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The Reversal of Large Stock-Price Decreases

MARC BREMER and RICHARD J. SWEENEY*

ABSTRACT

Extremely large negative 10-day rates of return are followed on average by larger-than-expected positive rates of return over following days. This price adjustment lasts approximately 2 days and is observed in a sample of firms that is largely devoid of methodological problems that might explain the reversal phenomenon. While perhaps not representing abnormal profit opportunities, these reversals present a puzzle as to the length of the price adjustment period. Such a slow recovery is inconsistent with the notion that market prices quickly reflect relevant information.

RECENT RESEARCH ON STOCK returns has uncovered a substantial number of empirical findings that are broadly inconsistent with popular asset pricing models. For example, Keim and Stambaugh (1985), Cross (1973), French (1980), Gibbons and Hess (1981), and Rogalski (1984) find evidence of day-of-the-week and weekend effects on stock returns, while Banz (1981) and Reinganum (1983) find evidence of a size effect. This paper presents evidence of another empirical puzzle.

Consider the behavior of a firm's rate of return on days after it has experienced a large, negative one-day rate of return less than, say, -10%. Observed daily stock returns after such an extreme event are significantly larger than average on following days; for a 10% fall, the return above average is 1.773% for the day after and rises cumulatively to 2.215% by the second day. This multiple day price adjustment is observed in a sample of firms that is largely devoid of methodological problems that might explain the reversal phenomenon. The major interest of this phenomenon is the long recovery period of the stock price reversal; such a slow recovery is inconsistent with the notion that market prices fully and quickly reflect relevant information.

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The existence of the reversal phenomenon is broadly consistent with the work of other researchers. In particular, research by Brown, Harlow, and Tinic (1988) (BHT) using daily data supports the existence of the reversal phenomenon. They develop a theory of investor behavior under conditions of uncertain information which suggests that price changes following favorable or unfavorable news should be positive on average. The reversal phenomenon's positive price changes following bad news are consistent with this theory, but the phenomenon's size and duration differ significantly from BHT who use a -2.5% trigger on residuals from daily market model regressions, finding a rebound of only 0.045% on the first day, with a cumulative rebound of 0.112% on day 2 and increasing to 0.532% by the 60th day. The reversal phenomenon's price adjustment is approximately complete by the second day and is much larger.

Section I below presents the empirical result that extreme negative rates of return are followed on average by statistically significant higher-than-average rates of return. Section II explores robustness and pays particular attention to missing observations and data errors. The section also shows that the phenomenon is not another aspect of recognized anomalies such as day-of-the-week effects and the January effect. Section III is a brief conclusion.

I. The Reversal Phenomenon

The stock returns of every firm listed in the *Fortune* 500 as of 1962 and included on the daily CRSP (Center for Research in Security Prices) tape covering the period 1962 to 1986 were compared to a specific trigger value, say -10%. If on any single day the return was less than the trigger value, the return was defined as an event. For each stock, daily returns are then examined following the event date and compared with the stock's average return over the entire sample period. Figure 1 shows the average daily cumulative excess returns occurring near event days for a -10% trigger for *Fortune* 500 stocks over the period 1962 to 1986.

The figure shows a substantial reversal after large stock price falls. The figure should be interpreted with caution, however, for two important reasons. First, it is possible that the phenomenon could be related to CRSP's occasional reporting of returns that are based on averages of bid-ask prices, not transactions prices. It is not clear that trades could be made at or near such averages. In the work below, we use only transactions prices.

 $^{^1}$ In related research Howe (1986) uses residuals from market model regressions on weekly data with a -50% trigger, Brown and Harlow (1988) use monthly returns in excess of the market with -20% to -60% triggers, while DeBondt and Thaler (1985) look for companies with the largest losses over a 3-year estimation period and follow these firm's returns over the following 3 years. Since this study uses a -10% trigger on daily data and observes an average 2.2% rebound over the first 2 days, the large majority of these events have not been examined in previous research using more extreme triggers and longer intervals of observation.

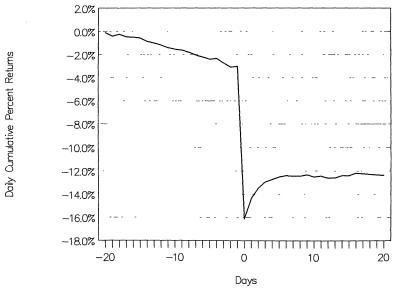


Figure 1. Cumulative average daily percent returns for stocks in the Fortune 500 as of 1962 within 20 days of an extreme negative return defined as a -10% or less one-day decrease in stock price. The average extreme event return on day 0 was about -13%. The cumulative average returns are excess to their mean value as measured from all available CRSP return observations for each stock from 1962 to 1986 but exclude extreme observations. There were 1373 events in this sample.

Second, because stock prices tend to be reported in terms of whole dollars and eighths, it is possible that very low price stocks may report large negative rates of returns, followed by reversals due to price oscillation between bid and ask prices. Such oscillations would give rates of return that do not represent prices at which stocks could be bought or sold. For example, a stock might close at an ask price of \$1 one day and a bid price of 7/8ths the next, with a reported rate of return of -12.5%; if the next trade were at the \$1 ask price, this would produce a reversal of 14.3%. If bids and asks are equally likely, the expected return would be 7.15%. In the work below, we use only stocks whose prices were at least \$10 per share before the event.

There is one bias in the data that we were unable to eliminate even by using only transactions data in calculating returns from buying on the event day and selling on later days. A certain percentage of transactions are market orders crossing; think of this as the price at the intersection of that instant's demand and supply curves. Other transactions have the specialist as one side, with the transaction price the bid if the specialist buys, the ask if the specialist sells. If the recorded transaction price is from market orders crossing, reasonably, the would-be buyer could buy at this price. If the recorded price is from a transaction in which the specialist sells at the ask price, again, the would-be buyer could likely make the purchase. But if the

recorded transaction price is from a purchase by the specialist at the bid price, the would-be buyer could buy only at a higher price. The return obtainable is overstated in those cases where the closing price on the event day is from a transaction at the bid price. Of course, there is the same possibility of overstatement if the price on the day the investor sells is from a transaction at the ask price. How likely is this to happen and how wide is the bid-ask spread that has to be paid? Baesel, Shows, and Thorp (1983) quote NYSE data for 1 year, in which the specialist figures in only 11–12% of all transactions. If the closing price on the event date is actually the bid price $5\frac{1}{2}$ –6% of the time, Sweeney (1988) shows for two estimates of the bid-ask spread in the literature that this would raise one-way transactions costs by from 0.0165% to 0.035% of asset value on the average trade of the average priced stock. Of course, on event days there is the possibility that a much larger share of recorded prices are at the bid price if investors are selling and specialists are accumulating shares.

Table I shows a detailed analysis of the reversal phenomenon that only (a) includes stocks whose price was at least \$10 per share before the event and (b) excludes stocks whose prices were based on bid-ask averages. We also limit the observations to one reversal per day to maintain statistical independence; on multievent days we order event stocks alphabetically and include only the first stock. Other stocks are excluded from the sample.

In Table I, each horizontal block of values depicts the cumulative return starting on the day indicated by the block label at the left. For example, starting with the reversal event on day 0, the average excess return on day 1 is 1.773%; on day 2, the cumulative excess return is 2.215%; and on day 3, the cumulative excess return is 2.641%. In the second block, the average return from the close of day 1's price to the close of day 2's price is 0.442%; and the cumulative average excess return from the close of day 1 to the close of day 3 is 0.868%. The logic of the table repeats. These sample means in Table I give a measure of the economic significance of the reversal returns. The average stock's rate of return on the first day after an event is 1.773% per day greater than its average return over the whole sample.²

One potential explanation for these remarkably large returns is illiquidity.

$$r = \left[\prod_{j=1}^{823} \left(1 + r_j \right) \right]^{1/823} - 1.$$

Delistings and bankruptcies can occur, so at least one of the r_j 's could be -1. Such a strategy is likely to lose everything, with a geometric return of -1 if there is even one case of a complete loss on a stock purchase. (No delistings occur in the sample of events examined in Table I.)

² This arithmetic rate of return is appropriate for a diversified strategy in which an investor invests in the risk-free asset and periodically invests some portion of the portfolio in stocks experiencing large price decreases. When the investor observes a negative return in excess of the trigger, some of the funds in the risk-free asset are used to buy shares in the stock at the event day's closing price, selling the shares the next day. On average such a transaction earns 1.773% before transactions costs. An alternative strategy would be to invest the entire portfolio in any stock whose return falls below the trigger. In this case, the appropriate rate of return is geometric,

Table I Cumulative Returns-Above-Average for Days after a Reversal Event of -10%

The sample is the *Fortune* 500 stocks as of 1962 that were listed on the New York or American stock exchanges as of 1962, while allowing only one event per day and excluding stocks with minimum prices less than \$10 or bid-ask average prices. The number of events in this sample was 823.

From End of:		Day 1	Day 2	Day 3
Day 0	Cum. Excess Return ^a t-statistic ^b	0.01773 (5.86)** ^d	0.02215 (6.38)**	0.02641 (6.61)**
	Percent Ret. $> zero^c$	55.28%**	58.08**	58.81**
Day 1	Cum. Excess Return	4	0.00442	0.00868
	Adj. t-statistic		$(2.12)^*$	(3.05)**
	Percent Returns > zero		46.05%	48.60%
Day 2	Cum. Excess Return			0.00425
	Adj. t-statistic			(1.61)
	Percent Returns > zero			41.19%

^a For each stock, its average return is calculated over the entire sample excluding extreme observations; its "Excess Return" for any day is found by subtracting this sample average from the day's actual return. The "Cumulative Excess Return" for day 1 is the simple average across the sample stocks of these returns above average. The average of this "return-above-average" for day 2 is added to that of day 1 to get the "Cumulative Excess Return" for day 2, and so on. The sample period is July 2, 1962 to December 31, 1986.

^b The t-statistic is based on the null hypothesis that the expected "Cumulative Excess Return" is zero for each stock for each day and on the assumption that the "Cumulative Excess Returns" are independent. Individual t-statistics for day h after the event for stock j are

$$t_{j,h} = \frac{r_{j,h} - \bar{r}_{j,h}}{s_h}$$
,

where $r_{j,h}$ is the actual return for stock j, $\bar{r}_{j,h}$ is the sample mean and s_h is the cross-sectional sample standard deviation for h days after the event. The overall t-statistic presented here is $t_h = N^{-1/2} \sum_{i=1}^{N} t_{i,h} (h = 1.5)$, where N is the number of events.

 $t_h = N^{-1/2} \sum_{j=1}^N t_{j,h}$ (h=1,5), where N is the number of events. °Assuming that there is an equal chance of a success where success is defined as "Cumulative Excess Return" greater than zero, the variance of this binomial distribution is $(0.5)^2/N = 0.25/823 = 0.3038 \times 10^3$, and the standard error is 0.01743. The binomial z-statistic is the ratio of the percentage of excess returns greater than 0.5 to this standard error. Proportions of cumulative returns significantly greater than 0.5 are marked with an *.

d*Significant at the 95% confidence level.

Dann, Mayers, and Raab (1977) document that stock prices tend to be temporarily depressed after large blocks of stock are traded. It is not practically possible, however, for investors to profit from this price fall and subsequent rebound; the adjustment tends to be complete in a matter of minutes. Rather than showing a prolonged adjustment, the reversal phenomenon could actually consist of daily returns generated by prices depressed by large block trades executed near the close of the event day and normal closing prices on the following day. This can only explain the day 1 rebound, however; it is very unlikely that the 0.442% rebound on day 2 and the smaller rebound on

^{**} Significant at the 99% confidence level.

day 3 are also a result of block trade illiquidity. The 0.868% cumulative rebound from the end of day 1 to day 3 is both large and significant.

Also included in Table I are *t*-statistics for the null hypothesis that cumulative rates of return on response days are randomly distributed around the sample mean of each of the stocks. More precisely, the *t*-statistic for day *h* after the event is calculated as

$$t_h = N^{-1/2} \sum_{j=1}^{N} t_{j,h} \tag{1}$$

$$t_{j,h} = \frac{r_{j,h} - \bar{r}_{j,h}}{s_h} \tag{2}$$

where $t_{j,h}$ is the t-statistic for stock j on day h after the event, $\bar{r}_{j,h}$ is the sample average cumulative (arithmetic) return for h days, $r_{j,h}$ the actual return, and N the number of observations. The h-day standard deviation s_h is estimated as the cross-sectional variance of returns of event stocks on days after an event. This standard deviation is substantially larger than the average of the time series standard deviations of individual event stocks. We use this nonstandard estimate of variance because daily rates of return do not seem to be generated by constant-variance distributions; the cross-sectional variance of returns on days following an event is much larger than the average sample variance of the returns of stocks experiencing events. Statistics using this alternative estimate of variance are more appropriate than statistics that use a conventional estimate of variance. The impact of this adjustment is to lower conventional t-statistics. Yet these adjusted t-statistics show that the cumulative excess return is significantly larger than its sample average.

Another approach to the problem of nonconstant variance is to use distribution-free statistics. Table I also reports a non-parametric test of whether the returns on days following the event fluctuate randomly around the sample mean for the return of each stock. The data strongly reject the null hypothesis for day 1. This test, based on the binomial theorem, uses as a null hypothesis that on any response day after an event a stock's return in excess of its overall sample return has an equal probability of being greater than zero or not. Hence, the expected fraction of positive returns is 50%. In the day 0 block, on the first day, the fraction is 55.28% which differs significantly from its expected value. The fraction of positive cumulative returns increases to 58.81% by the third day. On days 2 and 3 the fraction of positive returns is less than 50%. This suggests that the reversal is complete for most stocks by the end of day 1. The fact that average returns remain large means that an important minority of stocks are continuing to rebound on the second day and, to a lesser extent, on the third day. Although negative excess returns are significantly more likely than positive excess returns on days two and three, positive excess returns tend to be larger in absolute value than negative excess returns—the distribution of post event returns is positively skewed.

II. Further Results

This section briefly discusses some further robustness experiments. The significance of the phenomenon is insensitive to these experiments. We tried different values (e.g., -7.5% and -15%), and the results are essentially unchanged, with larger (absolute value) triggers tending to give larger rebounds. The reversal phenomenon is essentially unchanged by various partitions of the Fortune 500. The phenomenon remains robust in different sub-periods. Though the size of the cumulative excess return varies, it remains statistically significant in every subperiod examined. Approximately 15% of the reversal events occur in 1973 and 1974; when these years are excluded, however, the reversal phenomenon is still present and significant. Similarly, 20% of the reversal events occur in October and November; yet when events in these months are excluded, the reversal phenomenon remains significant. The industrial classification of the stocks involved in each event was also examined. Events occur more often to stocks of manufacturing firms; however, the proportion is in line with proportion of manufacturing firms listed in the Fortune 500.3

The reversal phenomenon is unrelated to the January effect. If the events were scattered randomly across months, roughly 8.5% would occur in each; yet only 6.3% of the events occurred in January, and 9% occurred in December. If the events were scattered randomly across weeks, 1.9% of the events would occur in each; however, 1% fell in the last week of December, and 1.3% in the first week of January. It also might be suggested that the reversal phenomenon is really a variation on the weekend or Monday effect. For the -10% trigger, 24% of the observed events occurred on Mondays or after holidays. Almost 76% of the relationship is driven by events unrelated to the Monday or weekend effect. Excluding all events that occurred in January or December or after a weekend or holiday results in no essential change.

Large negative returns on individual stocks might foreshadow major rises in the market, with large, positive responses simply due to the rising market. A detailed examination CRSP's value weighted market index confirms that the market does indeed tend to go down when events occur; the average market return on such days is -0.33%, which is significantly less than the market's overall average return. On the first day after an event the market decreases by 0.05% on average, while the average event stock goes up 1.773%. On the second day after the event, the average market return is small and positive. Market movements do not explain the statistically significant positive returns obeserved on the event stocks. 4

³ Nor does the concentration of events in any particular firm drive the results. Excluding all stocks that had more than 1% of the events does not introduce significant change in the reversal phenomenon.

⁴Another approach to the market's influence is to examine the reversal phenomenon by defining all stocks' rates of return as the excess over the market's return on the same day. This implicitly assumes that each stock's beta is unity. Tests not reported here indicate that the significance of the reversal phenomenon is unchanged when excess to market returns after events are examined.

III. Conclusion

This paper documents that large negative daily rates of return tend to be followed by positive rebounds over the next 2 days. For a -10% trigger, the average day 1 rebound is 1.773%, and by day 2 the cumulative rebound is approximately 2.2%. The phenomenon is robust and distinct from other anomalies such as the weekend and turn-of-the-year effects. Further, the stock price reversal is observed in a sample of firms that is largely devoid of methodological problems that might explain the phenomenon. While perhaps not representing abnormal profit opportunities, these reversals present a puzzle as to the length of the price adjustment period. Such a slow recovery is inconsistent with the notion that market prices quickly reflect relevant information.

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