The Journal of Behavioral Finance
2003, Vol. 4, No. 4, 201–216

Investor Confidence and Returns Following Large One-Day Price Changes

Ray R. Sturm

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 behavioral theories 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 price decreases generally drive positive post-event abnormal returns, while large price increases do not drive positive or negative abnormal returns. However, my main finding 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 and thereby drives post-event returns. However, investor 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 have detected overreactions by examining the market's response to a large price shock. The presence of an abnormal price reversal following such a shock has been presented as evidence of the overreaction hypothesis.

The purpose of this study is to determine if the market's response to a price shock differs depending on 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 the debt-to-equity ratio. If so, these characteristics contain information about investor confidence[1] in the market's ability (or inability) to provide future returns.

I hypothesize that post-event price behavior will differ based on investor 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 appear to overreact. In addition, I test the relationship between long-term pre-event returns and short-term post-event abnormal returns. Certain pre-event characteristics appear to cause a different investor response given similar price shocks, which suggests that the characteristics tested here 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. This mitigates the reversal, and I refer to it as the *price shock effect*.

The paper is organized as follows: The first section presents the motivation and variable selection method. The second section is a review of related literature. The third section describes the data and methodology. The fourth section presents the results, and the final section provides a summary and conclusion.

Motivation and Variable Selection

During the investor decision-making process, the use of different analytical methods will result in different conclusions and 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, I offer four investor confidence hypotheses based on various cognitive behavioral theories. In addition, I test whether a stock's return over prior periods, and/or the change in certain key firm characteristics over prior periods, appears relevant in the formation of these expectations.

To that end, I calculate explanatory variables based on prior returns for the periods [-260, -10], [-135, -10],

Ray R. Sturm is a Ph.D. candidate at Florida Atlantic University, and a visiting instructor at the University of Central Florida.

Requests for reprints should be sent to Ray Sturm, Department of Finance, College of Business Administration, PO Box 161400, Orlando, FL 32816–1400. Email: RSturm@bus.ucf.edu

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 to approximate returns for one year, six months, and one month, respectively.

The explanatory variables based on firm fundamentals are earnings per share (EPS), book value per share (BVPS), and the debt-to-equity ratio (DE). These variables are chosen to capture the most basic and key components of 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, I control directly for size of the initial price change and Monday and January effects. I control for firm size via sample selection by using firms in the Fortune 500 index, and for bid-ask bounce by eliminating events that are less than $10.00 at the event day's close. Since it is assumed that price shocks result 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 here are the only ones that could proxy for investor confidence. My results are intended to be a foundation upon which future research can be based.

Prior Literature

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 the quality of information increased twenty-day abnormal returns. Their results were robust to both positive and negative events.

Similarly, Larson and Madura [2003] found that subsequent reversals were related to whether 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 U.S. 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 is not caused by the bid-ask bounce or investor panic. 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 et al. [1999] also looked at intraday data, but they 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 et al. [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: the size of the initial price change, the time necessary to achieve that change, the quality of the information and whether it was publicly released, firm size, and the Monday and January effects. There are contradictory results regarding the relationship between returns, the trading activity accompanying the initial price change, and the bid-ask bounce. Furthermore, the studies found that the behavior was not driven by investor panic, specialist market-making or quote activities, or increased post-event stock risk.

Longer-Term Price Behavior

Others have studied longer-term price behavior. De Bondt and Thaler [1985, 1987] used a portfolio formation methodology. They found that post-formation returns (especially in January) are 1) negatively related to both long- and short-term formation returns, 2) not attributable to changes in risk, and 3) not related to size. Jegadeesh and Titman [1993] also used a portfolio formation methodology, and found that post-formation returns are positively related to pre-formation returns over a six-month period.

Chopra, Lakonishok, and Ritter [1992] and Zarowin [1990] also studied overreactions over longer-term time periods using a portfolio formation methodology. Cooper [1999] studied weekly returns of NYSE and AMEX stocks using a filter rule methodology. He found that, for large firms, subsequent returns were related to trading volume.

These studies tested the relationship between pre-event and post-event returns on a longer-term time horizon. By forming winning and losing portfolios based on long-term returns, they found that post-portfolio formation returns are negatively related to pre-portfolio formation returns. Some also used filter rule methodologies.

Implicit in these longer-term findings is that investors often over- or undervalue 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]). This therefore 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 their portfolios, they will continue to buy, hence prices will continue to rise. The opposite is true if investors are confident that the market will diminish their portfolio value. The degree of confidence, or perhaps overconfidence, is directly related to the imbalance in supply and demand as reflected in returns.

One way this study extends 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, I test the effect of one-day price shocks on subsequent short-term price behavior within those long-term trends.

Theories of Behavior

Most of the prior work outlined thus far falls under the behavioral theory known as *overreaction*. This theory, which suggests that people attach too much importance to dramatic events (De Bondt and Thaler [1985]), 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 overconfident investors are likely to adjust their expectations slowly (rather than quickly) in the presence of contradictory evidence 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 hold losing stocks too long in hopes of a recovery and sell winners too quickly.

Odean [1998] tested the *disposition effect*, a related theory documenting the tendency of 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, Statman, and Constantinides [1985], and lead to asymmetric post-event price behavior.

This study contributes to these findings by testing whether the price shock's direction changes this investor preference.

Many behavioral theories have been tested in the area of consumer behavior, and perhaps the largest is *attribution theory*. Recently, Weiner [2000] examined attribution theory for the role that it might play in consumer behavior. He stated that rational choice theory suggests that product selection is partly determined by the anticipated satisfaction with the product. The role of attribution theory is not in forming expectations about initial outcomes, but about forming expectations of subsequent outcomes *in light of* prior outcomes. Attributions are formed when evaluating the outcome with respect to expectations. Weiner [2000] gave three known properties of causal reasoning that guide this evaluation: causal stability, causal locus, and causal controllability. Causal stability is the most relevant here.

Causal stability posits that if an outcome is attributed to a stable cause, the same outcome will be anticipated in the future. Conversely, if an outcome is attributable to a non-stable cause, the future expectation will be either uncertain or different from the immediate past.

For example, if a box of cereal is purchased and tastes bad, 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, we might consider it just a "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, the same outcome will be anticipated in the future, which will result in price drift. Conversely, if the price shock is attributed to a non-stable cause, the future outcome will either be uncertain or 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 expectations. Ganzach [2000] conducted a related study of how people judge the risk and return of financial assets. He found that 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 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.

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. Various theories exist to 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 later I offer four investor confidence hypotheses as a behavioral model of expected returns.

Data and Methodology

Data

To construct the sample, I use daily returns for companies from the 2002 Fortune 500 index. The initial sample consists of all the companies in the index. I use the Fortune 500 index because these firms are among the most widely followed by analysts and have a sufficient history from which to collect data. Using these firms also reduces the number of events that must be eliminated when controlling for potential bid/ask bounce.

First, the fundamental variables are obtained from Research Insight. The three variables I use are 1) basic earnings per share, including extraordinary items, 2) book value per share, and 3) total debt to total equity. Since the observation period starts on January 1, 1988, and the three-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 January 1, 1988-December 31, 2000. If there is no data available for a particular firm, 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 variables, so I drop those firms 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.

Daily return information is obtained from the CRSP database for the surviving firms for January 1, 1988-December 31, 2000. From this set, the event days are identified. Consistent with Bremer and Sweeney [1991], Cox and Peterson [1994], Larson and Madura [2003], 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:

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

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 the 2,254 events, 1,406 are positive and 848 are negative, 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 have proxies greater (less) than zero. The exception is for the debt-to-equity ratio, where strong (weak) markets have proxies less (greater) than zero.

Investor Confidence Hypotheses

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

$H1_0$: If investors are confident in the strength of the market, a large price decrease will be interpreted as a temporary opportunity to buy quality shares at a discount. Buyers will thus be attracted to the market, which will lead to a reversal in prices. This hypothesis is consistent with both *overreaction* (De Bondt and Thaler [1985]) 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 considered a "lemon" that would not stop investors from purchasing the good "product."

$H1_A$: Alternatively, if prices continue down, investors would attribute large price shocks to *stable causality* (Weiner [2000]). That is, the large price decrease in a good market would be attributed to a stable cause. Consistent with the *overconfidence theory* (Scott and Stumpp [1999]), investors would continue to sell. This could support *prospect theory* (Scott and Stumpp [1999]) and the *disposition effect* (Odean [1998]) if the results are different than those in $H3_A$.

Table 1. *Summary of Hypotheses*

Hypothesis	Market	Event	CAR	Behavioral Theory
$H1_0$	Strong	Negative	Positive	Overreaction, Causal Non-Stability
$H1_A$	Strong	Negative	Negative	Causal Stability, Overconfidence, Prospect Theory if Different from $H3_A$
$H2_0$	Strong	Positive	Positive or Stable	Causal Stability or Efficient Market Hypothesis
$H2_A$	Strong	Positive	Negative	Overreaction, Causal Non-Stability, Prospect Theory if Different from $H4_A$
$H3_0$	Weak	Positive	Negative	Overreaction, Causal Non-Stability
$H3_A$	Weak	Positive	Positive or Stable	Causal Stability, Overconfidence, or Efficient Market Hypothesis, and Prospect Theory if Different from $H1_A$
$H4_0$	Weak	Negative	Negative or Stable	Causal Stability, Efficient Market Hypothesis
$H4_A$	Weak	Negative	Positive	Overreaction, Causal Non-Stability, Prospect Theory if Different from $H4_A$

Note: This table presents a summary of the investor confidence hypotheses and the supporting behavioral theory. For example, if the first null hypothesis is correct, it provides evidence for the overreaction hypothesis and the causal non-stability theory of behavior.

$H2_0$: If investors are confident in the strength of the market, large price increases will be interpreted as further confirmation of its strength. Hence, no new sellers would be attracted to the market and investors would continue to buy, causing prices to either be stable or to drift higher. In this situation, the efficient market hypothesis (EMH) predicts that prices should be stable. Because the event is in the same direction as the pre-event characteristics, however, price drift would be observed under *causal stability* (Weiner [2000]).

$H2_A$: Alternatively, both *overreaction* (De Bondt and Thaler [1985]) and *non-stable causality* (Weiner [2000]) predict price reversals, which would provide support for *prospect theory* (Scott and Stumpp [1999]) if the results are different than those in $H4_A$.

$H3_0$: If investors are confident in the weakness of the market (that is, its potential to diminish portfolio value), large price increases will be interpreted as a temporary opportunity to sell low-quality shares at a premium. Thus, sellers would be attracted to the market, leading to price reversals as investors exit. 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 EMH, and possibly *prospect theory* (Scott and Stumpp [1999]) and the *disposition effect* (Odean [1998]) if the results are different from those in $H1_A$. Positive subsequent returns would be consistent with *overconfidence* (Scott and Stumpp [1999]) and *stable causality* (Weiner [2000]). Price drift would be consistent with Ganzach [2000], and imply that 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, large price decreases are interpreted as further confirmation of the market's weakness. No new buyers would be attracted to the market and no subsequent reversal should occur. Thus, *causal stability* (Weiner [2000]) predicts price drift, while EMH 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 the results are different from those in $H2_A$. Furthermore, a price reversal would be consistent with Ganzach [2000].

Methodology

I use event study methodology to test the relationship between pre-event variables and post-event cumulative abnormal returns. I first test the data 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. Control variables are then introduced using regression analysis, and the results are compared to those from 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.

Test of Means. 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.

For each of the six test variables, I then divide the entire database into two other groups: strong and weak markets (defined as in Section IIIA). The mean CARs for each group are tested as outlined above to determine whether abnormal returns appear to be associated exclusively with pre-event characteristics.

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 about these groups are in Table 2. For each group, the mean CARs are tested and the results compared and contrasted with the previous results.

Regression Analysis. The essence of the tests of means is to get a feel for potential drivers of abnormal returns. Consistent with EMH, 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, the particular grouping criteria are related to abnormal returns. Until now, no variables have been introduced for known drivers of abnormal returns; the next set of tests introduces these variables.

I use regression analysis to control specifically for the effects of Monday, January, and the size of the price shock effects. The database is grouped by exactly the same method as in the test of means. For each grouping, the following model is estimated:

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

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 with the value of 1 if the CAR period includes a Monday and 0 otherwise, and JAN is a dummy variable with the value of 1 if the CAR period includes a day in the month of January and 0 otherwise. The test variables are the intercept term (α) together with the coefficient (β_1) of the event day's return.

Again, consistent with EMH, there should be no drift in the database no matter 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 β_1, so the intercept term is interpreted together with β_1 as well as with 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 β_1 will measure the price shock effect. Taken together, I can form an inference about the effect of the grouping and the size of the price shock on the post-event cumulative abnormal returns.

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:

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

where CAR_{it} is as defined earlier, TEST is the specific test variables identified earlier (PR260, PR135, PR30,

Table 2. *Descriptive Statistics*

	Strong		Weak		
Proxies	Positive	Negative	Positive	Negative	Total Events
Panel A. Number of 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	1,150	697	256	151	2,254
DE	480	310	926	538	2,254
Panel B. Proxy Averages					
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	153.00%	232.00%	–308.00%	–173.00%	
BVPS	33.40%	28.34%	–48.59%	–45.16%	
DE	–26.87%	–23.82%	151.00%	355.00%	

Note: Strong markets have a proxy that is greater than zero, and negative markets have a proxy that is less than zero, and vice versa for the DE proxy. Positive events are one-day price increases of greater than 10%, and 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 three years prior to the event for earnings per share (EPS), book value per share (BVPS), and total debt to total equity (DE).

EPS, BVPS, and DE), and the remaining control variables are the same as defined earlier. Because each test variable has two subsets and each post-event period is tested individually, this regression is estimated thirty-six times. If β_1 is positive, there is a relationship between post-event cumulative abnormal returns and the magnitude of pre-event characteristics. If β_1 is negative, the opposite is true. I refer to this relationship as the magnitude effect.

Results

Test of Means

Panel A of Table 3 shows the results of testing the mean post-event 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 shows the results of grouping the database into positive and negative events to determine if the event day's direction affects investor behavior. None of the CARs following positive events are significantly different from zero, but all 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 show the results of grouping the database into strong and weak markets to determine if pre-event variables affect investor behavior. All the CARs except one are positive and significant for all the strong market groupings. Very few of the CARs are significantly different from zero in the weak mar-

Table 3. *Test of Means*

	CAR [1, 1]	CAR [1, 2]	CAR [1, 3]
Panel A. Entire Database			
n	2254	2254	2254
Mean	0.42%	0.55%	0.78%
t-stat	3.38*	3.58*	4.70*
Panel B. Positive and Negative Events			
n	1406	1406	1406
Mean – Positive	0.07%	–0.04%	0.35%
t-stat	0.49	–0.23	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	0.70%	0.84%	1.03%	0.59%	0.67%	0.84%	0.41%	0.64%	0.67%
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	0.50%	0.65%	0.94%	0.51%	0.62%	0.92%	0.28%	0.44%	0.80%
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	0.06%	0.05%	0.33%	0.22%	0.41%	0.70%	0.43%	0.48%	0.87%
t-stat	0.27	0.19	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	0.27%	0.35%	0.45%	0.03%	0.27%	0.12%	0.50%	0.61%	0.76%
t-stat	1.23	1.25	1.50	0.09	0.63	0.27	3.13*	3.05*	3.62*

kets, indicating that post-event abnormal returns appear to be associated with strong pre-event characteristics. In other words, investors generally use price shocks as buying opportunities 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 [-30, -10] are negative, a price shock appears to trigger buying for the three days following the shock. The same holds for the period [-135, -10], except that the buying apparently doesn't 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.

In sum, with 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, I group the database by both strong and weak markets as well as by positive and negative events. The results are in Table 4.

Overall, the results in Table 4 are not surprising. The large number of significant events in Panel B of Table 4 is consistent with expectations. However, Panel A shows that rising pre-event EPS and BVPS, in combination with a positive price shock, appear to induce buying. Furthermore, the buying starts at least three days after the shock, suggesting a delayed reaction and 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 shows that positive events can trigger delayed buying 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 shows that abnormal returns following negative price shocks disappear if the returns for the period [-260, -10] are negative or if the firm's BVPS 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, Panels C and D of Table 4 both show that the price shock's direction can influence this relationship. PR135, PR30, and DE are generally consistent with Table 3 for negative events. For positive events, the reaction is still present, but appears delayed. Moreover, if the weak market is defined by decreasing EPS, then negative events do trigger buying, contrary to Panel D of Table 3. Positive events do not appear to induce the same behavior, however.

Our main goal, however, is to determine if there is a relationship between certain pre-event firm and market characteristics and post-event returns. The results so far suggest there is a relationship, but it 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 induce abnormal investor behavior, but negative price shocks do, as evidenced by the post-event abnormal returns. Yet Panels A and C of Table 4 show that post-event abnormal returns follow positive price shocks for every pre-event characteristic grouping except PR260. This is strong evidence of a relationship between pre-event characteristics and post-event returns. In other words, pre-event characteristics seem to contain information beyond what is contained in the price shock itself.

Interestingly, all of these abnormal returns show a delayed reaction. However, the tests so far have not controlled for other variables that drive post-event returns. The next section presents the regression results after controlling for these variables.

Regression Analysis

Table 5 shows the regression results for the same groupings shown in Table 3. After controlling for the Monday and January effects, Panel A of Table 5 shows that the intercept term is positive and significantly different from zero, which is consistent with Panel A of Table 3. 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, as the day immediately following the price shock is not significantly different from zero. Additionally, exclusive of Monday and January effects, the CARs appear 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 because the price shock's direction would determine the effect on CARs. Conversely, in Panel B, the database is grouped into positive and negative events, which makes a joint inference more plausible. Consistent with Table 3, Panel B of Table 5 shows no significant results for positive events, and all significant results for negative events (at the 0.01 level nonetheless). Again, this suggests a relationship between negative events and post-event CARs.

More specifically, when the negative events are grouped together, all the intercept terms detect a positive drift in the data. This suggests that investors tend to buy following negative events. In addition, all the β_1 coefficients are significant but positive.[5] It thus appears that larger price shocks tend to mitigate the en-

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	0.08%	−0.11%	0.25%	−0.01%	−0.17%	0.20%	0.11%	−0.08%	0.15%
t-stat	0.47	−0.52	1.04	−0.06	−0.77	0.80	0.55	−0.33	0.54
		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	0.11%	0.04%	0.49%	0.12%	−0.08%	0.40%	−0.25%	−0.38%	0.13%
t-stat	0.61	0.19	2.13**	0.80	−0.44	2.00**	−1.00	−1.36	0.41
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%	0.92%	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*
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	0.07%	0.06%	0.50%	0.17%	0.11%	0.51%	0.04%	−0.01%	0.52%
t-stat	0.26	0.19	1.47	0.71	0.38	1.65***	0.18	−0.04	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	0.00%	−0.21%	0.08%	−0.12%	0.11%	0.10%	0.24%	0.13%	0.46%
t-stat	0.00	−0.62	0.22	−0.27	0.20	0.17	1.26	0.57	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	−0.31%	0.05%	0.00%	0.32%	0.96%	1.04%	1.07%	1.28%	1.43%
t-stat	−0.82	0.11	0.00	0.97	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	0.71%	1.31%	1.08%	0.28%	0.55%	0.16%	0.96%	1.44%	1.27%
t-stat	1.73***	2.73*	2.12**	0.51	0.79	0.22	3.31*	4.11*	3.43*

Note: *, **, and *** denote significance at the 0.01, 0.05, and 0.10 levels, respectively. For each grouping, the first line is the post-event test period, the second line is the sample size, the third line is the mean cumulative abnormal return for each test period, 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.

thusiasm of buyers following negative price shocks. But relative to the intercept term, β_1 is small. 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 is reduced by about 18% of the price shock's size. So if the price

Table 5. *Regression Analysis*

	CAR [1, 1]	CAR [1, 2]	CAR [1, 3]
Panel A. Entire Database			
Intercept	0.20%	0.40%	0.60%
	1.35	1.99**	3.17*
Coefficient	–0.019	–0.040	–0.024
	–2.06**	–3.57*	–2.06**
Panel B. Positive versus Negative Events			
Intercept – Pos	–0.40%	0.20%	1.0%
	–0.778	0.288	1.42
Coefficient – Pos	0.029	–0.021	–0.053
	0.708	–0.434	–0.991
Intercept – Neg	2.2%	2.9%	3.4%
	3.59*	3.75*	4.18*
Coefficient – Neg	0.121	0.151	0.180
	3.08*	3.03*	3.45*

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	0.4%	0.6%	0.8%	0.3%	0.3%	0.5%	0.2%	0.7%	0.7%
t-stat	2.35**	2.53**	3.39*	1.50	1.48	2.17**	0.99	2.69*	2.38**
β_1	–0.037	–0.061	–0.047	–0.039	–0.058	–0.037	–0.016	–0.055	–0.033
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	0.3%	0.4%	0.7%	0.3%	0.5%	0.7%	0.1%	0.1%	0.4%
t-stat	1.88***	2.09**	3.27*	2.16**	2.52**	3.66*	0.35	0.31	1.26
β_1	–0.029	–0.043	–0.028	–0.025	–0.049	–0.031	–0.038	–0.055	–0.040
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	–0.2%	–0.1%	0.2%	0.1%	0.4%	0.7%	0.2%	0.1%	0.5%
t-stat	–0.96	–0.27	0.54	0.36	1.26	2.27**	0.92	0.295	2.08**
β_1	0.019	0.004	0.019	0.5%	–0.018	–0.009	–0.020	–0.025	–0.015
t-stat	1.23	0.21	0.961	0.39	–1.05	–0.53	–1.57	–1.58	–0.95
	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	–0.1%	0.2%	0.3%	–0.5%	–0.2%	0.0%	0.2%	0.5%	0.7%
t-stat	–0.27	0.52	0.92	–1.12	–0.43	–0.08	1.36	2.16**	2.94*
β_1	0.000	–0.033	–0.017	0.012	0.000	0.003	–0.9%	–0.032	–0.017
t–stat	0.021	–1.68**	–0.81	0.50	–0.07	0.10	–0.78	–2.32**	–1.15

Note: *, **, and *** denote significance at the 0.01, 0.05, and 0.10 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 CAR_{it} is the cumulative 1-, 2-, or 3-day cumulative abnormal return, RET is the magnitude of the event day return, and MON and JAN are the Monday and January dummy variables, with the value of 1 if true and 0 otherwise. Proxies as well as positive and negative events are as defined in Table 2. Strong markets have a proxy that is greater than zero, negative markets have a proxy that is less than zero, and vice versa for the DE proxy.

shock is a 15% drop in prices, in the absence of Monday and January effects, the CARs for [1, 3] seem to be about 0.7%. There does appear to be buying following negative price shocks, but extremely large negative price shocks seem to drive buyers away.[6]

The results in Panels C and D of Table 5 are generally consistent with those from Panels C and D of Table 3. That is, for strong markets, the intercept term detects 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 DE has been decreasing. For weak markets, the results are similar, except that the buying seems to be more delayed in the presence of control variables.

Table 6 shows the regression results for the same groupings as in Table 4. When the database is grouped by pre-event characteristics and price shock direction, the regression results are similar to those from the tests of the means. For positive events in strong markets (Panel A), most of the results are insignificant. The exception is for EPS, which, similarly to Table 4, shows positive CARs.

In Panel B, most of the intercept terms are positive and significant, consistent again with Table 4. Additionally, most of the β_1 coefficients are positive and significant, consistent with Panel B of Table 5. This again suggests that even when the pre-event characteristics are strong, larger negative price shocks appear to reduce post-event investor buying.

The regression results for positive events in weak markets show that the control variables highlight additional significant relationships beyond those found in the tests of means (Panel C of Table 6). Specifically, both tests reveal positive and delayed CARs for the PR125 and DE groupings. However, PR30 is no longer significant. More interestingly, PR260, EPS, and BVPS become significant when the control variables are included.

The different signs indicate differing investor behavior. When the cumulative returns in the pre-event period [-260, -10] are negative, investors appear to use positive price shocks as a buying opportunity (indicated by the positive and significant intercept term). In addition, the β_1 coefficient is negative and mildly significant, suggesting that more positive price shocks reduce investor enthusiasm to buy. This could be due to investor caution about overreaction.

The same results hold for BVPS over the post-event period [1, 3]. However, in the post-event period [1, 1], EPS and BVPS have the opposite signs. The intercept terms suggest that when these two variables have been decreasing prior to the positive price shock, investors will use this as an opportunity to sell. However, the β_1 coefficients are positive. This implies a price shock effect, a mitigating effect imposed on the abnormal returns based on the size of the price shock.

The results in Panel D of Table 6 are consistent with those in Panel D of Table 4. But the presence of the control variables in the regression analysis again highlights additional significant relationships. PR135 becomes significant the day after the price shock when the control variables are added. In addition, PR260 and BVPS are significant for [1, 3]. Finally, for [1, 1], the intercept for 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, note that this appears to reverse starting the third day after the event.

Magnitude Effect

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

Panel B shows the results of strong markets with negative events. All the coefficients based on the prior return groupings are significant (at the 0.05 and 0.01 levels), but only one based on firm characteristics is significant (at the 0.10 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 has the largest coefficients. Investors not only buy stocks with a large price decline when prices have been rising (Table 4, Panel B), but the magnitude of the rise, especially over the prior month, influences their decisions. By contrast, none of the changes in firm characteristics[7] is related in magnitude to post-event returns.

Panel C shows the weak market, positive event day results, and Panel D shows the weak market, negative event day results. All are insignificant, suggesting no magnitude effect. However, for negative events, there appears to be a magnitude effect when pre-event prices are rising (strong markets) that disappears when pre-event prices are declining (weak markets). This implies that investors interpret large price declines differently based on the sign of the pre-event returns (Table 4, Panels B and D) and on the magnitude of the returns if positive.

Multivariate Investor Confidence

All the tests have attempted to isolate specific pre-event characteristics to determine if investors use them when making buy and sell decisions. However, instead of using any one variable exclusively, investors probably use multiple variables when making these decisions. To lay the groundwork for this probability, I conduct two additional tests of means.

I first group the data into strong and weak markets based on whether all six of the pre-event characteristics are contemporaneously strong or weak. I then 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

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	–0.2%	0.0%	–0.1%	–0.7%	0.0%	0.2%	–0.8%	0.9%	0.6%
t-stat	–0.356	–0.02	–0.17	–1.02	–0.04	0.21	–1.03	1.00	0.57
β_1	0.015	–0.006	0.035	0.040	–0.016	–0.002	0.055	–0.08	–0.037
t-stat	0.28	–0.09	0.49	0.77	–0.26	–0.03	0.95	–1.11	–0.44

	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	0.6%	1.0%	1.6%	0.6%	0.6%	0.3%	0.6%	1.0%	0.1%
t-stat	0.85	1.19	1.84***	0.97	0.76	0.34	0.56	0.84	0.04
β_1	–0.047	–0.072	–0.088	–0.042	–0.045	0.011	–0.058	–0.100	0.007
t-stat	–0.89	–1.20	–1.33	–0.90	–0.83	0.19	–0.72	–1.09	0.07

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%	0.30%	1.7%	2.3%	0.032	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	0.106	0.135	0.127	0.066	0.105	0.165	0.084	0.129	0.165
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	0.104	0.180	0.197	0.112	0.145	0.151	0.073	0.182	0.163
t-stat	2.04**	2.64*	2.80*	2.64*	2.70*	2.68*	1.16	2.14**	1.83***

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	–0.5%	0.6%	2.4%	–0.1%	0.5%	1.9%	–0.2%	–0.2%	1.4%
t-stat	–0.57	0.56	2.13**	–0.11	0.49	1.76***	–0.22	–0.27	1.42
β_1	0.035	–0.052	–0.158	0.015	–0.031	–0.107	0.011	0.011	–0.068
t-stat	0.54	–0.68	–1.93***	0.24	–0.42	–1.33	0.19	0.17	–0.97

	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%	–0.6%	0.5%	–2.8%	–0.1%	2.9%	–0.7%	0.1%	1.5%
t-stat	–2.11**	–0.56	0.41	–2.11**	–0.07	1.66***	–1.02	0.07	1.68***
β_1	0.133	0.025	–0.038	0.167	–0.017	–0.22	0.051	–0.003	–0.077
t-stat	2.04**	0.30	–0.41	1.77***	–0.15	–1.78***	1.06	–0.06	–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	0.119	0.139	0.256	0.147	0.170	0.178	0.155	0.171	0.191
t-stat	1.62	1.59	2.82*	2.74*	2.59*	2.59*	2.78*	2.44**	2.67*

(continued)

Table 6. *(Continued)*

	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	0.139	0.115	0.156	0.177	0.196	0.346	0.139	0.124	0.174
t-stat	2.23**	1.58	2.03**	1.67***	1.44	2.54**	2.78*	2.00**	2.71*

Note: *, **, and *** denote significance at the 0.01, 0.05, and 0.10 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 CAR_{it} 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 with the value of 1 if true and 0 otherwise. Proxies as well as positive and negative events are as defined in Table 2. Strong markets have a proxy that is greater than zero, negative markets have a proxy that is less than zero, and vice versa for the DE proxy.

Table 7. *Magnitude Effect*

	PR260	PR135	PR30	EPS	BVPS	DE
Panel A. Strong Markets, Positive Event Days						
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	0.10
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						
CAR [1, 1]	0.01	0.03	0.12	0.00	0.01	0.01
	**0.03	*0.00	*0.00	0.57	***0.09	0.35
CAR [1, 2]	0.02	0.05	0.14	0.00	0.01	0.01
	*0.00	*0.00	*0.00	0.67	0.25	0.37
CAR [1, 3]	0.02	0.05	0.17	0.00	0.00	0.01
	*0.01	*0.00	*0.00	0.73	0.60	0.41
Panel C. Weak Markets, Positive Event Days						
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						
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

Note: *,'**, and *** denote significance at the 0.01, 0.05, and 0.10 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 CAR_{it} is the cumulative 1-, 2-, or 3-day cumulative abnormal return, RET is the magnitude of the event day return, and MON and JAN are the Monday and January dummy variables, with the value of 1 if true and 0 otherwise. The first row is the coefficient ((β_1), and the second row is the related p-value. TEST is the specific proxy being tested; the coefficient of this variable captures the magnitude effect. Proxies are as defined in Table 1, and positive and negative events are as defined in Table 2. These results suggest there is only a magnitude effect for negative event days within strong markets.

pre-event return variables, and strong and weak markets based on all three pre-event firm characteristics. Each group is then further divided into two more groups based on positive and negative events.

For brevity, I do not show the results of these final tests, but they are consistent with those from Tables 3-6. That is, for the strong and weak market groupings that include positive and negative events, post-event returns in strong markets are 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 0.01 level). This is consistent with prior findings and provides further support for Hypotheses $H1_0$, $H2_0$, and $H4_0$.

Summary of Findings and 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, the shock will be attributable to a non-stable cause. Most of the results confirm this prediction, as evidenced by the positive CARs in Panel B of Table 4, and the positive intercept terms in Panel B of Table 6. In addition, investor confidence appears to be strengthened by the magnitude of positive pre-event returns, as shown by Panel B of Table 7. However, the beta coefficients in Panel B of Table 6 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. In this case, if there is such confidence, the shock will be attributable to a stable cause. Panels A of Tables 4, 6, and 7 appear to support this hypothesis. Very few of the results are significant; those that are suggest a post-event drift in prices. Taking Panels A and B together, all the pre-event characteristics seem to affect post-event abnormal returns, suggesting 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, investors will attribute the shock to a non-stable cause. As Panel C of Table 7 shows, two of the results support this prediction.

Specifically, decreasing earnings per share and book value per share appear to drive investors' lack of confidence in the market. If investors are presented with a positive price shock under such circumstances, they use it as an opportunity to sell. The magnitude of the decrease does not appear to influence investor confidence, but the size of the price shock does. The remaining results in Panels C of Tables 4 and 7 do not support the third hypothesis. The results appear 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, they attribute the shock to a stable cause. The results in Panels D of Tables 4 and 7 do not support this hypothesis. Investors attribute shocks under these circumstances to a non-stable cause, which is consistent with the overreaction literature and possibly with Ganzach [2000].

A secondary goal of this paper is to determine whether there is a difference in informational content between pre-event returns and pre-event fundamental firm characteristics. Although some pre-event variables seem more informative in certain situations than others, overall, there is no clear dichotomy.

A notable exception is the magnitude effect of pre-event positive returns on post-event positive abnormal returns following a negative price shock. In this situation, all the returns-based characteristics are significant at the 0.01 level (except for one, which is significant at the 0.05 level), and none of the firm fundamentals-based characteristics are significant (except for one, significant at the 0.10 level).

Conclusion

I offer four investor confidence hypotheses in this paper. Each suggests that investors will react differently to one-day price shocks based on how much confidence they have in the market to provide future returns. In an attempt to capture investor confidence, I compute and test six different proxies: pre-event arithmetic average daily returns over the periods [-260, -10], [-135, -10], and [-30, -10], and 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 (less than zero), they are referred to as strong markets (weak markets), and 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 or negative events, respectively. To determine investor reaction, I calculate cumulative abnormal returns over the periods [1, 1], [1, 2], and [1, 3].

My findings indicate that negative price shocks generally 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, this relationship is altered when these events are cross-sectionalized by the six pre-event characteristics, suggesting that these characteristics influence investor behavior and may proxy for investor confidence.

Additionally, I find evidence of a price shock effect whereby post-event reversals are smaller for larger price shocks. The larger the shock, the more likely investors are to attribute it to a stable rather than a non-stable cause. This suggests that investor confidence in the 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 in weak ones. 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 contain 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 trigger delayed buying when a firm's EPS has been rising.

By contrast, post-event abnormal returns appear to be triggered when five of the six pre-event characteristics have indicated a weak market. Positive post-event abnormal returns are related to declining returns over [-260, -10] and [-135, -10], as well as declining book value per share (for [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 [1, 1]).

The pre-event characteristics were also tested for the presence of a magnitude effect with post-event abnormal returns. I find a relationship in the context of negative price shocks when pre-event returns are strong. In this situation, post-event abnormal returns are 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 fundamental characteristics. The notable exception is the magnitude effect.

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

Acknowledgements

The author would like to acknowledge the very helpful and valuable comments received from Donna Bobek, Keith C. Brown, Gunduz Caginalp, Joel Harper, Jeff Madura, Ted Moore, and Stefan Ruenzi, as well as two anonymous referees.

Notes

1. I use the term "investor confidence" to refer to investor expectations about future returns and their conviction of those expectations.
2. Brown, Harlow, and Tinic [1988, 1993] show that the arrival of both favorable and unfavorable uncertain information tends to increase volatilities and required rates of return. Furthermore, risk decreases take a longer time to manifest than risk increases, which may help explain the asymmetrical nature of price behavior.
3. There are a number of overreaction models. As an example, see Barberis, Shleifer, and Vishny [1998] and the references 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 risk-adjusted returns are almost equally likely to detect abnormal returns at both the 0.05 and 0.01 levels. 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." 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. Size actually 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 from Panels A and B is that, for the entire database, $\beta 1$ is negative, but when grouped, $\beta 1$ for positive events is not significantly different from zero and $\beta 1$ 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 the other quartiles were positive and highly significant.
7. With the exception of book value per share over [1, 1], which is only significant at the 0.10 level.

References

Abraham, Abraham, and David L. Ikenberry. "The Individual Investor and the Weekend Effect." *Journal of Financial and Quantitative Analysis,* 29, (1994), pp. 263–278.

Aharony, Joseph, and Itzhak Swary. "Additional Evidence on the Information-Based Contagion Effects of Bank Failures." *Journal of Banking and Finance*, 20, (1996), pp. 57–69.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 49, (1998), pp. 307–343.

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

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

Brown, Keith, W.V. Harlow, and Seha M. Tinic. "The Risk and Required Return of Common Stock Following Major Price Innovations." *Journal of Financial and Quantitative Analysis*, 28, (1993), pp. 101–116.

Brown, Stephen J., and Jerold B. Warner. "Measuring Security Price Performance." *Journal of Financial Economics,* 8, (1980), pp. 205–258.

Chopra, N., J. Lakonishok, and J.R. Ritter. "Measuring Abnormal Performance: Do Stocks Overreact?" *Journal of Financial Economics*, 313, (1992), pp. 235–268.

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

Cox, Don R., and David R. Peterson. "Stock Returns Following Large One-Day Declines: Evidence of Short–Term Reversals and Longer-Term Performance." *Journal of Finance,* 49, (1994), pp. 255–267.

De Bondt, W.F.M., and R.H. Thaler. "Does the Stock Market Overreact?" *Journal of Finance,* 40, (1985), pp. 793–805.

De Bondt, W.F.M., and R.H. Thaler. "Further Evidence on Investor Overreaction and Stock Market Seasonality." *Journal of Finance*, 42, (1987), pp. 557–580.

Fabozzi, Frank J., Christopher K. Ma, William T. Chittenden, and Daniel R. Pace. "Predicting Intraday Price Reversals." *Journal of Portfolio Management*, 21, (1995), pp. 42–54.

Fama, Eugene F., and Kenneth R. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47, (1992), pp. 427–465.

Fung, Alexander Kwok-Wah, Debby MY Mok, and Kin Lam. "Intraday Price Reversals for Index Futures in the US and Hong Kong." *Journal of Banking & Finance*, 24, (2000), pp. 1179–1201.

Ganzach, Yoav. "Judging Risk and Return of Financial Assets." *Organizational Behavior and Human Decision Processes*, 83, (2000), pp. 353–370.

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

Kuhberger, Anton. "The Influence of Framing on Risky Decisions: A Meta-Analysis." *Organizational Behavior and Human Decision Processes,* 75, (1998), pp. 23–55.

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

Ma, Christopher K., James E. Mallett, R. Daniel Pace, and William Chittenden."Intraday Drifts." *Journal of Investing*, 8, (1999), pp. 86–98.

Odean, T. "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance*, 53, (1998), pp. 1775–1798.

Pritamani, Mahesh, and Vijay Singal. "Return Predictability Following Large Price Changes and Information Releases." *Journal of Banking & Finance*, 25, (2001), pp. 631–656.

Scott, James, and Mark Stumpp, 1999, "Behavioral Bias, Valuation and Active Management." *Financial Analysts Journal,* 55, (1999), pp. 49–57.

Shefrin, Hersh, Meir Statman, and George M. Constantinides. "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence/ Discussion." *Journal of Finance*, 40, (1985), pp. 777–793.

Weiner, Bernard. "Attributional Thoughts About Consumer Behavior." *Journal of Consumer Research*, 27, (2000), pp. 382–387.

Zarowin, Paul. "Size, Seasonality, and Stock Market Overreaction." *Journal of Financial and Quantitative Analysis*, 25, (1990), pp. 113–126.