

The Reversal of Large Stock Price Declines: The Case of Large Firms

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Abstract

This paper examines the long-run reversal pattern for a sample of large U.S. firms that experienced significant stock price declines of more than 20 percent during a specific month. The results from the analysis are largely consistent with the overreaction hypothesis and significantly greater in magnitude than those reported by previous studies. Six and 12 months after their initial price decline, the stocks of large firms earn approximately 4 and 12 percent in excess of what was expected, respectively. However, the magnitude and trend of that reversal differs substantially across industries. Technology stocks experience the largest and strongest reversal pattern followed by manufacturing stocks, while service industry stocks exhibit a clear downward drift that lasts up to three years and can be described as investor *under-reaction* to the large price drop. (JEL G14)

Introduction

In recent years, a growing and controversial body of research in the area of stock market efficiency has suggested that stock returns are predictable and provided evidence of systematic reversal patterns in stock returns. Such findings imply that unanticipated information is not as quickly assimilated into stock prices as once believed and, therefore, call into question the notion of efficient markets.

One of the most influential papers on this subject is by DeBondt and Thaler (1985), who based their study on experimental and survey evidence indicating that in revising their beliefs, individuals tend to overweight recent information and underweight past data. Their study was an attempt to examine whether such behavior matters at the market level and affects stock prices. They found that stocks that experienced poor performance over the past three to five years tended to outperform prior-period winners during the subsequent three to five years. Their results implied that investors are indeed overly sensitive to financial news, and they termed this kind of behavior “overreaction.” The overreaction hypothesis (OH) as formally stated by DeBondt and Thaler

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suggests that extreme movements in stock prices are followed by price movements in the opposite direction as investors realize they have overreacted, and that the greater the initial price movement, the greater the subsequent reversal. Since then, their work has inspired a large and controversial body of literature on this subject.

While there is a preponderance of evidence suggesting that returns are indeed predictable, there is no consensus about the underlying reasons for this predictability. Zarowin (1990) and Baytas and Cakici (1999) argue that the overreaction effect may be partly a manifestation of the well-known size effect. Some argue that the overreaction effect may be attributed to factors such as the bid-ask spread and infrequent trading (Conrad and Kaul 1993), while others suggest that long-term mean reversal in stock returns is attributable to errors in the measurement of risk (Chan 1988; Ball and Kothari 1989).

One way in which the overreaction hypothesis has been studied is by analyzing the behavior of stock returns following large stock price declines. Using daily data, Brown, Harlow, and Tinic (1988) provide evidence of a reversal phenomenon and suggest an uncertain information hypothesis. Atkins and Dyl (1990) try to determine if the stock market overreacts in the short run and find significant reversals for stocks that experience large one-day price declines. However, when transaction costs are considered, the overreaction hypothesis is no longer supported.

Bremer and Sweeney (1991) examine stock returns following one-day price declines of 10 percent or more and find there is a subsequent price adjustment that lasts approximately two days. They conclude that "... such a slow recovery is inconsistent with the notion that market prices fully and quickly reflect relevant information" and argue that one possible explanation may be the existence of illiquidity. Cox and Peterson (1994) continue in this line of research by trying to explain short-term stock return behavior following one-day price declines of 10 percent or more, based on the bid-ask bounce, market liquidity, and overreaction. Their findings are quite puzzling since, in contrast with previous studies, they do not find evidence consistent with the overreaction hypothesis and observe that stocks with large one-day price declines seem to perform poorly in the subsequent period. They conclude that most of the reversals are due to the bid-ask spread and market liquidity.

In studying the pattern of stock returns following extreme changes in price, clearly the results are contradictory and, in some cases, even puzzling. The purpose of this paper is to examine a sample of large and well-established firms that experienced significant stock price declines of more than 20 percent during a specific month and to determine whether there is a price reversal over a long-run horizon.

Large firms are of particular interest for several reasons. One of the most prevalent explanations for the reversal pattern observed in previous research is the existence of illiquidity and infrequent trading. The market for large firms is generally more liquid with a greater number of traders and analysts following their stock. To the extent that liquidity plays an important role in the reversal process, one would expect that the reversal—if any—would not be very pronounced. The sample examined in this study consists of large firms with the majority of them listed on the NYSE, which is undeniably the most liquid market in the United States. Additionally, the choice of large firms in the sample implies that investors should possess high quality and superior information about such companies in which case investors' reactions to company-specific bad news should hardly be an overreaction. Also, to the extent that institutional investors are the dominant holders of the stocks of large firms, then as hypothesized by Chopra, Lakonishok, and Ritter (1992), one would expect the reversal pattern for these stocks to be very limited.

However, if the large price decline is, in fact, due to an overreaction on the part of investors, one would expect to find evidence of a stock price reversal in the long run. We would also expect that the greater the degree of overreaction, the greater the subsequent reversal. Furthermore, to the extent that the overreaction is due to firm-specific news, the reversal may be more pronounced

than when it is due to industry-specific news. Finally, large firms are of particular interest since large price declines are more likely to “signal” their management of the need for remedial action. In other words, large and well-established firms have the necessary assets and potential to respond to an extreme decline of their stock, and are more likely than smaller firms to do so. An article in the *Wall Street Journal*, May 1998, states, “The population explosion may help explain why small stocks have struggled to keep up with large ones in recent years. Many small companies sag under competitive pressure or neglect, or are acquired.” When faced with difficult circumstances, small firms will find it difficult to react. However, the stock price of large firms may exhibit a significant reversal over the long run.

The research presented here suggests that the initial price reaction on the part of the investors is excessive. Six and 12 months after their initial price decline, the stocks of large firms earn approximately 4 and 12 percent more than expected. When the three main industry classifications of the sample are examined, the results for the technology and manufacturing sub-samples are consistent with the overreaction hypothesis. In particular, technology stocks appear to experience the largest and strongest reversal, suggesting that investors tend to overreact far more to whatever event or information caused the initial price change for technology stocks. In contrast, we find that service industry stocks experience a significant and continued downward drift that lasts up to three years, which can only be described as investor *underreaction* to a large price drop.

The remainder of the paper is organized as follows. The following section presents the existing literature in the area of overreaction. The third and fourth sections describe the data and methodology, respectively. The fifth section presents the results, and the sixth summarizes the findings of the study.

Literature Review

Extensive empirical work on stock market overreaction examines whether observed anomalous movements in stock prices, particularly long-term reversals of extreme past stock price changes, can be explained by the corrections of investors’ disproportionate reactions to new information. DeBondt and Thaler (1985), in their seminal study of long-term return anomalies, advanced their stock market overreaction hypothesis, which states that a given stock’s price decreases (increases) too far because of recent bad (good) news associated with the stock but eventually returns to its fundamental value as investors realize that they overreacted. Constructing loser and winner portfolios, they found that over a three-year test period, loser portfolios outperform the market by 19.6 percent on average, while winner portfolios earn about 5 percent less than the market. They conclude that their results are consistent with the overreaction hypothesis and that the overreaction effect is asymmetric since it is much larger for losers than for winners. Although our study also uses a three-year test period, it should be emphasized that in contrast with DeBondt and Thaler’s study, and for reasons mentioned in the introduction, it is limited only to a sample of large firms. In a later paper, DeBondt and Thaler (1987) re-evaluate their overreaction hypothesis and try to determine whether extreme price reversals are due to seasonal patterns, changes in risk as measured by beta, or the size effect. Their results are consistent with the overreaction hypothesis and do not support these alternate explanations.

Atkins and Dyl (1990) examine a sample of 835 losers and 836 winners and find that the stock market overreacts in the short run, especially when considering stocks that exhibit large price declines. However, they report that because of the magnitude of the bid-ask spread, traders cannot profit from the realized price reversals and conclude that the market is efficient when transaction costs are considered.

Lehmann 1990 finds that portfolios of stocks with positive returns in one week typically experience negative returns in the following week, while those with negative returns in one week

typically display positive returns in the following week. In contrast with the findings of Atkins and Dyl (1990), Lehmann reports that the apparent arbitrage profits from these return reversals persist even after corrections for bid-ask spreads and transaction costs are made. He concludes that the return reversals probably reflect imbalances in the market for short-run liquidity.

Adding to the body of contradictory and puzzling literature, Zarowin (1990) re-examines the stock market overreaction hypothesis, controlling for size differences between winners and losers. He finds little evidence of any return discrepancy after controlling for size. Furthermore, when losers are smaller they outperform winners, and when winners are smaller they outperform losers. Thus, he concludes that the tendency for losers to outperform winners is due to the fact that loser firms are typically smaller than winners.

Bremer and Sweeney (1991) examine the reversal pattern of large stock price decreases. Their results are inconsistent with the efficient market hypothesis since the average day-one rebound was 1.773 percent, and by day two the cumulative rebound was approximately 2.2 percent. Their results remain consistent even after trying various trigger values.

Chopra, Lakonishok, and Ritter (1992) perform a comprehensive evaluation of the overreaction hypothesis. They use the empirically determined price of beta risk and calculate abnormal returns using a comprehensive adjustment for price. They find an economically significant overreaction effect, which cannot be attributed to size or beta. Since the overreaction effect reported in their study is much more pronounced for smaller firms than for larger firms, they hypothesize that individuals, the predominant holders of stocks of small firms, may overreact, while the dominant holders of large stocks, namely institutions, do not.

Cox and Peterson (1994) argue that if liquidity plays an important role in the reversal process, we should observe stronger reversals in less liquid markets and for smaller firms, as well as a reduction in the degree of reversals over time. However, if the cause of the reversals is overreaction on the part of investors, then one would expect that the greater the one-day decline, the greater the reversal. Consistent with results from previous studies, they find significant reversals for days one through three. Furthermore, the degree of reversals declines over time—a finding consistent with increasing liquidity in the market.

They also find that small firms reverse more than large firms and that most of the reversals are due to the bid-ask bounce. Their results indicate that larger initial declines do not necessarily lead to greater subsequent reversals and do not support the overreaction hypothesis. In the longer term, they examine cumulative abnormal returns for days 4 through 20 and 21 through 120 and observe that securities with large one-day declines enter a period of relatively poor performance.

The role of liquidity in explaining stock price reversals is also supported by Jegadeesh and Titman (1995). They examine stock price reactions to common factors and firm-specific information and find that stock prices, on average, react with a delay to common factors but overreact to firm-specific information. Although the reversal of the firm-specific component of returns is usually attributable to stock-market overreaction, the authors suggest that a more plausible explanation may be price pressure generated by liquidity-motivated traders.

Dissanaike (1997) investigates the evidence on the stock market overreaction by restricting his sample to larger and better-known U.K. companies in an attempt to control for a possible size effect, bid-ask biases, and infrequent trading. His study provides results consistent with the overreaction hypothesis and suggests that time-varying risk does not seem to explain the reversal effect.

Finally, Baytas and Cakici (1999) evaluate the performance of arbitrage portfolios based on past performance, price, and size in seven industrialized countries. They find evidence in support of long-term overreaction in all countries except the United States. Furthermore, their results indicate that long-term investment strategies based on price and size produce higher returns than those based on past performance. Since losers tend to be low in price and low in market value

while the opposite holds true for winners, they argue that many of the long-term price reversals observed may be due to price and size effect.

Overall, there has been extensive research on the subject of overreaction, but not much attention has been paid to the reversal pattern that large firms may exhibit or even to the reasons why large firms represent such an interesting sample. This study attempts to address these issues by focusing on a sample of large and better-known U.S. firms.

Sample and Data Description

The sample analyzed in this study contains large and well-established U.S. firms. Accordingly, the S&P 100 index was used to identify such companies. Monthly returns for every firm listed in the S&P 100 were obtained for the period from May 1990 to May 2000.

These monthly returns were then compared to a specific trigger value. Determining what constitutes a “large” price decline is somewhat arbitrary, and therefore different studies have used different trigger values. This study uses a trigger value of -20 percent. If, on any given month, the return was equal to or less than the trigger value, that return was defined as an event observation. Monthly stock returns following the event date were then analyzed over a one-year, two-year, and three-year time horizon. This procedure identified 112 event observations involving 53 different companies. Table 1 provides a summary description of the distribution of events across years and months.

TABLE 1. DISTRIBUTION OF EVENTS ACROSS TIME

	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	Total
1990							2	9	9	3			23
1991						2	1		1	1	3		8
1992			1					1				1	3
1993		1				1	1					1	4
1994			1	1		2							4
1995										2			2
1996	1		1				1			1		1	5
1997		1	1					1		3		2	8
1998					2	1	3	35	4	1			46
1999	1	1	2				1	1	1	2			9
Total	2	3	6	1	2	6	9	47	15	13	3	5	112

We can see from Table 1 that the month of August 1998 accounts for approximately 31 percent of the 112 events examined in this study. Since during that month there was a drop in the market of about 14 percent, this paper uses a trigger value of -20 percent, well above the decline of the market, in order to account for firms that had a poor performance beyond that realized by the market. Of the 53 different companies, 49 or 92.4 percent are traded on the NYSE, and only 4 or 7.6 percent on the NASDAQ. Table 2 presents a breakdown of the sample by three main industry classifications.

TABLE 2. INDUSTRY CLASSIFICATION FOR SAMPLE OF 53 LARGE U.S. FIRMS

Industry Classification	Number of firms	Percentage
Technology	14	26
Services	21	40
Manufacturing	18	34

Methodology

To determine abnormal returns following the events, we calculate cumulative abnormal returns (*CARs*) using a risk-adjusted returns model. Fama (1998) explains how studies of long-term returns are sensitive to the way the tests are done and suggests that *CARs* should be used instead of buy-and-hold abnormal returns *BHARs*. He argues that "...*BHARs* can give false impressions of the speed of price-adjustment to an event" (p. 294), and are likely to grow with the return horizon even when there is no abnormal return after the first period. *CARs* correct for this long-term drift and pose fewer statistical problems than long-term *BHARs*.

The traditional single-factor market model used in many event studies to estimate expected returns assumes that the β and error term are constant over time. However, the time-series literature suggests that the market-model β , our standard estimate of systematic risk, is non-stationary (Chen and Keown 1981). Furthermore, the variance of the disturbance term does not follow the classical assumptions but rather is conditioned on prior information (Schwert and Seguin 1990). To account for the time-varying behavior of β , we employ a GARCH 1,1 process to estimate the parameters of the market model as suggested by Brockett, Chen, and Garven (1999). The market model is specified as:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}$$

where the error term is conditioned on the prior information set

$$\varepsilon_{jt} | \Omega_{t-1} \sim N(0, h_t)$$

$N(0, h_t)$ is the conditional distribution of the error term with a mean of 0 and a variance of h_t , and all information available at time t-1 is given by Ω_{t-1} . The conditional variance, h_t , is conditioned upon the squared past errors and the past conditional variance and specified as:

$$h_t = \phi_0 + \phi_1 \varepsilon_{t-1}^2 + \phi_2 h_{t-1} .$$

The parameters are estimated using the method of maximum likelihood, and the abnormal returns are defined as

$$AR_{j,t} = R_{j,t} - (\hat{\alpha}_j + \hat{\beta}_j R_{m,t})$$

For a number of N events, the monthly average abnormal return, (AR_t), is:

$$AR_t = \frac{1}{N} \sum_{j=1}^N AR_{j,t},$$

and the cumulative abnormal return over the window [b,e] is defined as:

$$CAR = \sum_{t=b}^e AR_t .$$

In addition to the risk-adjusted returns model described above, we use market-adjusted returns to estimate the abnormal returns following a large price decline as suggested by Brown and Warner (1985). This same model is employed by DeBondt and Thaler (1985), who point out that "the use of market-adjusted excess returns has the further advantage that it is likely to bias the

research design against the overreaction hypothesis” (p. 797). Our calculations of market-adjusted abnormal returns assume that a broad-market index like the S&P 500 captures investor expectations of returns for our sample of securities. Since the systematic risk of large stocks should approach that of the market as a whole, we can use the return of the market index as the expected return for each member of our sample. We therefore estimate monthly abnormal returns $AR_{j,t}$ as:

$$AR_{j,t} = R_{j,t} - R_{m,t}$$

where $R_{m,t}$ is the market rate of return in that month using the S&P 500 index and $R_{j,t}$ is the realized monthly return for each stock in our sample. Monthly average abnormal returns and cumulative abnormal returns are calculated in the same manner as above. To the extent that investor expectations are not fully represented by the return of the S&P 500, we can expect the market model to provide significantly different results than the GARCH estimated risk-adjusted model.

We employ a cross-sectional analysis to investigate the role of industry on the degree of overreaction. More specifically, the risk-adjusted $CARs$ for different time periods are regressed on the percentage decline in event month $t = 0$ and on two dummy variables indicating the industry to which the firm belongs. The cross-sectional model is specified as:

$$CAR_i = \gamma_0 + \gamma_1 ARO_i + \gamma_2 D_{1,i} + \gamma_3 D_{2,i} + \varepsilon_i$$

where:

- CAR_i = cumulative abnormal return for windows (1, 12), (1, 24), and (1, 36) taken from the corresponding sample of events.
- ARO_i = the abnormal return for the month of the large price decline, $t = 0$.
- $D_{1,i}$ = a dummy variable equal to 1 if the firm is in the service industry, 0 otherwise.
- $D_{2,i}$ = a dummy variable equal to 1 if the firm is in the technology industry, 0 otherwise.
- γ_s = the OLS regression coefficients.

The cross-sectional model is estimated using OLS and, due to the presence of heteroskedasticity, is corrected using the White (1980) correction.

Empirical Results

Reversal Patterns

The first part of the analysis examines stock returns following large one-month price declines for a sample of large firms and determines whether a reversal process exists. Table 3 presents the average monthly abnormal returns and their corresponding t-statistics for the sample of events over a one-year time horizon. ARs are reported using both the GARCH and the market-adjusted returns model.

Panel A of Table 3 shows that at $t = 0$, AR is -21 percent with an associated t-statistic of -17.301, significant at the 0.1 percent level. This is, of course, the result of the large price decline that caused the stocks of these companies to be included in the sample. The negative AR that occurs on month $t = +1$ is significantly smaller in magnitude. From month $t = +2$ to $t = +6$, all ARs with the exception of $t = +5$ are positive and, although not reported here, continue to be positive for all months until the end of the year. This reversal in price seems to indicate that the large stock price decline observed at $t = 0$ is due to an overreaction on the part of investors.

TABLE 3. AVERAGE MONTHLY ABNORMAL RETURNS FOR FULL SAMPLE

Event Month	ARs (%)	t-statistic
<i>Panel A: ARs estimated using GARCH(1,1) N=92</i>		
-3	-1.58	-1.30*
-2	-3.77	-3.10****
-1	-3.69	-3.04***
0	-21.05	-17.30****
1	-0.74	-0.61
2	1.72	1.41*
3	2.47	2.03**
4	0.80	0.65
5	-0.49	-0.40
6	0.37	0.31
<i>Panel B: ARs estimated using the Market Adj. Model N=107</i>		
-3	-0.35	-0.33
-2	-3.12	-3.05***
-1	-4.10	-4.15****
0	-20.24	-21.75****
1	-2.25	-1.43
2	2.69	1.94**
3	3.87	2.58***
4	2.87	2.06**
5	2.11	1.66*
6	2.93	2.57***

Notes: Each estimation method differs in sample size due to the estimation period requirements and the number of available useable returns following the event month; *, **, *** and **** denote significance at the 10 percent, 5 percent, 1 percent, and 0.1 percent level, respectively.

It is also interesting to note that prior to the event month, *ARs* are successively negative and statistically significant at the 10, 0.1, and 1 percent levels. These results may indicate the presence of information leakage if, in fact, the large price declines were due to the announcement of new information about the firms.

The most important and striking results are presented in Table 4, where *CARs* for various intervals after the month of the large price decline are reported. All *CARs* are positive, and most of them are statistically significant, at the 1 percent level. Investors who enter the market one month after the large drop in price earn about 12 percent more than they expected during the period of a year and at least 4 percent more during the first six months. What is more surprising is that even those who enter the market as late as six months after the large price decline earn approximately 9 percent more than expected. These results are substantially larger in magnitude than those reported in previous studies. De Bondt and Thaler (1985) found that losers, one year into the test period, earn almost 9 percent more than the market.

TABLE 4. CUMULATIVE ABNORMAL RETURNS (CARs) FOR FULL SAMPLE

Interval	CAR (%)	t-statistic
<i>Panel A: CARs estimated using GARCH (1,1) N=92</i>		
[1,6]	4.13	1.39*
[1,12]	12.53	2.97***
[2,12]	13.27	3.29****
[3,12]	11.55	3.00***
[6,12]	8.76	2.72***
<i>Panel B: CARs estimated using the Market Adj. Model. N=107</i>		
[1,6]	12.24	4.34****
[1,12]	24.42	6.11****
[2,12]	26.67	7.07****
[3,12]	23.97	6.40****
[6,12]	15.11	5.03****

Notes: *, **, *** and **** denote significance at the 10 percent, 5 percent, 1 percent and 0.1 percent level, respectively.

Finally, in all windows, the market-adjusted CARs confirm our findings of a substantial reversal pattern.¹ In fact, the market-adjusted model shows even larger significant CARs than those found using the GARCH estimation method.

Figure 1 graphs the GARCH CARs starting from month $t = -3$ to $t = +12$. It clearly shows the large decline in price and the subsequent reversal process. Figure 2 is a graph of CARs calculated from month $t = +1$, which is more interesting from an investor's point of view. As the time period during which CARs are studied is extended to two years, the observed reversal pattern is substantially reduced.

Table 5 presents the CARs over a two-year period using both the GARCH and the market-adjusted returns model. Under the GARCH method CARs are statistically insignificant, indicating that the reversal pattern has virtually disappeared. In contrast, under the market-adjusted returns model, CARs calculated for months $t = +6$ through $t = +24$ and $t = +12$ through $t = +24$ are 35.7 percent and 27.5 percent, respectively, statistically significant at the 1 percent level. One potential reason for these conflicting results may be the difference in the sample size. When using the GARCH method, our sample size reduces to $N = 37$ useable events—as opposed to $N = 57$ events when the market-adjusted returns model is employed—because of the need for an estimation period. Alternatively, the GARCH methodology may truly capture investors' expectations, indicating that the overreaction phenomenon does not persist into the second year. However, because of the difference in sample size, a conclusion is difficult to draw.

¹ Because the month of August 1998 accounts for approximately 31 percent of the events in the overall sample, one could argue that the results are biased. To control for that bias, the analysis was repeated by excluding the observations of that specific month. The results, not reported, are essentially the same.

FIGURE 1. CARs CALCULATED FROM T=3 FOR OUR SAMPLE OF EVENTS OVER THE PERIOD OF A YEAR

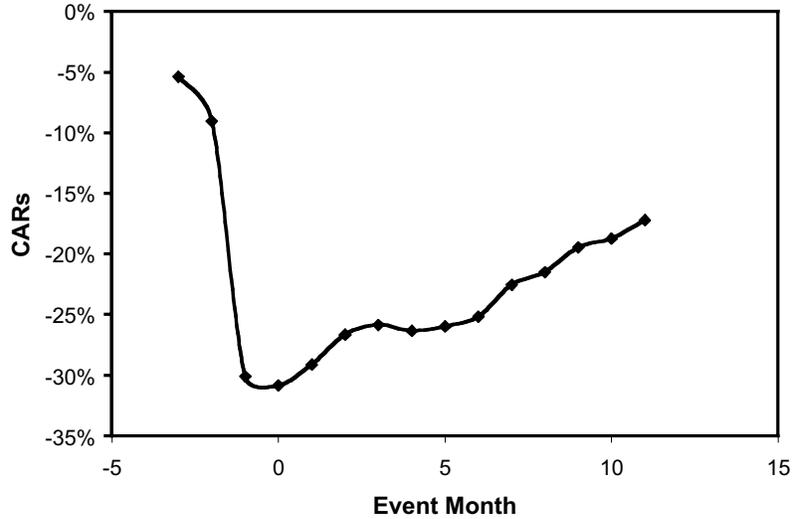
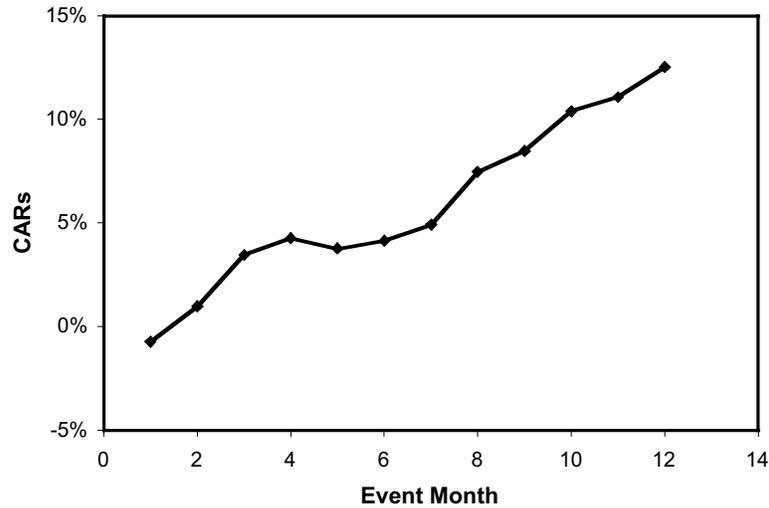


FIGURE 2. CARs OVER A ONE-YEAR PERIOD STARTING FROM T = +1



Despite the diminished sample size, a GARCH 1,1 process accounts for the autoregressive and heteroskedastic nature of the error terms. Therefore, following Garven et al. (1999), we will proceed with the remainder of the analysis using the more conservative GARCH approach.

TABLE 5. CUMULATIVE ABNORMAL RETURNS (CARs)
FOR SAMPLE OF FIRMS WITH TWO YEARS OF ABNORMAL RETURNS

Interval	CAR (%)	t-statistic
<i>Panel A: CARs estimated using the GARCH model N= 37</i>		
[1,24]	5.92	0.48
[6,24]	-0.1	-0.01
[12,24]	2.76	0.30
<i>Panel B: CARs estimated using the mkt adjusted model N=57</i>		
[1,24]	46.17	4.72***
[6,24]	35.76	4.07***
[12,24]	27.57	3.82***

Note: *, **, *** and **** denote significance at the 10 percent, 5 percent, 1 percent and 0.1 percent level, respectively.

Table 6 shows that over a three-year period, the reversal pattern that was clearly evident during the first year has disappeared. CARs are negative, although not statistically significant, for all the intervals examined. However, these results should be interpreted with caution due to the size of our sample $N = 31$.

TABLE 6. CUMULATIVE ABNORMAL RETURNS (CARs) FOR
SAMPLE OF FIRMS WITH 3 YEARS OF ABNORMAL RETURNS

Interval	CAR (%)	t-statistic
[1,36]	-7.91	-0.43
[6,36]	-17.68	-1.03
[12,36]	-14.54	-0.94

Notes: CARs estimated using a GARCH (1,1) process $N=31$; *, **, *** and **** denote significance at the 10 percent, 5 percent, 1 percent and 0.1 percent level, respectively.

Overall, the results from the analysis reveal that stocks of large firms that exhibit a decline in their price of more than 20 percent during a specific month subsequently earn positive and statistically significant abnormal returns. These positive and statistically significant abnormal returns last up to one year and indicate that much of the initial change in the price of these stocks was an overreaction on the part of investors. Six and 12 months after their initial price decline, the stocks of these large firms have earned approximately 4 and 12 percent more than was expected.

Cross-Sectional Analysis

In this portion of our analysis, we examine the three main industry classifications to identify the type of firms that exhibit the strong reversal patterns described in the first part of this study. Table 7 presents the average monthly abnormal returns and their corresponding t-statistics for the various events in the sample based on industry classification. These findings show that in the event month, $t = 0$, the abnormal return is greatest for the technology sector at -25 percent and declines for service and manufacturing at 19 percent and 17 percent, respectively. Of particular interest is the pattern of abnormal returns in the subsequent months. Technology and manufacturing exhibit strong reversal patterns. Manufacturing experiences +5.2 percent AR in month two, which is statistically significant at the 0.1 percent level, and technology shows +8.92 percent AR in month three and +5.77 percent AR in month four, both statistically significant. The technology industry exhibits the strongest reversal pattern, largely consistent with the overreaction hypothesis that states the more extreme the initial price movement, the greater will be the reversal. Conversely, the service industry exhibits negative abnormal returns in the months following a large price drop, which is inconsistent with the overreaction hypothesis. In fact, this finding indicates *underreaction* on the part of investors of service company stocks.

TABLE 7. AVERAGE MONTHLY ABNORMAL RETURNS BY INDUSTRY CLASSIFICATION

Event Month	Technology N = 31		Services N = 33		Manufacturing N = 28	
	AR (%)	t-statistic	AR (%)	t-statistic	AR (%)	t-statistic
-1	-3.61	-1.40*	-2.02	-1.13	-5.65	-3.79****
0	-25.70	-9.94****	-19.16	-10.76****	-17.65	-11.84****
+1	3.29	1.27	-6.26	-3.52****	0.63	0.42
+2	-2.77	-1.07	3.35	1.88**	5.21	3.50****
+3	8.92	3.45****	-1.09	-0.61	-1.18	-0.79
+4	5.77	2.23**	-4.36	-2.45***	0.64	0.43
+5	-0.19	-0.07	2.20	1.24	-3.82	-2.56***
+6	-1.74	-0.67	0.79	0.45	2.39	1.60

Notes: Abnormal returns are calculated using the GARCH (1,1) estimation of market model parameters *, **, ***, **** indicate statistical significance at the 10 percent, 5 percent, 1 percent and 0.1 percent level, respectively.

The findings above are confirmed in Table 8 where the cumulative abnormal returns by industry are presented. Panel A shows that *CARs* for the technology industry are significantly positive in the six-month, one-year, and two-year windows following a large price drop. Technology stocks experience a positive *CAR* in the three-year window following the event but that is statistically insignificant. The *CARs* for the manufacturing industry weakly support the results of the technology industry. Panel C shows positive abnormal returns for the manufacturing industry in all windows following a large price drop, however, only the one-year *CAR* is statistically significant. The *CARs* for the service industry firms tell a different story. Panel B of Table 8 presents the significant negative *CARs* in the one, two, and three-year windows following a large price drop. In fact, the service industry experiences increasingly negative abnormal returns as the window expands. Despite the diminished sample size, we find that the under-reaction continues for the service industry contradicting our original hypothesis.

TABLE 8. CUMULATIVE ABNORMAL RETURNS BY INDUSTRY CLASSIFICATION

Window	N	CAR (%)	t-statistic
<i>Panel A: Technology Industry</i>			
[1, 6]	31	13.28	2.10**
[1, 12]	31	30.74	3.43****
[1, 24]	11	34.69	1.65**
[1, 36]	10	26.78	0.66
<i>Panel B: Services Industry</i>			
[1, 6]	33	-5.37	-1.23
[1, 12]	33	-10.68	-1.73**
[1, 24]	19	-53.57	-2.87***
[1, 36]	15	-80.50	-3.49****
<i>Panel C: Manufacturing Industry</i>			
[1, 6]	28	3.87	1.06
[1, 12]	28	16.77	3.25****
[1, 24]	7	21.34	0.98
[1, 36]	6	26.39	0.60

Notes: Monthly abnormal returns estimated using a GARCH (1,1) process and summed across windows to calculate the cumulative abnormal returns (CARs)*, **, ***, **** indicate statistical significance at the 10%, 5%, 1% and .1% levels, respectively, using a 1-tailed test.

Overall, the results from the technology and manufacturing sub-samples confirm the overreaction hypothesis and show long-term persistence of the reversal trends, which support the findings of DeBondt and Thaler (1985) and Dissanaikie (1997). In particular, the findings of this study suggest that technology stocks display the largest and strongest reversals among the three main industry classifications and experience more than 30 percent abnormal returns in the year following a large price drop as opposed to the 9 percent abnormal returns found by DeBondt and Thaler (1985). Additionally, our study finds that service industry stocks experience significant and continued downward drift, which can be described as investor under-reaction to a large price drop.

Why would rational investors overreact to such a degree in relation to technology stocks and yet under-react to an even greater degree in service stocks? These questions remain to be answered. Arguably, technology companies are younger with greater growth potential, albeit more uncertainty. In a commentary about the DeBondt and Thaler paper, Bernstein (1985) maintains, "Uncertainty is the crucial ingredient in the answer to these questions" (p. 806). Stocks are risky assets, and when investors are faced with uncertainty, they will put more weight on recent information and underweight past data. Recent information in itself is associated with less uncertainty and, to the extent that certain stocks are perceived as riskier than others, investors will tend to value recent information on these stocks more heavily and react accordingly.

Figures 3, 4, and 5 display the patterns of reversals for the technology, service, and manufacturing sectors' CARs, respectively, beginning with month $t = -3$ through month $t = +12$. The figures provide a more detailed view of the reversal pattern experienced by technology and

manufacturing stock shareholders in contrast with the continued downward drift experienced by the service stock shareholders.

FIGURE 3. CARs FOR TECHNOLOGY INDUSTRY BEGINNING WITH T = -3

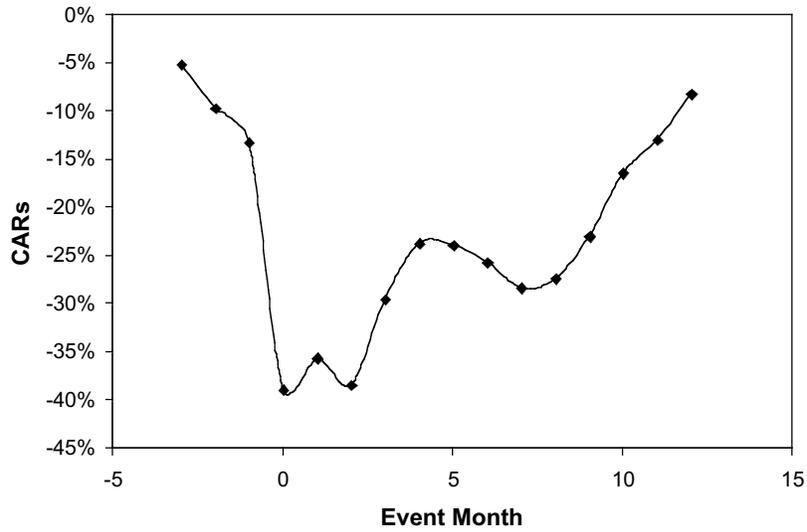


FIGURE 4. CARs FOR SERVICE INDUSTRY BEGINNING WITH T = -3

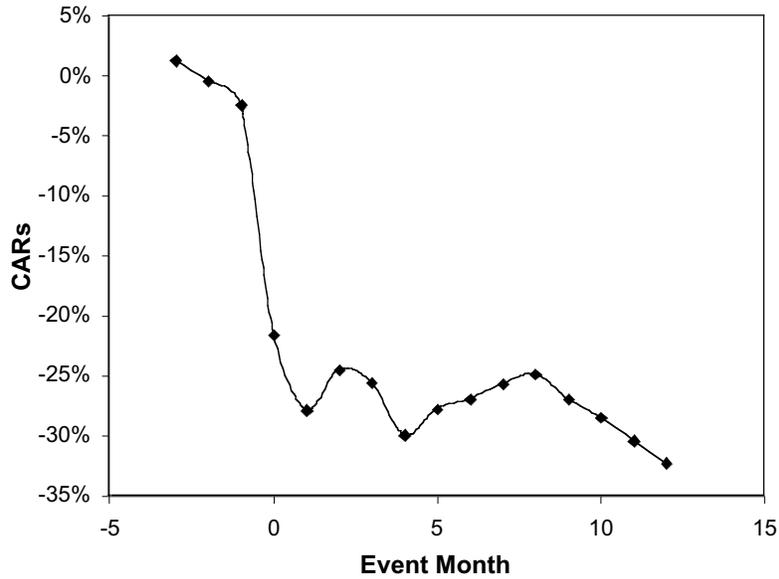


FIGURE 5. CARs FOR MANUFACTURING INDUSTRY BEGINNING WITH T = -3

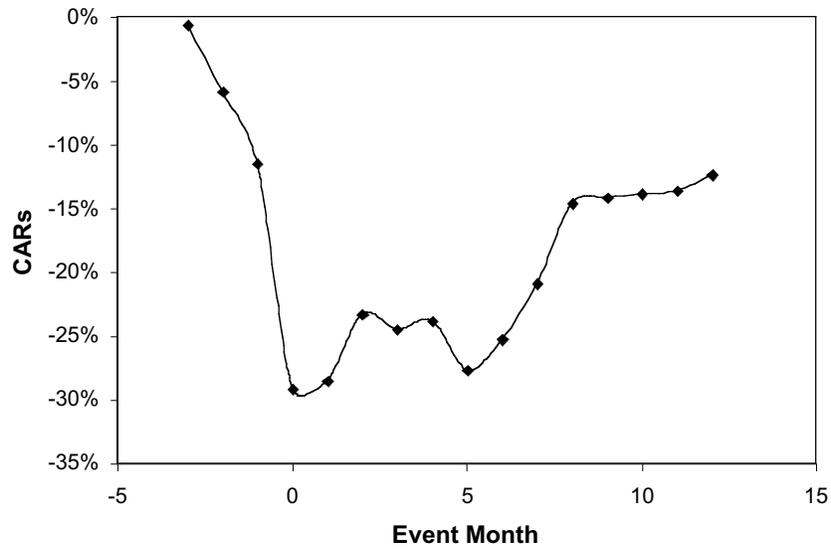


FIGURE 6. CARs FOR TECHNOLOGY INDUSTRY BEGINNING WITH T = -3 FOR STOCKS WITH TWO YEARS OF AR

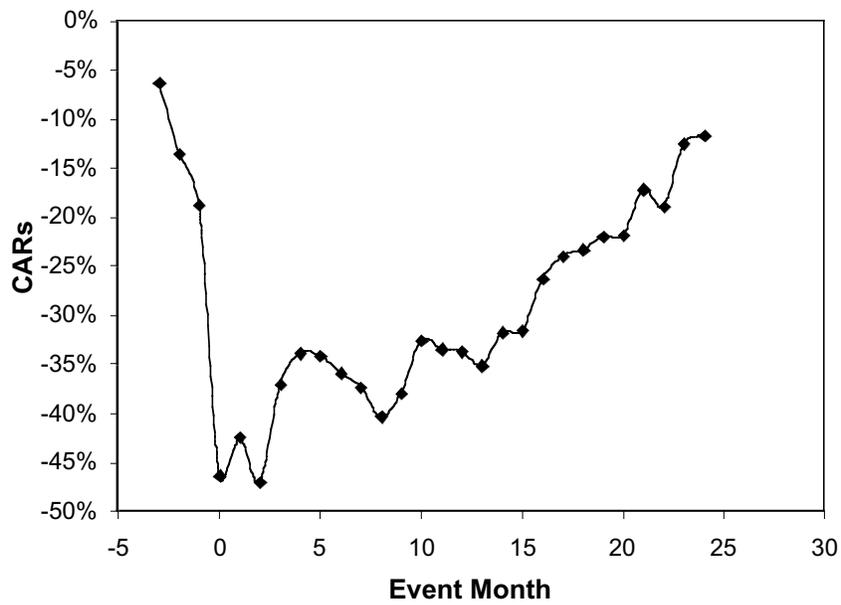
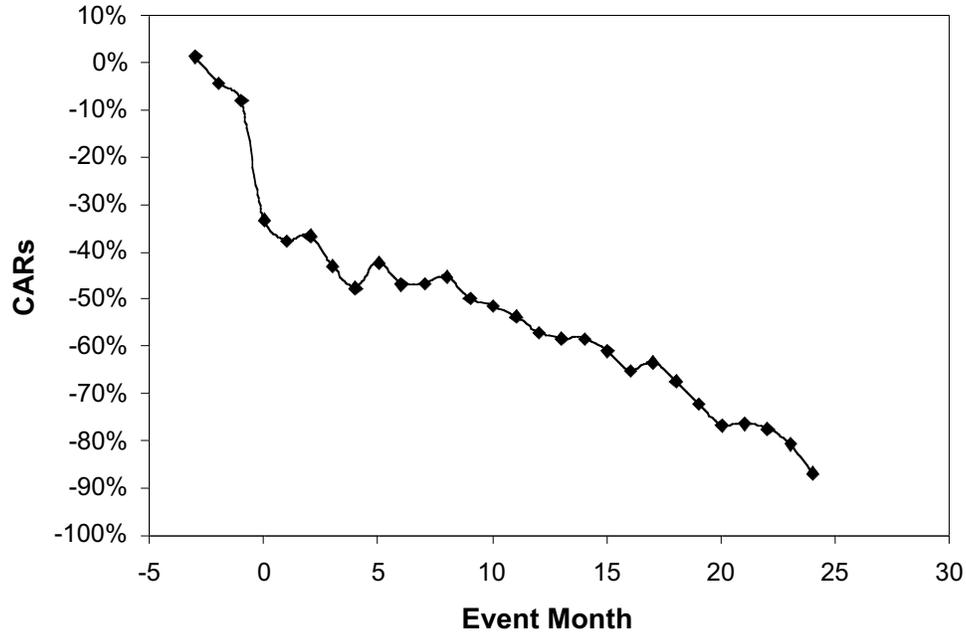
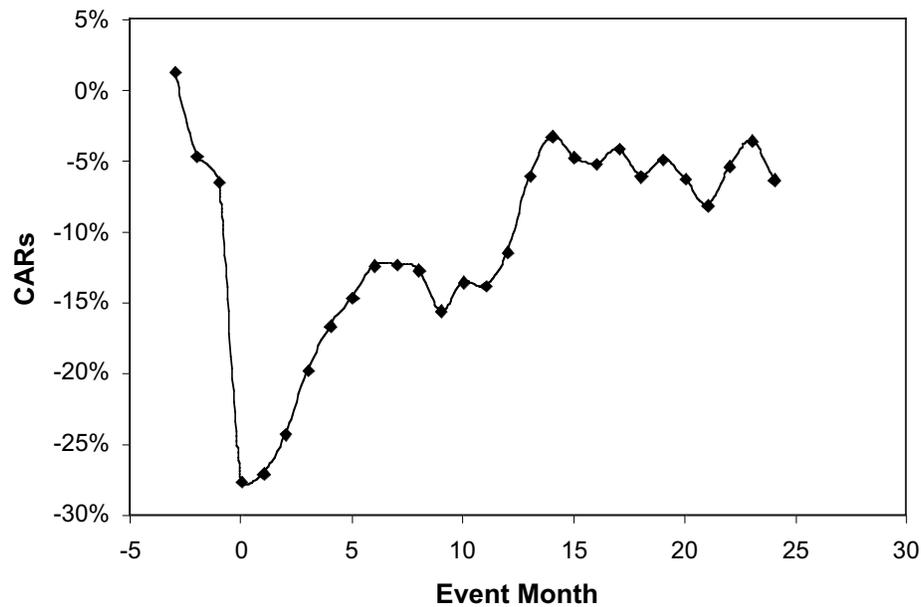
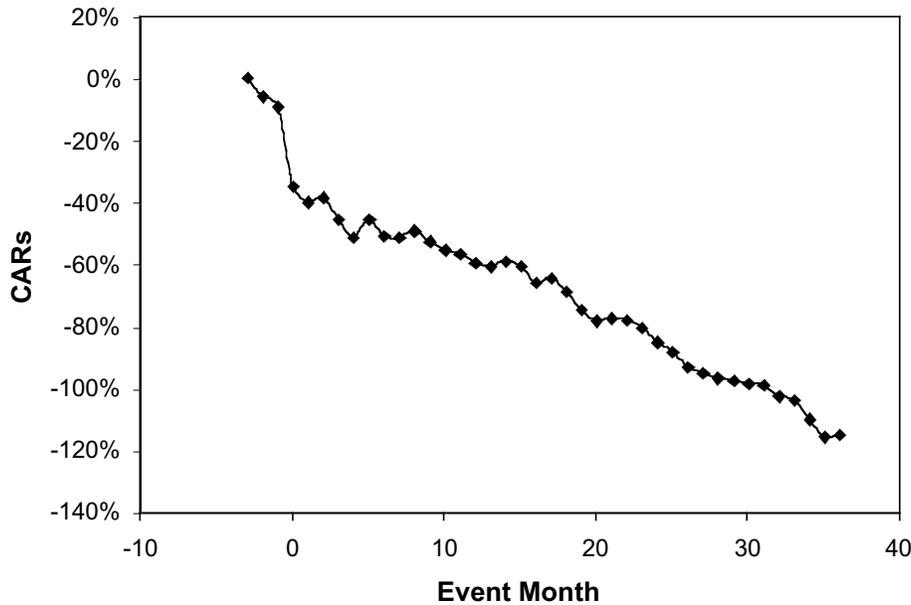


FIGURE 7. CARs FOR SERVICE INDUSTRY BEGINNING WITH $T = -3$ FOR STOCKS WITH TWO YEARS OF ARFIGURE 8. CARs FOR MANUFACTURING INDUSTRY BEGINNING WITH $T = -3$ FOR STOCKS WITH TWO YEARS OF AR

When the industry samples are further restricted to firms with two-year abnormal returns, the patterns become more pronounced. Figure 6 shows the persistent reversal pattern associated with

the technology stocks, while Figure 7 shows the continued drift associated with service stocks. Figure 8, on the other hand, shows that the stockholder reaction ends after the first year following a large price decline. Figure 9 is of particular interest because it shows the long-term persistent drift associated with the service sector. This chart displays the CARs for service sector stocks with three years of abnormal returns available.

FIGURE 9. CARs FOR SERVICE INDUSTRY BEGINNING WITH T = -3 FOR STOCKS WITH THREE YEARS OF AR



The results of the regression analysis are presented in Table 9. The regression model is estimated for three different specifications of the dependent variable depending on the sample of events used each time. Cumulative abnormal returns are regressed against the percentage decline in the event month of $t = 0$ and the two dummy variables identifying the industry classification of each stock. A similar model is used by Cox and Peterson (1994), who, in their analysis, use the day zero abnormal return, a size index variable, and two dummy variables for stocks being listed on the AMEX and NMS. However, since the sample used in this study consists of all large firms with the vast majority of them being traded on the NYSE, a size index variable and dummies for stock listing are not suitable. Instead, we choose dummy variables indicating the industry classification.

If investors overreact to information causing an initial large price decline, then we expect that the greater the decline during the event month $t = 0$, the greater the subsequent reversal in the post-event period. Therefore, we expect γ_1 will be negative. If the industry classification plays a significant role in explaining the degree of reversal, then we expect γ_2 and γ_3 to be significantly different from zero.

Table 9 shows that the first regression is statistically significant at the 1 percent level and the following two regressions decline in significance as the sample size decreases. Furthermore, all

four equations show negative coefficients for the event month abnormal return, which is consistent with the argument that companies with the largest declines tend to have the largest subsequent reversals. However, only when cumulative abnormal returns are calculated over months one through 24 is the γ_1 coefficient statistically significant at the 10 percent level.

Of particular interest is the significant negative coefficient for the first dummy variable representing firms in service industries. This coefficient is statistically significant at the 1 percent level for the full sample and two-year sub-sample and significant at the 5 percent level for the three-year sub-sample. This finding strongly confirms our earlier finding that service companies experience negative cumulative abnormal returns following large price declines. Surprisingly, the coefficient for the second dummy variable identifying technology sector firms is insignificantly different from zero.

TABLE 9. CROSS-SECTIONAL PARAMETER ESTIMATES

Intercept	ARO_i	D_{1i}	D_{2i}	F-value	Adj-R ²
<i>Panel A: CARs measured over months $t=+1$ to $t=+12$, $N=92$</i>					
0.077 (0.08)	-0.516 (0.12)	-0.282 (0.09)***	0.098 (0.44)	5.05***	0.1178
<i>Panel B: CARs measured over months $t=+1$ to $t=+24$, $N=37$</i>					
-0.784 (0.31)	-4.410 (0.31)*	-0.940 (0.55)***	-0.169 (2.50)	4.09**	0.2047
<i>Panel C: CARs measured over months $t=+1$ to $t=+36$, $N=31$</i>					
-0.917 (0.58)	-5.526 (0.55)	-1.302 (0.94)**	-0.393 (4.22)	2.25	0.1109

Notes: Parameter estimates using the model with standard errors in parentheses:

$$CAR_i = \gamma_0 + \gamma_1 ARO_i + \gamma_2 D_{1,i} + \gamma_3 D_{2,i} + \varepsilon_i$$

*, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Conclusions

This paper examines a sample of large firms that experienced stock price declines of more than 20 percent during a specific month, and attempts to determine whether there is a price reversal in the long run. The results from the analysis reveal that, following the month of the large price decline, the stocks of those large firms earn positive and statistically significant abnormal returns that last up to the period of one year. These positive and statistically significant abnormal returns indicate that much of the initial change in the price of these stocks was an overreaction on the part of investors. Investors who enter the market one month after the large drop in price earn about 12 percent more than expected over a one-year horizon and at least 4 percent during the first six months.

These results are puzzling, not only because of their magnitude, but also because of the fact that the sample was specifically restricted to large U.S. firms. Given that these firms held mostly

by institutional investors are being traded in highly liquid markets and that more and superior information is available about them, one would expect that the reversal—if any—would not be so pronounced.

The results from the analysis of the reversal patterns across industries reveal that the magnitude and trend of the observed reversal differs substantially among industries. In particular, it appears that technology stocks experience the largest and strongest reversal among our three industry classifications. In contrast, service industry stocks experience a significant and continued downward drift, which indicates *underreaction* on the part of investors in service company stocks.

Why investors would tend to overreact far more to whatever event or information caused the initial price change for technology stocks and *underreact* to news about service stocks is not clear. It may be the case that each industry sector is associated with different levels of uncertainty, leading to differences in the investors' reactions.

One can argue that from the investor's perspective, trading implications can be made based on such findings. Information on prior performance can be used to predict future performance, in which case investors can profit by buying the stocks of large firms that experienced large price declines and holding them six to 12 months following the decline. Furthermore, investors might be able to compose portfolios with long positions in technology stocks and short positions in service company stocks and thereby exploit the persistent drift patterns exhibited by the different industries.

References

- Atkins, B., and E. A. Dyl. 1990. "Price Reversals, Bid-Ask Spreads, and Market Efficiency." *Journal of Financial and Quantitative Analysis* 25: 536-547.
- Ball, R., and S. P. Kothari. 1989. "Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlation In Returns." *Journal of Financial Economics* 25: 51-74.
- Baytas, A., and N. Cakici. 1999. "Do Markets Overreact: International Evidence." *Journal of Banking and Finance* 23: 1121-1144.
- Bernstein, P. L. 1985. Discussion. *Journal of Finance* 40: 806-807.
- Bremer, M., and R. J. Sweeney. 1991. "The Reversal of Large Stock-Price Decreases." *The Journal of Finance* 2: 747-754.
- Brockett, P. L., H. M. Chen, and J. B. Garven. 1999. "A New Stochastically Flexible Event Methodology with Application to Proposition 103." *Insurance: Mathematics and Economics* 25: 197-217.
- Brown, K. C., W. V. Harlow, and S. M. Tinic. 1988. "Risk Aversion, Uncertain Information and Market Efficiency." *Journal of Financial Economics* 22: 355-385.
- Brown, S., and J. Warner. 1985. "Using Daily Stock Returns: The Case of Event Studies." *Journal of Financial Economics* 14: 3-31.
- Chan, K.C. 1988. "On the Contrarian Investment Strategy." *Journal of Business* 61: 147-163.
- Chen, C., and D. A. Sauer. 1997. "Is Stock Market Overreaction Persistent Over Time?" *Journal of Business Finance and Accounting* 24: 51-66.
- Chen, S. and A. Keown. 1981. "Risk Decomposition and Portfolio Diversification When Beta is Nonstationary: A Note." *Journal of Finance* 36: 941-947.

- Chopra, N., J. Lakonishok, and J. R. Ritter. 1992. "Measuring Abnormal Performance: Do Stocks Overreact?" *Journal of Financial Economics* 31: 235-268.
- Conrad, J., and G. Kaul. 1993. "The Returns to Long-Term Winners and Losers: Bid-Ask Biases or Biases in Computer Returns." *Journal of Finance* 48: 39-63.
- Cox, D., and D. R. Peterson. 1994. "Stock Returns Following Large One-Day Declines: Evidence on Short-Term Reversals and Longer-Term Performance." *Journal of Finance* 49: 255-267.
- De Bondt, W. F., and R. Thaler. 1985. "Does The Stock Market Overreact?" *Journal of Finance* 40: 793-805.
- De Bondt, W. F., and R. Thaler. 1987. "Further Evidence On Investor Overreaction and Stock Market Seasonality." *Journal of Finance* 42: 557-582.
- Dissanaike, G. 1997. "Do Stock Market Investors Overreact?" *Journal of Business Finance and Accounting* 24: 27-47.
- Fama, E. F. 1998. "Market Efficiency, Long-Term Returns, and Behavioral Finance." *Journal of Financial Economics* 49: 283-306.
- Jegadeesh, N., and S. Titman. 1995. "Overreaction, Delayed Reaction, and Contrarian Profits." *The Review of Financial Studies* 8: 973-993.
- Lehmann, B. 1990. "Fads, Martingales, and Market Efficiency." *Quarterly Journal of Economics* 105: 1-28.
- Schwert, G. W., and P. J. Seguin. 1990. "Heteroskedasticity in Stock Returns." *Journal of Finance* 45: 1129-1155.
- Zarowin, P. 1990. "Size, Seasonality, and Stock Market Overreaction." *Journal of Financial and Quantitative Analysis* 25: 113-125.