Investor Confidence and Returns Following Large One-Day Price Changes

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Ray R. Sturm*

College of Business
Florida Atlantic University
2912 College Avenue
Liberal Arts Building 444
Davie, Florida 33314

Telephone: (954) 236-1290
Fax: (954) 236-1298
Email: BassManRay@aol.com

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Abstract

In this study, I hypothesize that post-event price behavior following large one-day price shocks is related to pre-event price and firm-fundamental characteristics and that these characteristics proxy for investor confidence. Several theories of behavior suggest how investors form their expectations and I suggest four investor confidence hypotheses based on these theories. In addition to documenting further evidence of investor overreaction, my findings indicate that investors respond differently to negative price shocks than to positive price shocks. In particular, large decreases in price generally appear to drive positive post-event abnormal returns while large increases in price do not drive positive or negative abnormal returns. However, the main finding of this study is that this relationship is altered when pre-event return and firm characteristics are introduced. This suggests that certain pre-event characteristics influence investor confidence which in turn influences buying and selling decisions thereby driving post-event returns. However, investors' confidence appears to be lessened by a *price shock effect.*

Many studies have investigated and successfully documented the presence of stock price overreactions in the U.S. stock market. All of these studies detect overreactions by examining the market's response to a large price shock. The presence of a subsequent abnormal reversal in prices following such a shock has been presented as evidence to argue the overreaction hypothesis. The purpose of this study is to determine if the market's response to a price shock differs depending upon certain pre-event price and firm characteristics. In particular, I examine whether post-event abnormal returns are related to the price shock's direction, pre-event returns for the periods [-260, -10], [-135, -10] and [-30, -10] or three-year average changes in earnings per share, book value per share and debt-to-equity ratio. If so, then this suggests that these characteristics contain information about investors' confidence[1] in the market's ability or inability to provide future returns. In other words, I hypothesize that the post-event price behavior will differ based upon investors' perceptions of the market and that these perceptions will be at least in part formed by pre-event price and firm characteristics.

My findings extend the current literature in five ways. First, I provide further and more current evidence that price behavior is asymmetric[2] and that investors do appear to overreact. Also, although others have tested the relationship between long-term (short-term) pre-event returns and long-term (short-term) post-event returns, I test the relationship between long-term pre-event returns and short-term post-event abnormal returns. In addition, certain pre-event characteristics appear to cause a different response by investors given similar price shocks, suggesting that the characteristics tested herein may be valid proxies for investor confidence. Finally, although the size of large price changes has been shown to be inversely related to the subsequent reversal, I provide evidence that the price shock is actually positively related to post-event abnormal returns thereby mitigating the reversal. I refer to this as the *price shock effect.*

The paper is organized as follows: Section I presents the motivation and variable selection method, Section II is a review of related literature, Section III describes the data and methodology, Section IV presents the results and Section V gives a summary and conclusion.

I. Motivation and Variable Selection

During the decision making process, the use of different analytical methods by investors will result in different conclusions and therefore different expectations about the future distribution of returns in a particular market. I argue that these differing expectations will cause investors to interpret short-term price shocks differently, which will of course lead to differing post-event price behavior. Accordingly, in Section III, four investor confidence hypotheses are offered based on various theories of cognitive behavior. In addition to the behavioral theories that suggest how investors' expectations might be formed, I test whether a stock's return over prior periods and/or the change in certain key firm characteristics over prior periods appear to be relevant in the formation of these expectations.

To that end, the explanatory variables based on prior returns are calculated for the periods [-260, -10], [-135, -10] and [-30, -10]. For example, [-260, -10] covers the period 260 days through 10 days before the price shock. The cumulative raw returns over these periods are calculated with the intention of approximating returns for one year, six months and one month respectively.

The explanatory variables based on firm fundamentals are earnings per share, book value per share and the debt-to-equity ratio. These variables are chosen in an attempt to capture the most basic and key components to a firm's financial health – profitability, intrinsic value and risk. Because the intent of this study is to proxy for investor confidence rather than calculate valuations, the average three-year change in these variables is used.

Consistent with prior work, size of the initial price change and Monday and January effects are directly controlled for. Firm size is controlled for via sample selection by using firms in the Fortune 500 index and the bid-ask bounce is controlled for by eliminating events that are less than $10.00 at the event day's close. Since it is assumed that the price shock results from significant news, it is also assumed that the news is publicly available and of significant quality.

Finally, I do not suggest that the characteristics tested in this study are the only ones that could proxy for investor confidence. Rather, the results are intended to be a foundation upon which future research can be based.

II. Prior Literature

A. Explaining Post-Event Price Behavior

Several studies have identified variables that explain daily price returns immediately following large price changes. Pritamani and Singal (2001) examined post-event abnormal returns and found that quality of the information increased 20-day abnormal returns. Their results were robust with respect to both positive and negative events. Similarly, Larson and Madura (2002) found subsequent reversals to be related to whether or not the news driving the initial price change was publicly released by an announcement in the Wall Street Journal. Specifically, winners overreact to uninformed events but not to informed events.

In addition, several studies have examined intraday price behavior following large price changes. Fung, Mok and Lam (2000) studied intraday reversals for US and Hong Kong index futures. Their findings indicate that the subsequent price behavior following large opening price gaps is positively related to the initial price changes and not caused by the bid-ask bounce or by panic among investors. This contradicts Cox and Peterson (1994) who found that short-term post-event price behavior can be explained by the bid-ask bounce and market liquidity.

Ma, Pace and Chittenden (1999) also looked at intraday data, but examined equity prices. They found that investors require a risk premium on intraday returns for both positive and negative events. This premium is not driven by specialists, quotes or an increase in the stock's risk, but is related to the quality of the news.

Also testing intraday price reversals, Fabozzi, Ma, Chittenden and Daniel (1995) found that intraday reversals were related to the initial price change, the time necessary to achieve the initial price change, firm size, Mondays, January and lower trading activity accompanying the initial price change.

In sum, these studies have found that post-event price behavior is driven by the following short-term variables: size of the initial price change, the time necessary to achieve that change, the quality of the information and whether or not it was publicly released, firm size, and the Monday and January effects. There are contradictory results as to the relationship between returns, the trading activity accompanying the initial price change and the bid-ask bounce. Further, they found the behavior to not be driven by investor panic, specialists' market-making or quote activities, or the increased post-event stock risk.

B. Longer-term Price Behavior

Others have studied longer-term price behavior. DeBondt and Thaler (1985, 1987) used a portfolio-formation methodology finding that post-formation returns (especially in January) are negatively related to both long-term and short-term formation returns, are not attributable to changes in risk and are not related to size. Jegadeesh and Titman (1993) also used a portfolio-formation methodology finding that post-formation returns are positively related to pre-formation returns over a 6-month period. Chopra, Lakonishok and Ritter (1992) and Zarowin (1990) have also studied overreactions over longer-term time periods using the portfolio formation methodology. Cooper (1999) studied weekly returns of NYSE and AMEX stocks using a filter rule methodology. He found that conditional on large firms, subsequent returns were related to trading volume.

These studies tested the relationship between pre-event returns and post-event returns on a longer-term time horizon, most using a portfolio methodology. That is, they formed winning and losing portfolios based on long-term returns and found post-portfolio formation returns to be negatively related to the pre-portfolio formation returns. Some have used filter rule methodologies.

Regardless, implicit in these longer-term findings is that investors have often over or under valued a firm's stock over a long period of time. This can only be the result of investor expectations, not of short-term variables like those mentioned above, or panic as has been found in bank failures (Aharony and Swary 1996). Therefore, this supports the use of past market returns as a proxy for investor sentiment. Specifically, if investors are confident in the market's ability to add value to the investors' portfolio, then they will continue to buy, hence prices will continue to rise. Of course, the opposite is true if investors are confident that the market will diminish their portfolio value. The degree of confidence, or perhaps overconfidence, will be directly related to the imbalance in supply and demand as reflected in returns.

One way in which this study will extend existing research is by testing the relationship between pre-event long-term returns and post-event short-term returns. Although many studies have documented a long-term negative relationship, this study tests the effect of one-day price shocks on subsequent short-term price behavior within those long-term trends.

C. Theories of Behavior

Most of the prior work outlined thus far falls under the behavioral theory known as *overreaction*. This theory suggests that people attach too much importance to dramatic events (De Bondt and Thaler, 1985) and is well documented.[3] Scott and Stumpp (1999) place the overreaction theory into a broader category of behavioral biases called *overconfidence*. The overconfidence theory predicts that if investors are overconfident as to their expectations, then in the presence of contradictory evidence, they are likely to adjust their expectations slowly (rather than quickly) in an effort to protect their self esteem.

Another broad category of behavioral biases outlined by Scott and Stumpp (1999) is *prospect theory*. According to prospect theory, investors are risk seekers when holding losing stocks but risk averse when holding winning stocks. Thus, they will hold on to losing stocks in hopes of a recovery while selling winners too quickly. In a related study, Odean (1998) tested the *disposition effect* which is a tendency for investors to hold losing positions too long and sell winning positions too soon. He studied 10,000 trading accounts at a large discount brokerage and found that investors demonstrate a strong preference for realizing winners rather than losers. These findings are also consistent with Shefrin and Statman (1985), and would lead to asymmetric post-event price behavior. This study contributes to these findings by testing whether the price shock's direction changes this preference by investors.

Many behavior theories have been tested in the area of consumer behavior, perhaps the largest of which is *attribution theory*. Recently, Weiner (2000) examined attribution theory for the role that it might play in consumer behavior. To that end, he stated that rational choice theory suggests that product selection is in part determined by the anticipated satisfaction with that product. The role of attribution theory is not in the formation of the expectations about initial outcomes, but in the formation of expectations about the subsequent outcomes in light of the prior outcomes. Attributions are formed when evaluating the outcome with respect to the expectation of that outcome. Weiner (2000) gave three known properties of causal reasoning that guide this evaluation: causal stability, causal locus and causal controllability. Of these, causal stability is the most relevant to this study.

Causal stability posits that if an outcome is attributed to a stable cause, then the same outcome will be anticipated in the future. Conversely, if an outcome is attributable to a non-stable cause, then the future expectation is either uncertain or will be different from the immediate past. For example, if a box of cereal is purchased and tastes bad, then that negative outcome might be attributed to the product, which is a stable cause. Accordingly, because the same outcome would be anticipated in the future, there would be no further purchase of that cereal. Alternatively, if good boxes of cereal are repeatedly purchased and then a bad one is purchased, the bad one might be attributed to an unstable cause – that is, a so-called “lemon”. As such, this unstable cause would probably be interpreted as the bad purchase of a good product, and purchases of the product would continue.

As it relates to this study, causal stability posits that if a price shock is attributed to a stable cause, then the same outcome will be anticipated in the future resulting in price drift. Conversely, if the price shock is attributed to a non-stable cause, then the future outcome will either be uncertain or will be different from the price shock, resulting in a reversal. I hypothesize that pre-event returns and firm characteristics will influence investors’ attribution to stable or non-stable causes.

Finally, attribution theory addresses how people form their expectations. Ganzach (2000) conducted a related study of how people judge the risk and return of financial assets. According to Ganzach (2000), low firm characteristics and low stock returns are correlates of low preference. This low preference should lead to a higher perceived risk and a lower perceived expected return, resulting in an unwarranted depression in price. Once this low preference disappears, he conjectures that excessive returns will follow.

In sum, these behavioral theories predict how post-event returns should be related to the price shock. Overreaction predicts that the price shock will be followed by a reversal. Overconfidence predicts that it will be followed by price drift if the price shock is contrary to expectations. Prospect theory and the disposition effect predict that regardless of the event's direction, post-event returns will be abnormally negative for winning stocks and insignificant for losing stocks. Finally, attribution theory predicts that reversals will be present if the price shock is attributable to a non-stable cause and price drift will be present if it is attributable to a stable cause.

D. Summary

To summarize, prior work has tested the effect of short-term variables on short-term post-event returns and the effect of long-term returns on long-term post event returns. To the extent that abnormal returns are found, they are explained away by irrational investor behavior. There have been various theories conjectured that explain this irrational behavior. In this study, I test the effect of both long-term and short-term returns as well as changes in valuation characteristics on short-term post-event returns. I argue that these relationships reflect investor confidence and I offer four investor confidence hypotheses as a behavioral model of expected returns.

III. Data and Methodology

A. Data

Daily returns for companies from the 2002 Fortune 500 index are used to select the sample. The initial sample consists of all the companies in the index. The Fortune 500 index is chosen because these firms are among the most widely followed by analysts and have a sufficient history from which to collect data. Also, using these firms reduces the number of events that must be eliminated when controlling for the potential bid/ask bounce.

First, the fundamental variables are obtained from Research Insight. The three variables used are basic earnings per share including extraordinary items, book value per share and total debt to total equity. Since the observation period starts January 1, 1988 and the 3-year average change in these variables is used as a proxy, data are obtained starting in 1985. The most recent update of the database is through the year 2000, thus the sample period is 1/1/88 – 12/31/00. If there is no data available for a particular firm, then that firm is dropped from the sample.

Next, the average change in these variables for each three-year period is calculated. For some firms, data are only available for one or two of the variables. In these cases, the firm is dropped from the sample. Additionally, some data are missing for particular years. In these cases, the firm is retained in the sample, but that year is dropped from the sample.

Then, daily return information is obtained from the CRSP database for the surviving firms for the period 1/1/88 – 12/31/00. From this set, the event days are identified. Consistent with Bremer and Sweeney (1991), Cox and Peterson (1994), Larson and Madura (2002) and others, large stock price changes are defined as close-to-close changes of at least 10%. The final data consists of 2,254 events for 295 firms.

To proxy for investor confidence, cumulative raw returns are calculated over the periods [-260, -10], [-135, -10] and [-30, -10]. For the test period, cumulative abnormal returns[4]

(CARs) are calculated over the periods [1,1], [1,2] and [1,3]. These periods are the accumulated abnormal returns for the first, second and third day following the price shock. CARs at time j are calculated as follows:

$$(1) \qquad CAR_{ij} = \sum_{j=1}^{3} (AR_{ij} / j)$$

where AR_{ij} is the excess return of stock i at time j over the return of the S&P 500 index over the same period (without dividends). Finally, to control for potential bid/ask bounce contamination, all events with a closing price of less than $10.00 on the event day are dropped.

Of these 2,254 events, 1,406 are positive events and 848 are negative events which forms the two groups based on the price shock's direction. In addition, the data are grouped into strong and weak markets based on each of the six pre-event test variables. Finally, the data are grouped based on both the pre-event variables and the price shock direction. The resulting groups are: strong-positive, strong-negative, weak-positive and weak-negative. Strong (weak) markets are those with proxies greater (less) than zero. The exception is for the debt-to-equity ratio in which strong (weak) markets have proxies less (greater) than zero.

B. Investor Confidence Hypotheses

Prior literature documents several theories of behavior. The following investor confidence hypotheses are suggested which serve to fuse those theories. A summary of these hypotheses is presented in Table 1.

$H1_0$: If investors are confident in the strength of the market, then large price decreases will be interpreted as a temporary opportunity to buy quality shares at a discount. Thus, buyers should be attracted to the market leading to a reversal in prices. This hypothesis is consistent with both *overreaction* (De Bondt and Thaler, 1985) hypothesis and *causal non-stability* (Weiner, 2000). Overreaction is well-known. Under causal non-stability, the large price decrease within a good market would be attributed to a sporadic cause and would not change investors' positive expectations about the stock. In other words, it would be a "lemon" that would not stop investors from purchasing the good "product".

$H1_A$: Alternatively, if prices continued down, that would imply that investors attribute large price shocks to *stable causality* (Weiner, 2000) . That is, the large price decrease within a good market would be attributed to a stable cause. Accordingly and consistent with *overconfidence theory* (Scott and Stumpp, 1999), investors would continue sell. This could possibly support the *prospect theory* (Scott and Stumpp, 1999) and the *disposition effect* (Odean, 1998) if the results are different than the third alternative hypothesis.

$H2_0$: If investors are confident in the strength of the market, then large price increases will be interpreted as further confirmation of the market's strength. Hence, not only should no new sellers be attracted to the market, investors may continue to buy. Thus, prices should be either stable or drift higher.

In this situation, the efficient market hypothesis predicts that prices should be stable. In addition, because the event is in the same direction as the pre-event characteristics, price drift should be observed under *causal stability* (Weiner, 2000) .

$H2_A$: Alternatively, both *overreaction* (De Bondt and Thaler, 1985) and *non-stable causality* (Weiner, 2000) predict that prices will reverse. In addition, a price reversal would provide support for the *prospect theory* (Scott and Stumpp, 1999) if the results are different than those in the alternative fourth hypothesis.

$H3_0$: If investors are confident in the weakness of the market (that is, its potential to diminish portfolio value) then large price increases will be interpreted as a temporary opportunity to sell low quality shares at a premium. Thus, sellers should be attracted to the market leading to a reversal in prices as investors exit the market. This hypothesis is also consistent with *non-stable causality* (Weiner, 2000) and *overreaction* (De Bondt and Thaler, 1985).

$H3_A$: Alternatively, stable returns would be consistent with the efficient market hypothesis and possibly *prospect theory* (Scott and Stumpp, 1999) and the *disposition* *effect* (Odean, 1998) if different from the results in the alternative to the first hypothesis. Positive subsequent returns would be consistent with *overconfidence* (Scott and Stumpp, 1999) and *stable causality* (Weiner, 2000). Price drift would also imply that consistent with Ganzach (2000), positive price shocks in weak markets tend to dissipate the low preference bias.

$H4_0$: If investors are confident in the weakness of the market, then large price decreases will be interpreted as further confirmation of the market's weakness. Hence, no new buyers should be attracted to the market and therefore no subsequent reversal should be present. Thus, *causal stability* (Weiner, 2000) predicts price drift while the efficient market hypothesis predicts stable prices.

$H4_A$: Alternatively, a reversal in prices would be consistent with *overreaction* (De Bondt and Thaler, 1985), *non-stable causality* (Weiner, 2000), *prospect theory* (Scott and Stumpp, 1999) and the *disposition effect* (Odean, 1998) if different from the results in the alternative second hypothesis. Further, a reversal in prices would be consistent with Ganzach (2000).

[insert Table 1 about here]

C. Methodology

Event study methodology is used to test the relationship between pre-event variables and post-event cumulative abnormal returns. In summary, the data are first tested for abnormal returns with no control variables by testing the mean post-event cumulative abnormal return (CAR) of each pre-event grouping. The null hypothesis of this test states that the mean CAR is zero. Then, control variables are introduced using regression analysis and the results are compared to those in the first set of tests. Finally, post-event period cumulative abnormal returns are regressed on the six pre-event test variables (together with the three control variables) to determine if there is a magnitude effect.

1. Test of Means

Specifically, the entire database of 2,254 events is first tested to determine if the mean post-event CARs are significantly different from zero. The test statistic is calculated by dividing the mean CAR by the standard error of the mean. This is an initial test to determine whether price shocks appear to trigger abnormal returns.

Next, to determine whether abnormal returns are associated exclusively with the direction of the price shock, the database is divided into two groups: positive and negative events. Positive (negative) events are defined as event days on which the return is greater than (less than) zero. The mean CARs for each of these two groups are tested as outlined above.

Then, for each of the six test variables, the entire database of 2,254 events is divided into two other groups: strong and weak markets. Strong and weak markets are defined as explained in Section III A. The mean CARs for each of these two groups are tested as outlined above for the purpose of determining whether abnormal returns appear to be associated with pre-event characteristics exclusively.

Finally, in an effort to isolate the effect of both pre-event characteristics and the price shock's direction on CARs, the entire database is divided into four groups: strong markets and positive events, strong markets and negative events, weak markets and positive events, and weak markets and negative events. Descriptive statistics regarding these groups are presented in Table 2. For each group, the mean CARs are tested and the results compared and contrasted with the previous results.

[insert Table 2 about here]

2. Regression Analysis

The essence of the tests of means is to get a feel for potential drivers of abnormal returns. Consistent with the Efficient Market Hypothesis, the null hypothesis of each test states that no abnormal returns should be present, regardless of how the database is grouped. If the mean is significantly different from zero, then that suggests that the particular grouping criteria is related to abnormal returns. However, up to this point, no variables have been introduced for known drivers of abnormal returns. Therefore, the next set of tests introduces these variables.

To control specifically for the effects of Monday, January and size of the price shock effects, regression analysis is employed. The database is grouped by exactly the same method as in the test of means described above. Then, for each grouping, the following model is estimated:

$$(2) \qquad CAR_{it} = \alpha + \alpha_1 MOND_t + \alpha_2 JAND_t + \beta_1 RET_{it} + \varepsilon_{it}$$

where CAR_{it} is the cumulative one, two or three day abnormal return immediately following the event day, RET_{it} is the return of stock i at time t (the event day), MON is a dummy variable that takes the value of 1 if the CAR period includes a Monday, 0 else and JAN is a dummy variable that takes the value of 1 if the CAR period includes a day in the month of January, 0 else. The test variables are the intercept term (α) together with the coefficient (β_1) of the event day's return. Again, consistent with the Efficient Market Hypothesis, there should be no drift in the database regardless of how it is grouped. Accordingly, the null hypothesis states that the intercept should be zero. However, this value will be affected by the sign and value of $\beta_{1.}$ Therefore, the intercept term is interpreted together with β_1 as well as the corresponding test of the grouping's mean. The intercept term measures the drift in the groupings and β_1 measures the relationship between the price shock's size and subsequent abnormal returns. The results show that the β_1 will measure the price shock effect. Taken together, an inference regarding the effect of the grouping and the size of the price shock on the post-event cumulative abnormal returns is formed.

3. Magnitude Effect

In the final test, the post-event cumulative abnormal returns are regressed against each pre-event characteristic to determine if there is a magnitude effect. The regression is as follows:

$$(3) \qquad CAR_{it} = \alpha + \alpha_1 MOND_t + \alpha_2 JAND_t + \beta_1 TEST_{it} + \beta_2 RET_{it} + \varepsilon_{it}$$

where CAR_{it} is the same as defined earlier, TEST is the specific test variables identified earlier (PR260, PR135, PR30, EPS, BVPS, DE) and the remaining control variables are the same as defined above. Because each test variable has two subsets and each of the three post-event periods are tested individually, this regression is estimated 36 times. If β_1 is positive, then it suggests that there is a relationship between post-event cumulative abnormal returns and the magnitude of pre-event characteristics. If β_1 is negative, then the opposite is true. I refer to this relationship as the magnitude effect.

IV. Results

A. Test of Means

Table 3 Panel A presents the results of testing the mean post-event cumulative abnormal returns (CARs) for all 2,254 events. For the one, two and three day post-event test period, the means are all positive and significantly different from zero. This suggests that in general, large price shocks tend to induce positive post-event abnormal returns.

Panel B presents the results of grouping the database into positive and negative events to determine if the event day's direction appears to affect investor behavior. None of the CARs following positive events are significantly different from zero while all of the CARs following negative events are positive and significantly different from zero. These results suggest that negative price shocks trigger buying while positive price shocks trigger neither buying nor selling. These results also suggest asymmetrical investor behavior.

Panels C and D present the results of grouping the database into strong and weak markets to determine if pre-event variables appear to affect investor behavior. All except one of the CARs are positive and significant for all of the strong market groupings while very few of the CARs are significantly different from zero in the weak markets. This indicates that post-event abnormal returns appear to be associated with strong pre-event characteristics. That is, in general, investors apparently use price shocks as a buying opportunity if the various characteristics surrounding the stock are otherwise strong. By contrast, price shocks within weak markets, consistent with Odean (1998), generally do not trigger abnormal returns. The exceptions to this are for mid and short-term pre-event returns and growth in the firm's financial leverage.

More specifically, if the returns for the period [-30, -10] are negative, then a price shock appears to trigger buying for the three days following the shock. The same result holds for the period [-135, -10] except that the buying apparently does not start for at least three days following the shock, suggesting a delayed reaction by investors. Additionally, if a firm’s financial leverage has been increasing prior to the shock, investors appear to use the shock as a buying opportunity.

[insert Table 3 about here]

In sum, with some exceptions for certain weak market pre-event characteristics, abnormal returns appear to be associated with strong markets and negative events. To isolate the effect of each, the database is lastly grouped by both strong and weak markets as well as positive and negative events. The results are presented in Table 4.

Overall, the results in Table 4 are not surprising. Table 3 shows that abnormal returns are associated with strong markets and negative events. Hence, the large number of significant events in Panel B of Table 4is consistent with expectations. However, Panel A shows that rising pre-event earnings-per-share and book-value-per-share in combination with a positive price shock appears to induce buying. Further, this buying does not appear to start until at least three days following the shock, suggesting a delayed reaction. These results also suggest price drift following the shock.

Table 3 also shows that abnormal returns are associated exclusively with negative events. However, the results in Table 4 show that in the presence of certain weak market characteristics, this exclusivity no longer holds. Specifically, Panel C of Table 4 shows that positive events can apparently trigger buying, albeit delayed, if the mid and short-term returns (PR125 and PR30) are negative or if the firm’s financial leverage has been increasing. In addition, Panel D of Table 4 shows that abnormal returns following negative price shocks apparently disappear if the returns for the period [-260, -10] are negative or if the firm's book-value-per-share is decreasing.

Similarly, Table 3 shows that with the exception of PR135, PR30 and DE, weak markets are not associated with post-event abnormal returns. However, both Panels C and D of Table 4 show that the price shock's direction can apparently influence this relationship. That is, PR135, PR30 and DE are generally consistent with Table 3 for negative events. But for positive events, the reaction is still present but appears to be delayed. Moreover, if the weak market is defined by decreasing earnings-per-share, then contrary to the findings in Table 3 Panel D, negative events seem to trigger buying. Positive events do not appear to induce this same behavior.

[insert Table 4 about here]

The main goal of this paper is to determine if there is a relationship between certain pre-event firm and market characteristics and post-event returns. In summary, the results so far suggest that there is such a relationship. However, this relationship is not independent of the effect of the price shock's direction on the post-event returns. For example, positive price shocks alone do not appear to induce abnormal investor behavior while negative price shocks do, as evidenced by the post-event abnormal returns. But, Panels A and C of Table 4 show that post-event abnormal returns do follow positive price shocks for every pre-event characteristic grouping except with the exception of PR260. This provides strong evidence of a relationship between pre-event characteristics and post-event returns. That is, pre-event characteristics seem to contain information beyond that contained in the price shock itself. Interestingly, all of these abnormal returns show a delayed reaction in that they don't appear for at least three days following the shock. However, the tests so far have not controlled for other variables that have been shown to drive post-event returns. Hence, the next section presents the regression results after controlling for these variables.

B. Regression Analysis

Table 5 presents the regression results for the same groupings as tested and presented in Table 3. Panel A of Table 5 shows that consistent with the findings in Panel A Table 3 and after controlling for the Monday and January effects, the intercept term is positive and significantly different from zero. This provides further evidence of positive abnormal returns following price shocks. However, with the control variables, there appears to be more of a delayed reaction in that the day immediately following the price shock is not significantly different from zero. Additionally, exclusive of Monday and January effects, the CARs appear to be smaller. Moreover, the coefficient of the RET variable (β_1) is negative and significantly different from zero. Consistent with the literature on overreaction, this suggests an inverse relationship between the price shock's size and the subsequent CARs.

For the grouping in Panel A (and in Panel C), it is difficult to draw a joint inference from the intercept and β_1 together since the price shock's direction would determine the effect on CARs. Conversely, in Panel B, the database is grouped into positive and negative events making a joint inference more plausible. Consistent with Table 3, Table 5 Panel B shows no significant results for positive events, and all significant results (at the .01 level nonetheless) for negative events. Again, this suggests a relationship between negative events and post-event CARs.

More specifically, when the negative events are grouped together, all of the intercept terms detect a positive drift in the data suggesting that investors tend to buy following negative events. In addition, all of the β_1 coefficients are significant, but positive. [5] Thus, it appears that larger price shocks tend to mitigate the enthusiasm of buyers following negative price shocks. However, relative to the intercept term, β_1 is small. So taken together and using CAR[1,3] as an example, for the three days following a negative shock, the CARs appear to be approximately 3.4%, but this will be reduced by about 18% of the price shock's size. So if the price shock is a 15% drop in prices, then in the absence of the Monday and January effects, the CARs for the period [1,3] seems to be about .7%. Therefore, while there does appear to be buying following negative price shocks, extremely large negative price shocks seem to drive away buyers. [6]

The results in Panels C and D of Table 5 are generally consistent with the results in Panels C and D of Table 3. That is, for strong markets, the intercept term is detecting a positive drift within the various groupings in the presence of the control variables. Again, this suggests that pre-event strong market characteristics are associated with post-event buying by investors. The notable exception is for price shocks when the DE variable has been decreasing. For weak markets, the results are similar except that in the presence of the control variables, the buying seems to be more delayed.

Table 6 presents the regression results for the same groupings as presented in Table 4. When the database is grouped by both pre-event characteristics and price shock direction, the regression results are similar to the results from testing the means. For positive events within strong markets (Panel A), most of the results are insignificant. The exception is for EPS which, similar to Table 4, shows positive CARs. In Panel B, most of the intercept terms are positive and significant consistent with Table 4. Additionally, most of the β_1 coefficients are positive and significant consistent with Table 5 Panel B. Taken together, this again suggests that even when the pre-event characteristics are strong, larger negative price shocks appear to reduce the post-event buying by investors.

The regression results for positive events within weak markets show that the control variables illuminate additional significant relationships beyond those found in the tests of means. These results are presented in Table 6 Panel C. Specifically, both tests reveal positive and delayed CARs for the PR125 and DE groupings. However, the PR30 grouping is no longer significant. More interestingly, the PR260, EPS, and BVPS groupings become significant when the control variables are included. Moreover, the different signs indicate differing investor behavior.

That is, when the cumulative returns in the pre-event period [-260, -10] are negative, then investors appear to use positive price shocks as a buying opportunity as indicated by the positive and significant intercept term. In addition, the β_1 coefficient is negative and mildly significant. This suggests that the more positive the price shock, the less buying enthusiasm there will be on the part of investors. This could possibly be due to a belief of overreaction by investors. The same results hold true for BVPS over the post-event period [1,3]. However, EPS and BVPS for the post-event period [1,1] have the opposite signs. The intercept terms suggest that when these two variables have been decreasing prior to the positive price shock, investors seem to use this as an opportunity to sell. However, the β_1 coefficients are positive implying a price chock effect. That is, a mitigating effect imposed on the abnormal returns based on the size of the price shock.

The results in Table 6 Panel D are consistent with those in Table 4 Panel D. But, the presence of the control variables in the regression analysis again highlights some additional significant relationships. The PR135 grouping becomes significant the day after the price shock when the control variables are added. In addition, the PR260 and BVPS groupings are significant for the period [1,3]. Finally, for the period [1, 1], the intercept for the BVPS is not significant but the coefficient of the RET variable is, suggesting that investors sell the day after negative price shocks when BVPS has been decreasing. However, notice also that this appears to reverse starting on the third day following the event.

C. Magnitude Effect

Table 7 presents the coefficient results of regressing pre-event characteristics against post-event cumulative abnormal returns in an effort to determine if the magnitude of the pre-event characteristics affect post-event investor behavior. Panel A presents the results for strong markets with positive events. None of the coefficients are significant suggesting that there is no magnitude effect.

Panel B presents the results of strong markets with negative events. All of the coefficients based on the prior returns groupings are significant (at .05 and .01 levels) while only one based on firm characteristics is significant (.10 level). Specifically, post-event cumulative abnormal returns tend to be positive and larger based on the magnitude of pre-event returns. This magnitude effect is especially pronounced for the period [-30, -10] which have the largest coefficients. Therefore, not only do investors tend to buy stocks that have a large price decline when prices have been rising (Table 4, Panel B), the magnitude of the rise, especially over the prior month, appears to influence their decisions. By contrast, none of the changes in firm characteristics[7] are related in magnitude to post-event returns.

Panel C presents the weak market, positive event day results and Panel D presents the weak market, negative event day results. These results are all insignificant suggesting that there is no magnitude effect. However, for negative events, there appears to be a magnitude effect when pre-event prices are rising (strong markets) which disappears when pre-event prices are declining (weak markets). This implies that investors interpret large price declines differently based not only on the sign of the pre-event returns (Table 4, Panels B and D), but also on the magnitude of the returns if positive.

[insert Table 7 about here]

D. Multivariate Investor Confidence

All of the tests in this study have attempted to isolate specific pre-event characteristics to determine if investors appear to use them when making buy and sell decisions. However, rather than using any one variable exclusively, it is more probable that investors use multiple variables upon which to base their decisions. To lay the groundwork for this probability, two additional tests of means are conducted.

In the first test, I group the data into strong and weak markets based on whether all six of the pre-event characters tics are contemporaneously strong or weak. In addition, I further subdivide these two groups based on positive and negative events. In the second test, I divide the database into four groups: strong and weak markets based on all three pre-event return variables and strong and weak based on all three pre-event firm characteristics. Then, each of those groups are further divided into two more groups based on positive and negative events.

For brevity, the results of these final tests are not presented. However, the results are consistent with the results in Tables 3 – 6. That is, for the strong and weak market groupings that include both positive and negative events, post-event returns in strong markets appear to be abnormally positive while returns in weak markets are not abnormal. Moreover, when further subdivided into positive and negative events, the only significant post-event abnormal returns are those following negative events in strong markets (all at the .01 level). This is consistent with prior findings and provides further support for the first, second and fourth investor confidence hypotheses.

E. Summary of Findings and the Behavioral Implications

The first investor confidence hypothesis predicts that positive abnormal returns will follow negative price shocks if investors are confident in the market's strength. If such confidence exists, then the shock will be attributable to a non-stable cause. Most of the results confirm this prediction as evidenced by the positive CARs in Table 4 Panel B and the positive intercept terms presented in Table 6 Panel B. In addition, investors' confidence appears to be strengthened by the magnitude of positive pre-event returns as evidenced by the results in Table 7 Panel B. However, the beta coefficients in Table 6 Panel B suggest a price shock effect that causes investors to attribute the shock to a more stable cause.

The second investor confidence hypothesis predicts that non-negative abnormal returns will follow positive price shocks if investors are confident in the market's strength. If there is such confidence, then the shock will be attributable to a stable cause. Panel A in Tables 4, 6 and 7 all present evidence that appears to support this hypothesis. That is, very few of the results are significant and those that are suggest a post-event drift in prices. Thus, taking Panels A and B together, all of the pre-event characteristics seem to affect post-event abnormal returns suggesting that they may be valid proxies for investor confidence.

The third investor confidence hypothesis predicts that positive price shocks will be followed by negative abnormal returns if investors are confident in the market's weakness. If this confidence exists, then investors will attribute the shock to a non-stable cause. As presented in Panel C of Table 7, two of the results do support this prediction.

Specifically, decreasing earnings-per-share and book-value-per-share appear to drive a lack of confidence in the market by investors. Hence, if they are presented with a positive price shock under such circumstances, then they appear to use the opportunity to sell. The magnitude of the decrease does not appear to influence their confidence, but the size of the price shock does. The remaining results in Panel C of Tables 4 and 7 do not support the third hypothesis. Rather, the results appear to be more consistent with stable causality and possibly with the disposition effect.

Finally, the fourth investor confidence hypothesis predicts non-positive abnormal returns following negative price shocks if investors are confident in the market's weakness. If such confidence exists, then they will attribute the shock to a stable cause. The results in Panel D of Tables 4 and 7 do not support this hypothesis. Rather, investors appear to attribute shocks under these circumstances to a non-stable cause consistent with the overreaction literature and possibly with Ganzach (2000).

A secondary goal of this paper is determine whether there is a difference in informational content between pre-event returns and pre-event fundamental firm characteristics. Although some of the pre-event variables seem to be more informative in certain situations than others, as a whole, there does not appear to be a clear dichotomy. The notable exception appears to be the magnitude effect of pre-event positive returns on post-event positive abnormal returns following a negative price shock. In such situations, all of the return-based characteristics are significant at the .01 level (except for one which is significant at the .05 level) while none of the firm-fundamentals-based characteristics are significant (except for one which is significant at the .10 level).

V. Conclusion

In this study, four investor confidence hypotheses are offered. These hypotheses suggest that investors will react differently to one-day price shocks based on their confidence in the market's ability (or lack thereof) to provide future returns. In an attempt to capture investor confidence, I compute and test six different proxies. The proxies are pre-event arithmetic average daily returns over the periods [-260, -10], [-135, -10] and [-30, -10], three-year average changes in earnings per share, book value per share and the debt-to-equity ratio. If these proxies are greater than zero, they are referred to as strong markets and if they are less than zero, they are referred to as weak markets (vice versa for the debt-to-equity ratio). Further and consistent with prior work, one-day price shocks are defined as a close-to-close change in daily prices of at least 10% or –10% which I call positive and negative events respectively. To determine the reaction by investors, cumulative abnormal returns are calculated over the periods [1,1], [1,2] and [1,3].

My findings indicate that negative price shocks generally tend to trigger positive post-event cumulative abnormal returns over the periods [1,1], [1,2] and [1,3]. This reversal is further evidence of the overreaction hypothesis. However, when these events are cross-sectionalized by the six pre-event characteristics, then this relationship is altered, suggesting that these characteristics influence investor behavior and may indeed proxy for investor confidence.

Additionally, I find evidence of a price shock effect whereby post-event reversals are smaller for larger price shocks. That is, the larger the shock, the more likely investors are to attribute the shock to a stable rather than a non-stable cause. This suggests that investors' confidence in a market's ability to provide future returns is related to the size of the price shock.
Specifically, for negative price shocks, returns over the period [-260, -10] contain more information about post-event returns in strong markets than they do in weak markets. Conversely, returns over the periods [-135, -10] and [-30, -10] contain comparable information in both strong and weak markets. Earnings-per-share and book-value-per-share contains slightly more information in strong markets than in weak while the debt-to-equity ratio contains slightly more information in weak markets than in strong.

For positive price shocks, the results for strong markets are generally insignificant except for earnings-per-share. However, positive price shocks do seem to trigger delayed buying by investors when the firm's earnings-per-share have been rising.

By contrast, post-event abnormal returns do appear to be triggered when five of the six pre-event characteristics have indicated a weak market. That is, positive post-event abnormal returns are related to declining returns over the periods [-260, -10] and [-135, -10] as well as declining book-value-per-share (for the period [1, 3]) and an increasing debt-to-equity ratio. Conversely, negative post-event abnormal returns are related to declining earnings-per-share and book-value-per-share (for the period [1,1]).

In addition, the pre-event characteristics were tested to see if there was a magnitude effect with post-event abnormal returns. The primary relationship found was in the context of negative price shocks when the pre-event returns were strong. In such a situation, post-event abnormal returns appear to be driven by the magnitude of pre-event returns but not by pre-event firm-fundamental characteristics. This suggests that investors derive confidence from and attach value to large pre-event returns.

Finally, I find no clear dichotomy between post-event abnormal returns and pre-event returns as compared to the relationship between post-event abnormal returns and pre-event firm-fundamentals characteristics. The notable exception to this is the magnitude effect.

Taken together, the first and second investor confidence hypotheses are supported. The third investor confidence hypothesis is weakly supported and the fourth is not supported. Hence, the characteristics tested herein may indeed proxy for investor confidence.

Endnotes

[1] Throughout the paper, "investor confidence" refers to investors' expectations about future returns and their conviction of those expectations.

[2] Brown, Harlow and Tinic (1993, 1988) show that the arrival of both favorable and unfavorable uncertain information tends to increase volatilities and required rates of return. Further, risk decreases take a longer time to manifest itself than risk increases which may help explain the asymmetrical nature of price behavior.

[3] There are a number of overreaction models. Interested readers should see Barberis, Shleifer and Vishny (1993) and the references contained therein.

[4] While risk-adjusted returns may produce a slightly different result than market-adjusted returns, Brown and Warner (1980) show through controlled simulation that market-adjusted and market-and-risk-adjusted returns are almost equally likely to detect abnormal returns at both the .05 and .01 levels. Indeed, they find that "tests which used risk-adjusted returns were no more powerful than tests which used returns which had not been adjusted for systematic risk." Further, when computing market-and-risk-adjusted returns, they admittedly presume that some version of the CAPM generates expected returns. However, Fama and French (1992) and others have shown that market betas do not help explain average stock returns. Rather, size holds more explanatory power than beta. In this study, size is controlled for via sample selection. Also, Brown, Harlow and Tinic (1993) show that the volatility change associated with the price shock and the uncertainty associated with the level of firm risk may have a material impact on the post-event abnormal returns. However, in contrast to this study, their measure of abnormal returns is based on market model residuals.

[5] Another interesting result between Panels A and B is that for the entire database, β_1 is negative but when grouped, β_1 for positive events is not significantly different from zero and the β_1 for negative events is positive. This is a function of CARs for negative events being positive while CARs for positive events are generally not significantly different from zero. Hence, this phenomenon does not appear to be informative.

[6] This interpretation was confirmed by further dividing the negative event grouping into quartiles based on the size of the price shock and testing the mean post-event CARs. The quartile with the most negative

price shocks (i.e. the highest absolute value) was the only quartile with mean CARs not significantly different from zero. All of the other quartiles were positive and highly significant.

[7] With the exception of book-value-per-share over the period [1, 1] which is only significant at the .10 level.

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Table 1. Summary of Hypotheses

Hypothesis	*Market*	*Event*	*CAR*	*Behavioral Theory*
$H1_0$	Strong	Negative	Positive	Overreaction, Causal Nonstability
$H1_A$	Strong	Negative	Negative	Causal Stability, Overconfidence, Prospect Theory if different from H3a
$H2_0$	Strong	Positive	Positive or Stable	Causal Stability or Efficient Market Hypothesis
$H2_A$	Strong	Positive	Negative	Overreaction, Causal Nonstability, Prospect Theory if different from H4a
$H3_0$	Weak	Positive	Negative	Overreaction, Causal Nonstability
$H3_A$	Weak	Positive	Positive or Stable	Causal Stability, Overconfidence, or Efficient Market Hypothesis and Prospect Theory if different from H1a
$H4_0$	Weak	Negative	Negative or Stable	Causal Stability, Efficient Market Hypothesis
$H4_A$	Weak	Negative	Positive	Overreaction, Causal Nonstability, Prospect Theory if different from H4a

This table presents a summary of the Investor Confidence Hypotheses and the supporting behavioral theory. For example, if the first null hypothesis is correct, then it provides evidence for the overreaction hypothesis and causal nonstability theory of behavior.

Table 2. Descriptive Statistics

Panel A. Number of Events

Proxies	Strong Positive	Strong Negative	Weak Positive	Weak Negative	Total Events
PR260	849	579	557	269	2,254
PR135	746	483	757	365	2,254
PR30	649	377	757	471	2,254
EPS	929	568	477	280	2,254
BVPS	1150	697	256	151	2,254
DE	480	310	926	538	2,254

Panel B. Proxy averages

Proxies	Strong Positive	Strong Negative	Weak Positive	Weak Negative
PR260	0.23%	0.21%	-0.13%	-0.10%
PR135	0.30%	0.27%	-0.08%	-0.17%
PR30	0.65%	0.59%	-0.65%	-0.56%
EPS	153%	232%	-308%	-173%
BVPS	33.40%	28.34%	-48.59%	-45.16%
DE	-26.87%	-23.82%	151%	355%

Strong markets are markets in which the proxy is greater than zero and negative markets are markets in which the proxy is less than zero. The DE proxy is the opposite. Positive events are one-day price increases of greater than 10% while negative events are one-day price decreases of less than -10%. The proxies using prior returns are arithmetic average daily returns for the periods [-260,-10](PR260),[-135,-10](PR135), and [-30,-10] (PR30). Proxies using firm fundamental information are the average annual change for the 3-years prior to the event for earnings per share (EPS), book value per share (BVPS) and total debt-to-total equity (DE).

Table 3. Test of Means.

Panel A. Entire Database

	CAR [1,1]	CAR [1,2]	CAR [1,3]
n	2254	2254	2254
Mean	.42%	.55%	.78%
t-stat	3.38*	3.58*	4.70*

Panel B. Positive and Negative Events

	CAR [1,1]	CAR [1,2]	CAR [1,3]
n	1406	1406	1406
Mean – Positive	.07%	-.04%	.35%
t-stat	.49	-.23	1.77
n	848	848	848
Mean – Negative	1.01%	1.54%	1.48%
t-stat	4.57*	5.47*	5.08*

Panel C. Strong Markets

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	1428	1428	1428	1229	1229	1229	1026	1026	1026
Mean	.70%	.84%	1.03%	.59%	.67%	.84%	.41%	.64%	.67%
t-stat	4.67*	4.42*	4.90*	3.69*	3.35*	3.82*	2.41**	2.91*	2.79*
	EPS			**BVPS**			**DE**		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	1497	1497	1497	1847	1847	1847	790	790	790
Mean	.50%	.65%	.94%	.51%	.62%	.92%	.28%	.44%	.80%
t-stat	3.33*	3.42*	4.70*	3.92*	3.88*	5.11*	1.40	1.76***	2.96*

Panel D. Weak Markets

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	826	826	826	1025	1025	1025	1228	1228	1228
Mean	.06%	.05%	.33%	.22%	.41%	.70%	.43%	.48%	.87%
t-stat	.27	.19	1.18	1.10	1.71	2.80*	2.39**	2.18**	3.78*
	EPS			**BVPS**			**DE**		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	757	757	757	407	407	407	1464	1464	1464
Mean	.27%	.35%	.45%	.03%	.27%	.12%	.50%	.61%	.76%
t-stat	1.23	1.25	1.50	.09	.63	.27	3.13*	3.05*	3.62*

*, **, *** significant at the .01, .05 and .10 levels respectively.
For each grouping, the first line is post-event test period, the second line is the sample size, the third line is the mean cumulative abnormal return for each of the test periods and the fourth line is the related t-stat. The null hypothesis states that the mean equals zero, and the t-stat is calculated by dividing the mean by the standard error of the mean.

Table 4. Test of Means.

Panel A. Strong Markets Positive Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	849	849	849	746	746	746	649	649	649
Mean	.08%	-.11%	.25%	-.01%	-.17%	.20%	.11%	-.08%	.15%
t-stat	.47	-.52	1.04	-.06	-.77	.80	.55	-.33	.54
	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	929	929	929	1150	1150	1150	480	480	480
Mean	.11%	.04%	.49%	.12%	-.08%	.40%	-.25%	-.38%	.13%
t-stat	.61	.19	2.13**	.80	-.44	2.00**	-1.00	-1.36	.41

Panel B. Strong Markets Negative Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	579	579	579	483	483	483	377	377	377
Mean	1.62%	2.23%	2.17%	1.52%	1.98%	1.82%	.92%	1.86%	1.55%
t-stat	6.00*	6.37*	6.03*	5.24*	5.21*	4.55*	2.79*	4.43*	3.44*
	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	568	568	568	697	697	697	310	310	310
Mean	1.15%	1.65%	1.69%	1.16%	1.75%	1.77%	1.09%	1.71%	1.85%
t-stat	4.42*	4.71*	4.69*	4.83*	5.65*	5.53*	3.21*	3.64*	3.85*

Table 4. Test of Means.

Panel C. Weak Markets Positive Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	557	557	557	660	660	660	757	757	757
Mean	.07%	.06%	.50%	.17%	.11%	.51%	.04%	-.01%	.52%
t-stat	.26	.19	1.47	.71	.38	1.65***	.18	-.04	1.86***

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	477	477	477	256	256	256	926	926	926
Mean	.00%	-.21%	.08%	-.12%	.11%	.10%	.24%	.13%	.46%
t-stat	.00	-.62	.22	-.27	.20	.17	1.26	.57	1.84***

Panel D. Weak Markets Negative Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	269	269	269	365	365	365	471	471	471
Mean	-.31%	.05%	.00%	.32%	.96%	1.04%	1.07%	1.28%	1.43%
t-stat	-.82	.11	.00	.97	2.34**	2.42**	3.57*	3.37*	3.76*
	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
N	280	280	280	151	151	151	538	538	538
Mean	.71%	1.31%	1.08%	.28%	.55%	.16%	.96%	1.44%	1.27%
t-stat	1.73***	2.73*	2.12**	.51	.79	.22	3.31*	4.11*	3.43*

*, **, *** significant at the .01, .05 and .10 levels respectively.

For each grouping, the first line is post-event test period, the second line is the sample size, the third line is the mean cumulative abnormal return for each of the test periods and the fourth line is the related t-stat. The null hypothesis states that the mean equals zero, and the t-stat is calculated by dividing the mean by the standard error of the mean.

Table 5. Regression Analysis.

Panel A. Entire Database

	CAR [1,1]	CAR [1,2]	CAR [1,3]
Intercept	.20% 1.35	.40% 1.99**	.60% 3.17*
Coefficient	-.019 -2.06**	-.040 -3.57*	-.024 -2.06**

Panel B. Positive versus Negative Events

Intercept - Pos	-.40% -.778	.20% .288	1.0% 1.421
Coefficient - Pos	.029 .708	-.021 -.434	-.053 -.991
Intercept - Neg	2.2% 3.59*	2.9% 3.75*	3.4% 4.18*
Coefficient – Neg	.121 3.08*	.151 3.03*	.180 3.45*

Table 5. Regression Analysis.

Panel C. Strong Markets

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	1428	1428	1428	1229	1229	1229	1026	1026	1026
Intercept	.4%	.6%	.8%	.3%	.3%	.5%	.2%	.7%	.7%
t-stat	2.35**	2.53**	3.39*	1.50	1.48	2.17**	.99	2.69*	2.38**
β_1	-.037	-.061	-.047	-.039	-.058	-.037	-.016	-.055	-.033
t-stat	-3.43*	-4.47*	-3.15*	-3.38*	-4.00*	-2.34**	-1.27	-3.52*	-1.89***

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	1497	1497	1497	1847	1847	1847	790	790	790
Intercept	.3%	.4%	.7%	.3%	.5%	.7%	.1%	.1%	.4%
t-stat	1.88***	2.09**	3.27*	2.16**	2.52**	3.66*	.35	.31	1.26
β_1	-.029	-.043	-.028	-.025	-.049	-.031	-.038	-.055	-.040
t-stat	-2.61*	-3.21*	-1.98**	-2.66*	-4.14*	-2.41*	-2.61*	-3.00*	-2.03**

Panel D. Weak Markets

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	826	826	826	1025	1025	1025	1228	1228	1228
Intercept	-.2%	-.1%	.2%	.1%	.4%	.7%	.2%	.1%	.5%
t-stat	-.96	-.27	.54	.36	1.26	2.27**	.92	.295	2.08**
β_1	.019	.004	.019	.5%	-.018	-.009	-.020	-.025	-.015
t-stat	1.23	.21	.961	.39	-1.05	-.53	-1.57	-1.58	-.95

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	757	757	757	407	407	407	1464	1464	1464
Intercept	-.1%	.2%	.3%	-.5%	-.2%	.0%	.2%	.5%	.7%
t-stat	-.27	.52	.92	-1.12	-.43	-.08	1.36	2.16**	2.94*
β_1	.000	-.033	-.017	.012	.000	.003	-.9%	-.032	-.017
t-stat	.021	-1.68**	-.81	.50	-.07	.10	-.78	-2.32**	-1.15

*, **, *** significant at the .01, .05 and .10 levels respectively.

The cumulative abnormal returns are regressed against the independent variables for the periods [1,1], [1,2] and [1,3] using the following model:

$$CAR_{it} = \alpha + \alpha_1 MOND_t + \alpha_2 JAND_t + \beta_1 RET_{it} + \varepsilon_{it}$$

where CARit is the cumulative one, two or three day cumulative abnormal return, RET is the magnitude of the event day return and MON and JAN are the Monday and January dummy variables taking the value of 1 if true and 0 if else. Proxies as well as positive and negative events are defined in Table 2. Strong markets are markets in which the proxy is greater than zero and negative markets are markets where the proxy is less than zero. The DE proxy is the opposite.

Table 6. Regression Analysis.

Panel A. Strong Markets Positive Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	849	849	849	746	746	746	649	649	649
Intercept	-.2%	.0%	-.1%	-.7%	.0%	.2%	-.8%	.9%	.6%
t-stat	-.356	-.02	-.17	-1.02	-.04	.21	-1.03	1.00	.57
β_1	.015	-.006	.035	.040	-.016	-.002	.055	-.08	-.037
t-stat	.28	-.09	.49	.77	-.26	-.03	.95	-1.11	-.44

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	929	929	929	1150	1150	1150	480	480	480
Intercept	.6%	1.0%	1.6%	.6%	.6%	.3%	.6%	1.0%	.1%
t-stat	.85	1.19	1.84***	.97	.76	.34	.56	.84	.04
β_1	-.047	-.072	-.088	-.042	-.045	.011	-.058	-.100	.007
t-stat	-.89	-1.20	-1.33	-.90	-.83	.19	-.72	-1.09	.07

Panel B. Strong Markets Negative Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	579	579	579	483	483	483	377	377	377
Intercept	2.4%	3.1%	.30%	1.7%	2.3%	.032	1.8%	3.4%	3.6%
t-stat	3.32*	3.25*	3.05*	1.91***	2.02**	2.64*	2.02**	2.98*	3.01*
β_1	.106	.135	.127	.066	.105	.165	.084	.129	.165
t-stat	2.28**	2.22**	1.99**	1.13	1.38	2.08**	1.51	1.81***	2.158**

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	568	568	568	697	697	697	310	310	310
Intercept	2.1%	3.3%	3.7%	2.2%	3.0%	3.2%	1.2%	2.9%	2.8%
t-stat	2.72*	3.21*	3.44*	3.27*	3.55*	3.61*	1.25	2.17**	2.06**
β_1	.104	.180	.197	.112	.145	.151	.073	.182	.163
t-stat	2.04**	2.64*	2.80*	2.64*	2.70*	2.68*	1.16	2.14**	1.83***

Table 6. Regression Analysis.

Panel C. Weak Markets Positive Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	557	557	557	660	660	660	757	757	757
Intercept	-.5%	.6%	2.4%	-.1%	.5%	1.9%	-.2%	-.2%	1.4%
t-stat	-.57	.56	2.13**	-.11	.49	1.76***	-.22	-.27	1.42
β_1	.035	-	-.158	.015	-	-.107	.011	.011	-.068
t-stat	.54	.052	-1.93***	.24	.031	-1.33	.19	.17	-.97
		-.68			-.42				

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	477	477	477	256	256	256	926	926	926
Intercept	-2.0%	-.6%	.5%	-2.8%	-.1%	2.9%	-.7%	.1%	1.5%
t-stat	-2.11**	-.56	.41	-2.11**	-.07	1.66***	-1.02	.07	1.68***
β_1	.133	.025	-.038	.167	-.017	-.22	.051	-.003	-.077
t-stat	2.04**	.30	-.41	1.77***	-.15	-1.78***	1.06	-.06	-1.22

Panel D. Weak Markets Negative Events

	PR260			PR135			PR30		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	269	269	269	365	365	365	471	471	471
Intercept	1.3%	2.0%	3.8%	2.3%	3.2%	3.4%	2.6%	2.6%	3.2%
t-stat	1.15	1.44	2.64*	2.57*	2.92*	3.03*	3.01*	2.40**	2.90*
β_1	.119	.139	.256	.147	.170	.178	.155	.171	.191
t-stat	1.62	1.59	2.82*	2.74*	2.59*	2.59*	2.78*	2.44**	2.67*

	EPS			BVPS			DE		
CAR	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]	[1,1]	[1,2]	[1,3]
n	280	280	280	151	151	151	538	538	538
Intercept	2.1%	2.4%	3.0%	2.5%	2.7%	4.7%	2.6%	2.8%	3.5%
t-stat	2.07**	2.01**	2.34**	1.53	1.33	2.28**	3.33*	2.89*	3.45*
β_1	.139	.115	.156	.177	.196	.346	.139	.124	.174
t-stat	2.23**	1.58	2.03**	1.67***	1.44	2.54**	2.78*	2.00**	2.71*

*, **, *** significant at the .01, .05 and .10 levels respectively.

The cumulative abnormal returns are regressed against the independent variables for the periods [1,1], [1,2] and [1,3] using the following model:

$$CAR_{it} = \alpha + \alpha_1 MOND + \alpha_2 JAND + \beta_1 RET_{it} + \varepsilon$$

where CARit is the cumulative one, two or three day cumulative abnormal return, RET is the magnitude of the event day return and MON and JAN are the Monday and January dummy variables taking the value of 1 if true and 0 if else. Proxies as well as positive and negative events are defined in Table 2. Strong markets are markets in which the proxy is greater than zero and negative markets are markets where the proxy is less than zero. The DE proxy is the opposite.

Table 7. Magnitude Effect.

Panel A. Strong Markets, Positive Event Days

	PR260	PR135	PR30	EPS	BVPS	DE
CAR [1,1]	0.00	0.01	(0.02)	0.00	0.00	0.01
	0.82	*0.21*	*0.30*	*0.27*	*0.86*	*0.31*
CAR [1,2]	0.00	0.00	(0.02)	0.00	0.00	0.01
	0.65	*0.64*	*0.25*	*0.78*	*0.61*	*0.104*
CAR [1,3]	0.00	0.00	(0.01)	0.00	0.00	0.01
	0.31	*0.80*	*0.78*	*0.91*	*0.88*	*0.42*

Panel B. Strong Markets, Negative Event Days

	PR260	PR135	PR30	EPS	BVPS	DE
CAR [1,1]	0.01	0.03	0.12	0.00	0.01	0.01
	*.03***	*.00**	*.00**	*0.57*	*.09****	*0.35*
CAR [1,2]	0.02	0.05	0.14	0.00	0.01	0.01
	*.00**	*.00**	*.00**	*0.67*	*0.25*	*0.37*
CAR [1,3]	0.02	0.05	0.17	0.00	0.00	0.01
	*.01**	*.00**	*.00**	*0.73*	*0.60*	*0.41*

Panel C. Weak Markets, Positive Event Days

	PR260	PR135	PR30	EPS	BVPS	DE
CAR [1,1]	0.00	0.01	0.00	0.00	0.00	0.00
	0.97	*0.44*	*0.84*	*0.34*	*0.89*	*0.48*
CAR [1,2]	(0.01)	(0.01)	(0.01)	0.00	0.00	0.00
	0.59	*0.69*	*0.76*	*0.66*	*0.84*	*0.82*
CAR [1,3]	(0.01)	(0.01)	(0.02)	0.00	0.00	0.00
	0.46	*0.55*	*0.49*	*0.55*	*0.55*	*0.99*

Panel D. Weak Markets, Negative Event Days

	PR260	PR135	PR30	EPS	BVPS	DE
CAR [1,1]	0.00	0.01	0.01	0.00	0.00	0.00
	0.82	*0.72*	*0.68*	*0.26*	*0.77*	*0.93*
CAR [1,2]	(0.02)	(0.01)	(0.01)	0.00	0.00	0.00
	0.31	*0.66*	*0.82*	*0.31*	*0.75*	*0.87*
CAR [1,3]	(0.02)	(0.01)	(0.02)	0.00	0.00	0.00
	0.32	*0.79*	*0.67*	*0.90*	*0.94*	*0.57*

*,'**,*** Significant at the .01, .05 and .10 levels respectively.
The cumulative abnormal returns are regressed against the independent variables for the periods [1,1], [1,2] and [1,3] using the following model:

$$CAR_{it} = \alpha + \alpha_1 MOND + \alpha_2 JAND + \beta_1 TEST_{it} + \beta_2 RET_{it} + \varepsilon$$

where CARit is the cumulative one, two or three day cumulative abnormal return, RET is the magnitude of the event day return and MON and JAN are the Monday and January dummy variables taking the value of 1 if true and 0 if else. The first row is the coefficient (β_1) and the second row is the related p-value. TEST is the specific proxy being tested and the coefficient of this variable captures the magnitude effect. Proxies are defined in Table 1 and positive and negative events are defined in Table 2. These results suggest that there is only a magnitude effect for negative event days within strong markets.