | 0.29*** | 0.25*** | 0.07 | 0.21* | 0.25* |
| Week 4 | 0.31*** | 0.26*** | 0.32*** | 0.17* | 0.26** | 0.37*** |
| | 0 to +2 | +2 to +4 | +4 to +6 | +6 to +8 | +8 to +10 | > +10 |
| Day 0 | 1.61*** | 2.89*** | 4.78*** | 6.81*** | 8.82*** | 13.74*** |
| Day 1 | 0.03*** | 0.15*** | 0.16*** | 0.13*** | 0.20*** | -0.06 |
| Skip-day, Week 1 | 0.21*** | 0.01 | -0.15*** | -0.15** | -0.41*** | -0.52*** |
| Week 2 | 0.20*** | 0.15*** | 0.13** | 0.05 | 0.07 | -0.04 |
| Week 3 | 0.21*** | 0.23*** | 0.22*** | 0.21*** | 0.18** | 0.20* |
| Week 4 | 0.24*** | 0.20*** | 0.16*** | 0.23*** | 0.12 | 0.14 |
| | Negative | Positive | | | | |
| Panel B: All Stocks (NYSE/Amex) | | | | | | |
| Day 0 | -4.81*** | 5.65*** | | | | |
| Day 1 | 0.84*** | 0.01 | | | | |
| Skip-day, Week 1 | 0.76*** | -0.04 | | | | |
| Week 2 | 0.53*** | 0.16** | | | | |
| Week 3 | 0.44*** | 0.27*** | | | | |
| Week 4 | 0.41*** | 0.29*** | | | | |
| Panel C: All Stocks (Nasdaq) | | | | | | |
| Day 0 | -7.52*** | 8.96*** | | | | |
| Day 1 | 1.76*** | -0.31*** | | | | |
| Skip-day, Week 1 | 0.84*** | 0.47*** | | | | |
| Week 2 | 0.75*** | 0.35*** | | | | |
| Week 3 | 0.62*** | 0.38*** | | | | |
| Week 4 | 0.61*** | 0.41*** | | | | |
| Panel D: NYSE/Amex (1990-92) | | | | | | |
| Day 0 | -5.65*** | 6.73*** | | | | |
| Day 1 | 1.28*** | -0.31*** | | | | |
| Skip-day, Week 1 | 0.85*** | 0.10 | | | | |
| Week 2 | 0.68*** | 0.25*** | | | | |
| Week 3 | 0.50*** | 0.30*** | | | | |
| Week 4 | 0.47*** | 0.33*** | | | | |

***, **, and * indicate statistical significance at the 0.001, 0.01, and 0.05 level

## Conclusions

When analyzing stock price overreactions and underreactions to events, there is a surprising lack of agreement between daily and weekly return horizons. This study helps reconcile the conflict by examining stock return behavior after large price changes, with negative and positive events identified through the use of a self-exciting threshold autoregressive model. The technique permits estimation of thresholds directly from the data and allows the event definition to vary across securities and subperiods.

Following negative events, there is strong evidence of overreaction with reversal in the short term (days 1 to 3) and in the longer term (days 4 to 20). The result is pervasive for all sizes, markets, subperiods, and post-event holding periods including and excluding day 1 returns. This is in contrast to nearly all of the recent studies since Cox and Peterson (1994) that show continuation in daily returns. Our daily return outcomes support the weekly return results of Cooper (1999).

After positive events, the results are mixed although there is generally evidence of overreaction in the short term. Cooper's (1999) weekly overreaction result is supported in the short term and long term for the largest stocks with high magnitude positive events. But, when smaller stocks are included, the longer-term results over week 3 and week 4 bear some resemblance to Pritamani and Singal (2001), as well as others. Overall, when both negative and positive events are considered, this daily return based study strongly supports the weekly return results of Cooper.

Regression analysis 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 finding demonstrates that the result depends upon the magnitude of the filters.

## References

1. Atkins, A., and E. Dyl, "Price Reversals, Bid-asked Spreads, and Market Efficiency," *Journal of Financial and Quantitative Analysis,* 25(1990), pp. 535-547.

2. Barber, B.M., and T. Odean, "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *Journal of Finance,* 60 (2000), pp. 773-806.

3. Bremer, M., and R.J. Sweeney, "The Reversal of Large Stock Price Decreases," *Journal of Finance,* 46 (1991), pp. 747-754.

4. Brown, K.C., W.V. Harlow, and S.M. Tinic, "Risk Aversion, Uncertain Information, and Market Efficiency," *Journal of Financial Economics,* 22 (1988), pp. 355-385.

5. Campbell, J., S. Grossman, and J. Wang, "Trading Volume and Serial Correlation in Stock Returns," *Quarterly Journal of Economics*, 108 (1993), pp. 905-940.

6. Chan, L. K.C., N. Jegadeesh, and J. Lakonishok, "Momentum Strategies," *Journal of Finance,* 51 (1996), pp. 1681-1714.

7. Chopra, N., J. Lakonishok, and J.R. Ritter, "Measuring Abnormal Performance: Do Stocks Overreact?" *Journal of Financial Economics,* 31 (1992), pp. 235-268.

8. Chordia, T., and B. Swaminathan, "Trading Volume and Cross-autocorrelations in Stock Returns," *Journal of Finance,* 55 (2000), pp. 913-935.

9. Clements, M.P. and J. Smith, "Evaluating Forecasts from SETAR Models of Exchange Rates," *Journal of International Money and Finance,* 20 (2001), pp. 133-148.

10. Conrad, J., M. Gultekin, and G. Kaul, "Profitability and Riskiness of Contrarian Portfolio Strategies," *Journal of Business and Economic Statistics,* 15 (1997), pp. 379-386.

11. Conrad, J.S., A. Hameed, and C. Niden, "Volume and Autocovariance in Short-Horizon Individual Security Returns," *Journal of Finance,* 49 (September 1994), pp. 1305-1329.

12. Cooper, M., "Filter Rules Based on Price and Volume in Individual Security Overreaction," *Review of Financial Studies,* 12 (1999), pp. 901-935.

13. Cox, D.R., and D.R. Peterson, "Stock Returns Following Large One-day Declines: Evidence on Short-term Reversals and Longer-term Performance," *Journal of Finance,* 49 (1994), pp. 255-267.

14. DeBondt, W., and R. Thaler, "Does the Stock Market Overreact?" *Journal of Finance,* 40 (1985), pp. 793-805.

15. DeBondt, W., and R. Thaler, "Further Evidence on Investor Overreaction and Stock Market Seasonality," *Journal of Finance,* 42 (1987), pp. 557-581.

16. Dufrénot, G., D. Guégan, and A. Péguin-Feissolle, "Long-memory Dynamics in a SETAR Model—Applications to Stock Markets," *Journal of International Financial Markets, Institutions and Money,* 15 (2005), pp. 391-406.

17. Fama, E., and K. French, "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy,* 96 (1988), pp. 246-273.

18. Investment Technology Group Global Trading Cost Review Q1 2008, http://www.itg.com/news_events/papers/GlobalTradingCostReviewQ108.pdf

19. Jedadeesh, N., and S. Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance,* 48 (1993), pp. 65-91.

20. Kaul, G., and M. Nimalendran, "Price Reversals: Bid-asked Errors or Market Overreaction?" *Journal of Financial Economics,* 28 (1990), pp. 67-93.

21. Kräger, H., and P. Kugler, "Non-linearities in Foreign Exchange Markets: A Different Perspective," *Journal of International Money and Finance,* 12 (1993), pp. 195-208.

22. Lakonishok, J., A. Shleifer, and R.W. Vishny, "Contrarian Investment, Extrapolation, and Risk," *Journal of Finance,* 49 (1994), pp. 1541-1578.

23. Larson, S.J., and J. Madura, "What Drives Stock Price Behavior Following Extreme One-day Returns?" *Journal of Financial Research,* 26 (2003), pp. 113-127.

24. Lehmann, B., "Fads, Martingales, and Market Efficiency," *Quarterly Journal of Economics* 105 (1990), pp. 1-28.

25. Lo, A., and C. MacKinlay, "When are Contrarian Profits Due to Stock Market Overreaction?" *Review of Financial Studies,* 3 (1990), pp. 175-205.

26. Lo, A., and C. MacKinlay, *A Non-Random Walk Down Wall Street* (Princeton, New Jersey: Princeton University Press, 1999).

27. Mitchell, M., and E. Stafford, "Managerial Decisions and Long-term Stock Price Performance," *Journal of Business,* 73 (2000), pp. 287-329.

28. Park, J., "A Market Microstructure Explanation for Predictable Variations in Stock Returns Following Large Price Changes," *Journal of Financial and Quantitative Analysis,* 30 (1995), pp. 241-256.

29. Poterba, J.M., and L.H. Summers, "Mean Reversion in Stock Prices: Evidence and Implications," *Journal of Financial Economics,* 22 (1988), pp. 27-59.

30. Pritamani, M., and V. Singal, “Return Predictability Following Large Price Changes and Information Releases,” *Journal of Banking and Finance,* 25 (2001), pp. 631-656.

31. Tiao, G.C., and R.S. Tsay, “Some Advances in Non-linear and Adaptive Modeling in Time Series,” *Journal of Forecasting,* 13 (1994), pp. 109-131.

32. Tong, H., “On the Threshold Model,” in C.H. Chen, ed.: *Pattern Recognition and Signal Processing* (Amsterdam: Sijthoff and Noordhoff, 1978).

33. Tong, H., “Threshold Models in Non-linear Time Series Analysis,” in *Lecture Notes in Statistics,* No. 21 (Heidelberg, Springer Verlag, 1983).