Stock Overreaction to Extreme Market Events

Mo Chaudhury[*] and Pedro Piccoli**

ABSTRACT

In this paper we find that stocks overreact to both positive and negative extreme daily movements of the broader market, but more intensely in the latter case. The overreaction is even more pronounced when the market exhibits clustered extreme swings, indicating that the overreaction is related to market volatility. Indeed, a contrarian investment strategy earns a significant Fama-French daily alpha of 0.34% (85.68% annualized) with a Sharpe ratio of 5.23 in highly volatile circumstances. Stock overreaction appears to be driven by the loser stocks that revert more strongly, even as they exhibit a lower market beta than the winners.

Keywords: Overreaction, contrarian strategy, momentum crash, market efficiency, extreme market events.
EFM Classification Codes: 350, 320.

---

[*]Desautels Faculty of Management, McGill University, 1001 Sherbrooke St W, Montreal, QC, Canada H3A 1G5, Tel: +1 (514) 398 5927, Email: mo.chaudhury@mcgill.ca.
**(Corresponding author) Graduate Research Trainee, Desautels Faculty of Management, McGill University, 1001 Sherbrooke St W, Montreal, QC, Canada H3A 1G5, and PhD student in Finance Pontifical Catholic University of Paraná Business School, Brazil, Euzébio da Motta, 768 ap. 42, Curitiba, Paraná, Brazil 80.530-260, Tel: 55 41 9262-6661, Email: pedro.r.piccoli@gmail.com.

1 Introduction

Stock market movements on some days can be considered unusually high compared to their fluctuations on most other days. If such extreme daily market movements represent an efficient/rational response to major value relevant information and events, trading the individual winning and losing stocks on such days should not offer profits in the days following. Alternatively, the extreme market movements may not be efficient in the sense that the immediate response is an overreaction meaning more than due adjustment in prices. If prices in the days following revert to the proper level, a contrarian strategy may generate abnormal trading profit. On the other hand, despite a large move, the immediate response may still represent an underreaction or the later adjustments may be delayed overreactions. In this case, a momentum style strategy may generate abnormal trading profit.

Despite an ever growing literature on market efficiency/rationality and contrarian versus momentum strategies, there is a lack of empirical evidence in this regard in the context of extreme daily market movements. Using daily returns from 1926 to 2013, this paper attempts to reduce this gap by providing empirical evidence on the short-term (21 trading days) profitability of contrarian versus momentum portfolios of US stocks formed on the days of extreme daily movements in the broader US market.

The empirical exercise in this paper brings together three major strands of literature, the overreaction (cum irrational exuberance-excess volatility) hypothesis (De Bondt and Thaler, 1985, Shiller, 1981), the momentum strategy as an investment style (Jegadeesh, 1990, Jegadeesh and Titman, 1993), and the extreme or tail risk phenomenon in financial markets. The overreaction and momentum literatures are mostly based on portfolio formation and performance evaluation using typical returns over many sequential long intervals of a month to more than a year. In contrast, as the extreme risk phenomenon refers to market moves that are high in severity but low in frequency, it is relatively short in duration. This is most dramatically illustrated by the US market crash of 1987 and the 2008-09 financial crisis. Extreme market movements, however, can also occur on days of major macroeconomic or leading company information and geopolitical events, or simply due to technical trading (overbought/oversold).

To our knowledge, there is not much published evidence about the extreme risk phenomenon from the perspectives of the overreaction and momentum literatures. An extreme market movement may indeed represent an appropriate and immediate price adjustment warranted by a significant change in the drivers (growth and risk perceptions and risk preference) of valuation. It may, however, be an immediate overreaction or even an underreaction. The informational efficiency of extreme market movements is thus an empirical issue that we strive to answer first.

Second, while the extreme negative events (market returns) draw headlines, extreme positive events do also happen and cannot be ignored. An interesting empirical question is whether the market's informational efficiency is different in the context of extreme negative versus positive developments. If there is indeed a difference, then the profitable trading strategies will also be different conditional upon extreme negative versus positive market movements.

Third, the profitability of a contrarian strategy (long the past losers, short the past winners) in support of the overreaction hypothesis rests on return reversal while that of a momentum style strategy (short the past losers, long the past winners) relies upon return continuation. Whether returns reverse or continue may, however, depend on the term structure of returns and the investment horizon (De Bondt and Thaler, 1985, Jegadeesh and Titman, 2001, Novy-Marx, 2012, Goyal and Wahal, 2013). Short term return reversal is reported by Brown, Harlow and Tinic (1988), Lehman (1990) and Atkins and Dyl (1990).[1] There is, however, little published research about return continuation versus reversal of extreme market movements, that is, whether an extreme fall in the market on one day is followed by an extreme fall or rise in the market in the following days and vice versa.[2] As our events are defined using the broader market

[1] The extant literature shows that past losers tend to outperform past winners in the long run (three to five years), while the opposite pattern prevails in a shorter horizon (few months to a year). The evidence is mixed for very short horizons like a day. Varied explanations for these phenomena (Amini et al, 2013) relate to market microstructure (Cox and Peterson, 1994; Campbell, Lo and MacKinlay, 1997), change in risk (Brown, Harlow and Tinic, 1988; Pastor and Stambaugh, 2003), behavioral biases (Atkins and Dyl, 1990; Choi and Hui, 2014) and misinformation (Chan, 2003; Savor, 2012).

[2] Chaudhury (2011a) reports that the US stocks had many days of extreme upswings in the midst of the general downturn during the recent financial crisis, leading to unprecedented volatility but reduced skewness.

movements,[3] microstructure effects (bid-ask bounce, volume, etc.) and group or stock specific issues (e.g., size, earnings, book to market ratios, analyst coverage, etc.) should have minimal influence on our results. Further, as all individual stocks in this paper share the same event dates, our results are unlikely to be driven by misinformation about individual stocks.

Fourth, Daniel and Moskowitz (2013) report that the conventional static momentum strategy "crashes" during periods of high market volatility following a bear market (cumulative negative return of the CRSP VW Portfolio over the last 24 months). Although not studied directly, this result is indicative of the implication of extreme movements in the overall market. This paper provides additional evidence in this regard by examining portfolios that are formed conditional upon the infrequent but extreme daily movements in the broader market.

Our results show that the US market overreacts for both positive and negative events, but more intensely in the latter case where the contrarian strategy reaches a statistically and economically significant abnormal return of 4.17% (50.04% annualized) by the end of the post-event window. We study subsamples such as the non-overlapping and overlapping events, and overlapping events of same or opposite signals (signs) of extreme market movements. We find an economically and statistically significant overreaction in all cases, even when the overlapping events are of the same sign. This latter subsample, where the subsequent event reinforces the earlier one, the portfolio should exhibit momentum. Instead this subsample exhibits overreaction and the contrarian strategy yields a Fama-French daily alpha of 0.08% (20.16% annualized) over the post-event window of the earlier event.

The overreaction is of course stronger when the overlapping events are of opposite signals, with the contrarian strategy earning a Fama-French daily alpha of 0.19% (47.88% annualized) over the post-event window, and thus implying the possibility of volatility and overreaction being related. Indeed, the cumulative return of the contrarian strategy over the post-event window is 7.42% (1.99%), or 89.04% (23.88%) annualized, for the subsample of events with the highest (lowest) 30 percent instances of high market volatility. In the case of events in an environment of

[3] The days of extreme market movements are not necessarily also days of extreme movements for individual stocks.

high (above median) market volatility, the Fama-French daily alpha of the contrarian strategy is quite impressive at 0.21% (52.92% annualized) with a Sharpe ratio of 5.29.[4]

We also investigate if the contrarian profits are driven by the reversal of the winner or the loser portfolios, and find that the return reversal is generally more consistent and stronger for the losers than for the winners. Such a result is quite unexpected for the non-overlapping events as well as for the overlapping events with the same signal since for both the loser stocks exhibit a lower market beta than the winners.

Overall, our results provide consistent and strong support for the overreaction hypothesis hypothesis (De Bondt and Thaler, 1985, Shiller, 1981). Our finding of stock overreaction being very strong in the backdrop of high market volatility also lends support to the momentum strategy crashes in turbulent periods (Daniel and Moskowitz, 2013; Barroso and Santa-Clara, 2014). However, the overreaction of stocks cannot be explained by their systematic risk. Information based hypotheses such as the Uncertain Information Hypothesis (Brown, Harlow and Tinic, 1988) or the Information Hypothesis (Chan, 2003; Savor, 2012; Baule and Tallay, 2014) are not supported either by our results. A more appealing explanation is the behavioral bias (Griffin and Tversky, 1992) that investors exhibit overconfidence in events that are sizable/grave in magnitude but low in frequency, and hence they overreact.

The remaining of this paper is organized as follows. Starting with a brief review of studies dealing with large stock price movements in Section 2, data and methodology are described in Section 3. The empirical results are presented in Section 4 and summary and concluding remarks follow in Section 5.

2 Literature review

[4] In this paper, we calculate the Sharpe ratio as the average differential return of the contrarian portfolio over the market return deflated by the standard deviation of the differential return, all measured over the post-event window. As such, our Sharpe ratio is 0.0 for the market. A positive (negative) Sharpe ratio of the contrarian portfolio indicates that the contrarian portfolio outperforms (underperforms) relative to the market.

The focus in this paper is on the short-term reaction of individual stocks to extreme movements in the broader market. To place the empirical evidence of this paper in perspective, it is nonetheless worthwhile to briefly review the prior findings where events are defined in terms of large movements in individual stock prices.[5]

Brown, Harlow and Tinic (1988) found positive abnormal returns in the 60 days following an individual stock price change greater than 2.5% in magnitude, for both positive and negative shocks. They advocate that this supports the Efficient Market Hypothesis (EMH) since the positive abnormal returns simply reflect the increase in risk following the event. The authors name this framework as the Uncertain Information Hypothesis (UIH). It is to be noted that the abnormal returns should not persist after controlling for risk if the UIH holds. Also, according to the UIH, the post-event abnormal returns should be positive for both positive and negative initial events. In comparison, under momentum or return continuation, positive (negative) returns follow positive (negative) events, and under overreaction or return reversal, negative (positive) returns follow positive (negative) events.

Corrado and Jordan (1997) argue that the 2.5% event threshold of Brown, Harlow and Tinic (1988) is too low, thus generating too many events. For example, assuming a Normal distribution, this threshold means that one event is expected to occur every ten days. Accordingly, Corrado and Jordan (1997) employed a much larger event filter of 10% price change and found that, consistent with the Overreaction Hypothesis (OH) of De Bondt and Thaler (1985), the negative (positive) events are followed by positive (negative) abnormal returns (AR). Similarly, Bremer and Sweeney (1991) reported a significant price reversal (above average returns), for the individual stocks of Fortune 500, in the days after a stock experiences a large price decline such as more than 10%. Also, they did not find this phenomenon to be related to market movements. Further studies for distinct stock sets (Atkins and Dyl, 1990; Akhigbe, Gosnell and Harikumar, 1998), thresholds (Howe, 1986; Sturm, 2003; Madura and Richie, 2004) and markets (Atanasova and Hudson, 2007; Nguyen, Pham, and To, 2008) also documented a short-term reversal pattern.

[5] See Amini et al (2013) for a review of the literature.

However, employing a ±20% threshold, Himmelmann, Schiereck, Simpson and Zschoche (2012) reported positive abnormal returns on European stocks after both negative and positive events, thus supporting the UIH of Brown, Harlow and Tinic (1988). In contrast, although adopting the same threshold, Ising, Shciereck, Simpson and Thomas (2006) found overreaction (underreaction) to positive (negative) events in the German market. But, using a qualitative approach to define favorable and unfavorable events, Mehdian, Nas and Perry (2008) reported positive abnormal return for both cases in the Turkish market, lending support to the UIH.

A behavioral explanation that the findings of return reversal are consistent with was provided by Griffin and Tversky (1992). They argue that, in revising beliefs, people tend to focus on the "strength" or extremeness of available evidence (e.g., size of an effect) and pay insufficient attention to its "weight" or credence (e.g., size of the sample). This leads to overconfidence when "strength" is high and "weight" is low, and underconfidence when the opposite is the case. In the context of stock prices, this means that investors would tend to have overconfidence in events (news, developments) that are sizable/grave in magnitude but low in frequency, and hence would tend to overreact. Underreaction, on the other hand, is to result from underconfidence in events that are less material but more frequent.

Several studies, however, contradict the behavioral explanation of Griffin and Tversky (1992) by reporting underreaction after large price swings (Pritamini and Singal, 2001; Benou and Richie, 2003; Lasfer, Melnik and Thomas, 2003). In a reconciliation effort, Choi and Hui (2014) argue that the behavioral bias depends on the surprise or unexpected component/dimension of an event. As such, even if an event is quite sizable, market participants may underreact to it if the event was largely expected. In spirit, this explanation is similar to the Information Hypothesis (Chan, 2003; Savor, 2012; Baule and Tallay, 2014) that the large price swings accompanied by new public information result in return continuation (immediate underreaction/ delayed overreaction) while those without such information lead to return reversal (immediate overreaction). As the broader market does not generally experience a large daily swing without new publicly available information of broader market implications, we should expect return continuation (immediate underreaction/ delayed overreaction) in our tests according to the Information Hypothesis (IH).[6]

Aside from the fact that the above studies do not consider events in terms of extreme market movements, there is also an important methodological issue. With the exception of Corrado and Jordan (1997), most of the studies do not control their samples for overlapping events, that is, one or more days in the post-event period for calculating abnormal returns where the price change is of the magnitude used to define the event. It is thus not clear whether the reported abnormal returns support a given hypothesis (overreaction, momentum, IH or UIH), or simply reflect the influence of another extreme event in the "post-event" period. The extant evidence becomes even more confounded as many studies measure the expected (or normal) return from the "pre-event" window that itself contains an event in the case of an overlap.

This paper improves the event study methodology in question in a number of ways. First, we control for overlaps between events. We are not aware of any study that explicitly compares the results between overlapping and non-overlapping price shocks. Second, we divide the overlapping events into groups according to the signals (positive, negative) of the events: (a) momentum when they maintain the same signal, (b) contrarian when they reverse, and (c) mixed when several signals in the same window indicate a conflicting pattern. This procedure enable us to verify in which circumstances the abnormal reactions are more pronounced, enhancing the comprehension of the under and overreaction phenomena.

Third, our events are defined in terms of extreme market movement, but we employ the daily excess return of the stock (the return above or below the market) in the post-event period of abnormal return calculation. Thus, a given stock may have a movement of the market magnitude or more on the event day as well as in the pre-event or post-event window and still it is retained when eliminating overlapping market events. This allows all stocks under study to be retained in any experiment.

[6] We cannot test the Informatuion Surprise Hypothesis of Choi and Hui (2014) as it is a duanting task to measure the surprise component of multitude of information/news/developments worldwide that lead to extreme market movement on a given day.

Fourth, we examine if overreaction is more pronounced when volatility is high, as may be expected according to the behavioral models. At times of high volatility, cleaner information may be lacking and proper pricing may be more challenging.

Lastly, unlike the extant studies, we employ a Value at Risk based rolling threshold to determine whether the market movement on a given day is extreme. This is because a fixed percentage move may be too extreme or not quite extreme depending on the prevailing market circumstances.

3 Data and methodology

The primary data of the paper is the CRSP daily returns of the CRSP Value-Weighted Index and the component stocks of the S&P 500 Index over the 1926-2013 period. We use the CRSP Value Weight Index as a proxy for the market since its base is broader and it has daily return data dating back to 1926. The two indexes are almost perfectly correlated (99.92%) any ways.

We define an event as a daily return of the S&P 500 Index, either positive or negative, that exceeds its 99.50% Value at Risk for a short or long position in the index, based on the empirical distribution of the previous 500 trading days. Under a normal distribution with zero mean, this definition corresponds to an event that is expected to occur 2.52 times a year. This represents tail events that are more extreme than the Basel 99% Value at Risk based regulatory capital requirement for trading portfolios. Although arbitrary, we argue that this threshold should retain extreme enough events without making the events too rare for trading purposes. Our sample contains 663 events, 353 negative and 310 positive, representing 2.9% of the trading days in the sample, indicating that the empirical distribution has fatter tails than the Normal.

For a given event, only stocks with complete data on the event day and the post-event window were retained. Furthermore, to avoid liquidity and missing data bias, those stocks with more than 5 returns reported as "zero" during both windows of a given event were also deleted from the sample.

The abnormal return (AR) of the stocks is defined as the excess return of the stock over the return of the chosen market index (DeBondt and Thaler, 1985), namely the CRSP Value Weighted Index, both on the event day. The stocks are ranked according to their abnormal return on the event day. The top 10% and the bottom 10% stocks form, respectively, the equally weighted "Winner (W)" and "Losers (L)" portfolios for the event. The one-day portfolio formation window is in accordance with the literature (Brooks, Patel and Su, 2003; Coleman, 2012) reporting that the market reaction to unanticipated events occur on the day of the event.

The portfolios' performance is then measured by their cumulative abnormal return (CAR) during the 21 trading days after the event (post-event window). The CARs of each portfolio for all events are averaged, resulting in an Average Cumulative Abnormal Return (ACAR) for each portfolio for each post-event day t, t=1, 2, .., 21. If there is overreaction in individual stocks in response to market movement on the event day, then the loser stocks of the event day should outperform the winners stocks of the event day during the post-event window as the individual stock prices revert to their proper level, and the contrarian portfolio ACAR should be positive:

$$ACAR_t = ACAR_{L,t} - ACAR_{W,t} > 0$$

On the other hand, if the market underreacts on the event day or there is delayed overreaction, we would expect the opposite behavior, meaning that the winner stocks should outpace the losers during the post-event window, and the contrarian portfolio ACAR should be negative:

$$ACAR_t = ACAR_{L,t} - ACAR_{W,t} < 0$$

To test the significance of the results, the *t-statistic* is calculated using the formula:

$$t_t = (ACAR_{L,t} - ACAR_{W,t})/(2S_t^2/N)^{1/2}$$

where $ACAR_{L,t}$ and $ACAR_{W,t}$ are, respectively, the average cumulative returns of the loser and winner portfolios on day *t(subscript)*, and *N* is the number of events analyzed. The sample variance S_t^2 is estimated in the following manner:

$$S_t^2 = \left[\sum_{i=1}^{N} \left(CAR_{W,t} - ACAR_{W,t}\right)^2 + \sum_{i=1}^{N} \left(CAR_{L,t} - ACAR_{L,t}\right)^2 \right] / 2(N-1)$$

Thus, a positive and significant ACAR means overreaction and indicates that a contrarian strategy (long event day losers, short event day winners) is profitable, whereas a negative and significant ACAR implies underreaction (delayed overreaction) and now a momentum strategy (short event day losers, long event day winners) is profitable instead. Finally, a low absolute value of ACAR and/or the lack of its significance denotes due immediate and later reactions of the individual stocks to an extreme market shock.

Table 1 reports summary statistics of the daily raw returns of the market index as well as of the winner and loser portfolios during all 663 event days (portfolio formation windows) and the post-event windows. To facilitate the comparison the Table also includes the statistics of the market index during the days that are not in either the event or the post-event windows, named as out of sample in the table. As expected, on the events days, the average return of the loser (winner) portfolio is negative (positive) at -5.590% (+5.337%), while the average market index return is slightly negative (-0.144%), meaning that the average of positive and negative returns of the markets during the positive and negative events almost cancelled out. Considering skewness, both winner and loser portfolios are asymmetric, but in opposite directions, namely negative skew for the loser stocks and positive skew for the winner.

(Insert Table 1 about here)

During the post-event window, the losers seem to outperform the winners on average by a huge margin (losers: +0.206% daily, winners: +0.047% daily), thus indicating a pattern of strong overreaction. This behavior can only be partially attributed to risk, since the difference in the standard deviation of daily returns of the two portfolios (losers: +2.877%, winners: +2.371%) is much lower than the difference in their average daily returns. Meanwhile the market seems more volatile in the post-event window (standard deviation: 1.925%) than in the out of sample period (standard deviation: 0.871%), perhaps because of clustering of the extreme market movements. However, the average daily market return is almost identical between the post-event (+0.044%) and out of sample days (+0.43%). Interestingly, in the post-event window, the daily average return of the winner portfolio (0.047%) is very similar to that of the market (0.044%), while the daily average return of the loser stocks is strongly positive (0.206%). The very preliminary indication here is that the overreaction could be attributed to the reversal of the losers, rather than reversal of the winners. The next sections shed more light into this discussion by presenting the detailed empirical results.

4 Empirical results

We first present the results for all events and for positive and negative events separately. This is followed by the results for distinct groups that were formed regarding the sign of overlapping events resulting in 4 subsamples: Non-overlapping (no other event in the post-event window), Momentum (one or more events of same sign in a given post-event window), Reversal (one event of the opposite sign in the post-event window) and Mixed (more than one event of either sign in the post-event window). We then analyze the relationship between overreaction and volatility and propose an investment strategy that takes advantage of overreaction during stressful circumstances. Finally, we examine if the behavior that we document is driven by the loser or winner stocks.

4.1 All events

Panel A of Table 2 presents the average CARs of the contrarian strategy (long losers, short winners) for all events. Over all of the 21 days of the post-event window, the average CAR of the contrarian strategy remains positive and both economically and statistically significant. It starts at +1.50% on Day 1 and rises to 3.00% on Day 7. After that, it moves laterally for a few days, oscillating between 2.90% and 3.12%, and then rises again during the last 5 days of the window, ending the period with an annualized CAR of approximately 40%.

(Insert Table 2 about here)

To see if this behavior is symmetric, we divided the sample into two subsamples, based on the signal or direction of the market index return (positive or negative) on the event day. Panels B and C of Table 2, respectively, provide the results for the Positive and Negative signal subsamples. Even though the Overreaction Hypothesis is confirmed in both cases, the difference in magnitude is substantial. On the first (last) day of the post-event window, the average CAR of the contrarian strategy is 0.96% (2.38%) and 1.97% (4.17%) respectively in the Positive and Negative subsamples. This suggests that stocks overreact more strongly to the extreme negative market shocks than to the positive ones. These findings are in accordance with prior studies that document a short-term reversal of stocks after both positive and negative shocks to their own prices (Atkins and Dyl, 1990; Corrado and Jordan, 1997; Madura and Richie, 2004), but in a more pronounced way in the latter case (Corrado and Jordan, 1997; Liang and Mullineaux, 1994; Nam, Pyun and Avard, 2001).

Although the intensity differs, both Positive and Negative subsamples exhibit similar behavior over time. The CARs of the contrarian strategy rapidly increase during the first half of the post-event window, move laterally for a few days, and then rises toward the end of the post-event window. By Day 21, the CAR is 2.38% (annualized 28.56%) for the Positive subsample and is 4.17% (annualized 50.04%) for the Negative subsample, in comparison to 0.8% (annualized 9.6%) and 1.02% (annualized 12.24%) change of the market index in the two subsamples over the same window. Thus the contrarian strategy generates a robust profit that does not vanish even four weeks after the initial market shock (especially when the market falls on the event day).

In Figure 1 we plot the ACARs of the loser and winner portfolios as well as the contrarian strategy (loser minus winner). To put the results in perspective, the chart also plots the average cumulative returns of the market index. The loser portfolio seems to overreact rapidly after the event (between Days 1 and 4), with steady moderate growth after that. The winner portfolio, however, essentially retains the loss over the first two days over a few days, starts to recover after Day 7 albeit at a slow pace, and the loss of the first two days are paired back only in the last two days of the period. It's also worthwhile to mention that whereas the CARs exhibited by the loser portfolio are always positive over the entire post-event window, the CARs of the winner portfolio are mostly negative. This pattern is consistent with the OH, since, by construction, the losers (winners) earned negative (positive) abnormal returns on the event day.

(Insert Figure 1 about here)

To see if the results can be attributed to risk, we regress the returns of the contrarian strategy portfolio ($R_{L,t} - R_{W,t}$) on X_t, the set of risk factors:

$$R_{L,t} - R_{W,t} = \alpha + \beta X_t + \varepsilon_t \tag{1}$$

In the CAPM version, the sole risk factor is the market risk premium alone, and in the Fama-French three factors version, the two additional risk factors are the returns on the size portfolio (SMB) and the book to market portfolio (HML). The market risk premium is calculated as the difference between the daily returns of the CRSP Value Weighted Index and the risk-free rate obtained from Fama's website. The size (SMB) and book-to-market (HML) factors are also from the same source.

In theory, the betas are ex-ante expected systematic risk measures of the contrarian portfolio returns over the post-event window. Since these betas are not observed, we estimate them in two alternative ways. The results displayed in Panel A of Table 3 concern estimation of Equation 1 over the post-event window and are thus based on risk adjustment for ex-post beta(s) of the contrarian portfolio. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over all the pertinent events and then a single regression is run for the pooled data to generate the Panel A Jensen's alphas. In this case, we are pretending as if we have foresight about pending systematic risk. Further it is based on pooled data over many years and hence also assumes foresight about the events as well.

Alternatively, for Panel B of Table 3, we first run regression Equation 1 with the market risk premium as the sole risk factor for each pertinent event using the contrarian portfolio returns and the market returns over the 126 trading days prior to the event day (about six months), t= -10, -11, .., -135. For each pertinent event, the pre-event beta of the contrarian portfolio from this regression is taken to be its ex-ante expected beta for the post-event window. Using this ex-ante or pre-event beta estimate and the average market risk premium and the average contrarian portfolio returns during the post-event window, Jensen's alpha is estimated for each pertinent event. The alpha in Panel B is the average of these event alphas and the t-statistic is based on the standard deviation of the alphas of the pertinent events.

In Panel A of Table 3, for all groups, the contrarian strategy earns positive and significant alpha of 0.15% daily (annualized 37.80%) in both factor models, meaning that the overreaction documented is not due to a difference in the ex-post systematic risk(s) of the loser and winner stocks. As expected, the results for the Negative subsample are more pronounced than for the Positive one. For the Negative subsample, the CAPM and Fama-French alphas are both 0.17% daily (annualized 42.84%).

It's worth mentioning that the size and book-to-market factors do not seem to play a significant role in the phenomena since there is virtually no difference between the alphas of the CAPM and Fama-French three factor models.

(Insert Table 3 about here)

The results based on the event-specific ex-ante (pre-event) betas are presented in Panel B of Table 2. Again, the contrarian strategy earns positive alphas that are statistically and economically significant, especially after negative shocks, where the CAPM alpha is 0.18% daily (annualized 45.36%). The Panel A and B results together confirm that possible change in the betas from the pre-event to the post-event period does not explain the overreaction that we document.

4.2 Subsamples of events

The way we define an extreme event can create overlaps between the post-event window of an event and one or more subsequent event dates, thus possibly convoluting and distorting the results. Suppose an extreme decrease of the market on a given day D0 is followed by an extreme rebound on the following day D1. Thus D0 and D1 are both identified as events and they overlap. Under a CAPM-based Efficient Markets perspective, the long (short) loser (winner) portfolio would contain those stocks that fell most (least) on D0 due to their higher (lower) betas. When the market rebounds with an extreme magnitude on D1, the long loser stocks with their higher betas are expected to stage a stronger recovery than the short winner stocks with their lower betas. As a consequence, on Day 1 of the post-event window of D0, the outperformance of the loser portfolio over the winner would reflect returns warranted by the CAPM beta differential instead of overreaction of stocks on D0.

To address this issue we separate the events with no other event in their post-event window into the control subsample "Non-Overlapping". To provide a clearer picture, we further divide the overlapping events into different subsamples based on the signals of the overlapping events:

a) Reversal: Events that are followed by one other event in the opposite direction in the post-event window (positive/negative or negative/positive). Here we expect to find overreaction even when market reaction is truly rational and efficient.
b) Momentum: Events that are followed by one other event in the same direction in the post-event window (both-positive or both-negative). Since the second event reinforces the first one, underreaction or delayed overreaction is possible.
c) Mixed: Events with more than one event of either direction in the post-event window. During highly turbulent occasions like the 2008-09 financial crisis, the market gyrates wildly leading to a cluster of multiple events on close-by dates.

Figure 2 presents the distribution of the events over time. As expected, the years of 1929 and 2008 are dotted by a great number of events and many of these show up in Mixed subsample due to wild gyrations of the market in these years. In our sample, the Mixed subsample contains 251 events, followed by the Non-Overlapping subsample with 195 events. The Reversal and Momentum subsamples contain 114 and 103 events respectively.

(Insert Figure 2 about here)

Table 4 reports the average CAR of the contrarian strategy for each subsample. In the Non-Overlapping subsample in Panel A, the contrarian CAR starts with 1.43% on Day 1 and ends at 2.77% on Day 21, translating to an annualized abnormal return of 33.24% over the post-event window. Such positive and significant returns of the contrarian strategy in a clean subsample lead us to conclude that the market indeed overreacts to extreme events in the short run. This result is in line with prior studies (Corrado and Jordan, 1997; Liang and Mullineaux, 1994) that aim to control for overlap, albeit of stock-specific instead of market-based events.

(Insert Table 4 about here)

As expected, the Reversal subsample in Panel C of Table 4 exhibits a very strong overreaction, the CAR starting at 1.49% on Day 1 and ending at 4.85% on Day 21, racking up an annualized abnormal return of a whopping 58.20%. Whether this is due to changing betas will be examined later in the paper. The contrarian returns for the Momentum subsample in Panel B of Table 4 are interesting in that the CARs are of modest magnitude of around 1% but positive and statistically significant (except for Days 16 and 17). By construction, this subsample is biased against contrarian strategy profits and in favor of momentum strategy profits, and yet we find contrarian strategy profits (momentum strategy loss) in support of overreaction.

The results for the Mixed subsample in Panel D of Table 4 are also remarkable. The contrarian CARs during the first seven days are greater in magnitude and of stronger statistical significance compared to the Reversal subsample in Panel C. The contrarian strategy in the Mixed subsample remains highly profitable until the end of the window, with an impressive 46.92% annualized abnormal return over the post-event window, although below the 58.20% performance in the Reversal subsample.

To see the differential performance profile of the subsamples over the post-event days, Figure 3 plots the average CARs for them. Barring the Momentum subsample, the CAR rises at a good clip until Day 7, continuing to grow after that in the Reversal subsample and flattening out in the Non-overlapping and Mixed subsamples. In line with other studies (Madura and Richie, 2004; Corrado and Jordan, 1997; Liang and Mullineaux, 1994), this time profile indicates that the overreaction takes place shortly after the event.

(Insert Figure 3 about here)

To see performance on a risk-adjusted basis, Table 5 reports the alpha results, based on ex-post and ex-ante (pre-event) beta methods, estimated separately for each subsample. In all four subsamples, the contrarian strategy earns positive and significant CAPM and Fama-French alphas. However, going from ex-post beta to ex-ante (pre-event) beta, while the CAPM alpha (daily) in the Momentum subsample increases from 0.10% to 0.18%, it drops from 0.20% to 0.10% in the Reversal subsample. This is possibly due to the contrarian returns being biased in favor of (against) the OH in the Reversal (Momentum) subsample during the post-event window.

(Insert Table 5 about here)

In the Non-Overlapping subsample, the daily CAPM and Fama-French alpha of the contrarian strategy is 0.15% (37.80% annualized) based on ex-post beta and the daily CAPM alpha is 0.13% (32.76% annualized) based on ex-ante or pre-event beta. This indicates that the OH holds even after controlling for systematic risk and confounding events. The most striking results, however, are for the Mixed subsample, in which the contrarian strategy earns the most impressive daily alphas of 0.22% (CAPM, ex-post beta), 0.20% (CAPM, ex-ante or pre-event beta) and 0.23% (Fama-French, ex-post beta). In part, this is perhaps caused by the market exhibiting a negative average daily return of about -0.10% in the post-event window of this subsample. In absolute terms the contrarian strategy performance in the Mixed subsample is still robust with a daily average raw return of 0.19%. This is rather puzzling since this subsample contains a variety of events, many of them of the momentum subsample type.

One possible explanation may be increased mispricing caused by aggravated asymmetry of information in an environment of heightened market volatility. In our sample, the market volatility (estimated over 100 trading days prior to the event day) for the Mixed subsample is 0.070, much higher than for the other subsamples (0.013 for Non-Overlapping, 0.015 for Momentum and 0.047 for Reversal). We next explore the relationship between market volatility and the contrarian profits (overreaction).

4.3 Overreaction to extreme events and volatility

To investigate the link between overreaction and market volatility, we split the whole sample into four subsamples, based on the volatility (standard deviation) of the daily market returns estimated over the 126 trading days before the event. Events with volatility above the median were classified as "High Volatility" and those below the median, as "Low Volatility". The CARs of the contrarian strategy of these classifications are displayed in Panels A and B of Table 6. We also formed two other subsamples after ordering the events according to the market volatility and then choosing the highest 30% ("30% High") and the lowest 30% ("30% Low") volatility events. The CARs of the contrarian strategy of these classifications are displayed in Panels C and D of Table 6.

Once again, the OH is confirmed for all the classifications in Table 6, since the CARs are significant in each case over the entire post-event window. Although the t-statistic and statistical significance of the CARs between the High Volatility (Panel A) and Low Volatility (Panel B) subsamples are similar, the CAR in the Low Volatility subsample reaches 2% level by Day 9 and then hovers around this level during the remainder of the post-event window. In contrast, the CAR in the High Volatility subsample starts with 2.09% on Day 1, rises to exceed 4% mark by Day 11 and then and then ends with 4.58% at Day 21, translating to an impressive annualized abnormal return of 54.96% over the post-even window, more than the double the level (25.08%) of the Low Volatility subsample. The difference between the CARs of these two subsamples is statistically significant (t-statistic: 19.117).

The same pattern is observed for the 30 percent groups, but now with even higher intensity. The OH keeps holding for the 30% Low subsample (Panel D, Table 6), but the CARs are lower than for the Low Volatility subsample (Panel B, Table 6), remaining mostly below the 2% level and ending at 1.99% on Day 21 (annualized 23.88%). Meanwhile, the 30% High subsample (Panel C, Table 6) exhibits pronounced CARs that are, on average, approximately 3.75 times the respective CARs of the 30% Low subsample (Panel D, Table 6). In fact, the contrarian strategy in 30% High subsample ends the post-event window with an annualized abnormal return of 89.04%. These findings lead us to conclude that short-term overreaction is dominant in a high volatility environment possibly due to aggravated asymmetry of information leading to gross mis-adjustments in individual security prices at a time of extreme market movements.

(Insert Table 6 about here)

To provide a better view of the distinction of the contrarian strategy's performance among the groups, Figure 4 displays the average CARs of each sample. It is interesting to notice that the difference between the returns is clear not only between the High Volatility and Low Volatility subsamples, but also between the High Volatility and 30% High subsamples (not mutually exclusive). However, for the Low Volatility and the 30% Low subsamples (not mutually exclusive), this distinction is almost invisible. This observation indicates not only that the overreaction is more intense when the volatility is high, as stated before, but also that this relation is asymmetric. The market's overreaction is more sensitive to the increase in volatility in the backdrop of stressful circumstances (high market volatility) than under calmer circumstances.

(Insert Figure 4 about here)

Another interesting distinction between the low and high volatility environments relates to the time profile of overreaction. In both Low Volatility and 30% Low subsamples, overreaction seems to happen shortly after the event, and then drifting after Day 7. For the High Volatility and 30% High subsamples, however, although the ACAR rises faster during the first seven days, it keeps rising after this period and (except for two days) does not diminish until the end of the window. One possible explanation for this behavior could be related to overlapping events, since the high volatility subsamples contain a larger number of clustered events. Therefore, each event by itself would contribute to the intensity of the overreaction, inducing the ACAR to a continuous growth profile.

To see if any of the results presented on Table 6 could be explained by the risk factors, Table 7 presents Equation 1 alpha results, based on the ex-post beta method, for the high and low volatility subsamples.

(Insert Table 7 about here)

In conformity with the earlier results, the contrarian strategy generates positive alphas for all the subsamples. Although statistically significant, they are economically smaller in the low volatility subsamples, whereas they are quite high in the high volatility subsamples. The asymmetry is also visible since the alphas are fairly close for the low volatility subsamples, but are quite different for the high volatility subsamples. Both the 0.21% daily (annualized 52.92%) alpha in the High Volatility subsample and the 0.34% daily (annualized 85.68%) alpha in the 30% High subsample are remarkable nonetheless. It is also worthwhile to mention that even under less stressful circumstances, stocks still overreact to extreme market movements in a way that the systematic risk models cannot explain.

4.4 *Strategy implementation*

This section takes an investment perspective by examining a strategy that aims to exploit those circumstances when the contrarian strategy seems to be more profitable. Since the overreaction is more pronounced in a high volatility environment, we use this case for our implementation below. Previously, we ordered all events over many years to determine if an event is taking place in a high or low volatility environment. But an investment implementation in real time would not have this perfect foresight. Therefore, in order to relate a "High volatility" event to an ex-ante measure of volatility, we first estimate this regression equation:

$$Std\ Dev(R_M)_t = \alpha + \gamma_1 D_t + \varepsilon_t \tag{2}$$

Where D_t is a dummy variable that equals 1 when the event is classified as "High Volatility" and 0 otherwise. To focus more on events when the overreaction is even more pronounced we also estimate the following equation:

$$Std\ Dev(R_M)_t = \alpha + \gamma^H D_t{}^H + \gamma^L D_t{}^L + \varepsilon_t \tag{3}$$

$D_t{}^H$ is a dummy variable that equals 1 when the event is classified as "30% High" and equals zero otherwise, and $D_t{}^L$ is a dummy variable that equals 1 when the event is classified as "30% Low" and equals zero otherwise.

We then run the regressions on expressions (2) and (3) over the 663 events of the entire sample of events. The estimated equations are the following:

$$Std\ Dev(R_M)_t = \underset{(21.54)**}{6.8840} \times 10^{-3} + \underset{(21.61)**}{9.7758} \times 10^{-3} D_t + \varepsilon_t \tag{4}$$

and

$$Std\ Dev\ (R_M)_t = \underset{(62.52)**}{9.8428} \times 10^{-3} + \underset{(47.03)**}{1.7656} \times 10^{-2} D_t{}^H - \underset{(-12.67)**}{4.7391} \times 10^{-3} D_t{}^L + \varepsilon_t \tag{5}$$

As expected, the coefficients are all significant at 1% level, positive when the volatility is classified as high or 30% high and negative when classified as 30% low. So, the thresholds for daily market volatility that would retain the most profitable events would be 1.666% (High Volatility) and 2.750% (30% High Volatility).

The investment strategy consists of two straightforward steps. In the first step, on any given day, the investor assesses the market's short and long 99.5% Value-at-Risk over the last 500 days. Whenever the day's market return exceeds its short or long 99.5% VaR, it is considered as an extreme market event that is a potential candidate for contrarian trading. In step 2, if the market volatility of the candidate event, measured by the standard deviation of the daily market return during the last 126 days, is higher than 1.666% (26.447% annualized), then the contrarian strategy is implemented. If the investor prefers a more rigorous filter, then the market volatility threshold in step 2 would be 2.750% (43.655% annualized).

Table 8 reports the results of the above investment strategy employed over the entire sample period of 1926 to 2013. Without the more stringent filter, the strategy achieves an impressive daily average raw return of 0.35% (88.20% annualized) and positive and significant daily alpha, both CAPM and Fama-French, of 0.33% (83.16% annualized). With the more rigorous filter, the results are even better with daily average raw return of 0.41% (103.32% annualized) and CAPM and Fama-French daily alphas of 0.40% (100.80% annualized) and 0.38% (95.76% annualized) respectively.[7] Consequently, both Sharpe ratios are high (5.23 for the High Volatility subsample and 5.29 for the 30% High Volatility group). In contrast, if the strategy is implemented only for those events where the market volatility is below 0.510% for a day of extreme market movement, representing the 30% Low volatility case, the daily average raw return is lower at 0.07% (17.64% annualized) but positive and still sizable. In this case, the daily CAPM and Fama-French alphas are also lower at 0.06% (15.12% annualized) and 0.07% (17.64% annualized) respectively but are still sizable and significant at 5% level.

(Insert Table 8 about here)

These results confirm that an implementable short-term contrarian strategy after major market shocks is quite profitable, especially in the backdrop of high market volatility circumstances. Our findings are consistent with the recent literature (Daniel and Moskowitz, 2013; Barroso and Santa-Clara, 2014) documenting crashes (large drops) in the performance of momentum strategies (opposite of the contrarian) during more turbulent periods. To understand this phenomenon further, the next section explores if the contrarian profits are driven by the loser or winner stocks.

[7] Although arbitrary, we argue that the definition for High and Low volatilities is consistent with popular indexes for this construct, like the VIX. Our preference to use this definition, instead of VIX, for example, lies in the fact that much of the data would be screened out, since the VIX dataset begins in 1986. It is worthwhile to mention that, if the strategy was based on the VIX index, it would have generated positive CAPM and Fama-French annualized alphas of 49.92% and 50.16% but with lower significance due to the smaller number of observations. The correlation between our definition to volatility and VIX is 67%.

4.5 Which stocks drive the overreaction: losers or winners?

The overreaction consists in a reversal of the returns of the stocks previously classified as losers and winners. Hence their CARs should be negatively related to their returns in the portfolio formation period. To examine this relation we run the following regression:

$$CAR_{1,t2} = \gamma_0 + \gamma_1 AR_0 + \varepsilon_t \quad (6)$$

$CAR_{1,t2}$ is the cumulative return of the portfolio (loser or winner) during the post-event window (t_2) running from Day 1 to Day 21 and AR_0 is the return of the contrarian portfolio on the event date. Our focus is on the coefficient γ_1. A negative and statistically significant γ_1 would indicate a reversal, that is, during the post-event window ($1,t_2$), the portfolio returns moved in a direction opposite to that on the event day. Furthermore, a comparison of the coefficients of the loser and winner portfolios would enable us to infer which one is driving the contrarian strategy performance and if the reversal takes place shortly after the event day or not.

Table 9 presents the results for the four subsamples (Non-Overlapping, Momentum, Reversal, Mixed) defined in section 4.2. For brevity, we only reports the results for the holding periods t_2=1, 5, 10, 15 and 20. We also provide the ex-post market beta of each portfolio.

(Insert Table 9 about here)

In the Non-Overlapping subsample (Panel A of Table 9), the loser portfolio has a negative γ_1 coefficient for t_2=1, 5 and 10, but only t_2=1 γ_1 coefficient is statistically significant. For the winner portfolio, the γ_1 coefficient is negative for t_2=1, 10 and 15, and the γ_1 coefficients are all statistically significant except for t_2=1. Additionally, the market beta of the winner portfolio (1.08) is higher than that of the loser (0.96) portfolio. In the Momentum subsample (Panel B of Table 9) the betas are 1.10 (winner) and 0.93 (loser), and the reversal of the loser portfolio is more pronounced than the winner portfolio, as indicated by the γ_1 coefficients being all negative and statistically significant (except for t_2=20). In the Reversal (Panel C of Table 9) subsample, the γ_1 coefficients are mostly negative and statistically significant for the loser portfolio, especially during the earlier half of the post-event window. In the Mixed (Panel D of Table 9) subsample, the γ_1 coefficients of the loser portfolio are negative for the first half of the post-event window whereas they are negative during the second half of the window for the winner stocks. Interestingly, the loser portfolio has a higher beta (1.11 and 1.16) than the winner portfolio (0.87 and 0.93) in the Reversal and Mixed subsamples.

One of the most consistent and strongest pattern is that the loser stocks always reverse on the first trading day after an extreme market movement. Overall, it seems that the loser stocks more consistently and strongly reverse, especially during the first 10 trading days after an extreme market movement, thus driving the lucrative contrarian returns we have documented in this paper. As the CARs are cumulative over time, the earlier returns play a more dominant role and enhances the importance of the early reversal pattern of the loser stocks.

It is worth noting that the loser stocks have lower beta than the winner stocks in the Non-Overlapping and Momentum subsamples (Panels A and B of Table 9), and their reversal is still stronger and more consistent than the winner stocks in these subsamples, especially during the first half of the post-event window. We, of course, documented earlier in this paper that in both subsamples the loser portfolio earns a positive CAPM alpha that is economically and statistically significant. It, therefore, seems that the return reversals of the loser stocks that mostly generate the contrarian profits are not due to the level of risks or changes therein.

5. Summary and conclusions

This paper investigates the reaction of individual stock prices to extreme swings of the broader US market between 1926 and 2013. An event here is defined as those days in which the CRSP Value Weighted Index return exceeds its (prior 500 trading days, empirical) 99.5% Value at Risk for a short or long position in the index. The event definition in terms of the broader market removes microstructure issues as an explanation for the findings that we report. Also, this approach virtually filters out all uniformed events since a major shock to the US broader market is unlikely in the absence of publicly available macro/global news or other developments.

In total, we investigate 663 events (310 positive and 353 negative) and we find strong evidence of statistically and economically significant support for the Overreaction Hypothesis (De Bondt and Thaler, 1985, Shiller, 1981). This effect is relatively more pronounced after negative events, when the contrarian strategy (long losers, short winners on the event day) earns an annualized return of 50%. The strategy remains significantly profitable after controlling for systematic risk factors, providing an annualized Fama-French alpha of 30.24% after positive events and 42.84% after negative events.

The overreaction remains significant even when we control for overlapping events during our post-event window of 21 trading days following the event. In those cases, the contrarian strategy cumulative abnormal return is significant at 1% level throughout the window, generating a Fama-French annualized alpha of 37.80%. More interestingly, the Overreaction Hypothesis holds even in the case of momentum type overlaps (adjacent extreme shocks in the same direction) that are biased against this hypothesis.

We also document that overreaction is particularly pronounced when the extreme market movements are clustered, implying that overreaction and market volatility circumstances are perhaps related. Indeed, when we split the sample according to the market volatility circumstances immediately prior to the event date, we find that the overreaction is economically much more pronounced in the backdrop of stressful or high volatility situations. For the highest 30% volatility events, the CAPM annualized alpha is an overwhelming 85.68%. In this regard, we propose a practically implementable investment strategy, trading on the days of extreme market movements in high market volatility circumstances. A back test reveals that such strategy yields a Fama-French annualized alpha of 83.16% with a Sharpe ratio of 5.29. Our overreaction evidence is thus in conformity with the recent studies (Daniel and Moskowitz, 2013; Barroso and Santa-Clara, 2014) documenting crashes in the performance of the momentum strategy (opposite of the contrarian) during more turbulent periods.

Finally, we expose that the documented overreaction is driven by the returns of the loser stocks that exhibit a consistent and more pronounced reversal than the winners especially during the first day after an extreme market swing and the next nine trading days. This happens even when their market beta is lower than that of the winners. This shows that the beta levels and their changes are not driving the contrarian profitability in the wake of the extreme market movements. Combined with the alpha results based on both post-event and pre-event betas, our results suggest that the well-known risk factor models are inadequate in explaining the short-term overreaction of stocks in the context of extreme movements in the broader market.

Our evidence cannot be reconciled with the Uncertain Information Hypothesis (Brown, Harlow and Tinic, 1988) or the Information Hypothesis (Chan, 2003; Savor, 2012; Baule and Tallay, 2014) either. We believe a more plausible explanation for the overreaction we report is the behavioral bias (Griffin and Tversky, 1992) that investors tend to have overconfidence in events (news, developments) that are sizable/grave in magnitude but low in frequency, and hence tend to overreact.

References

Akhigbe, Aigbe; Gosnell, Thomas; Harikumar, T., 1998, Winners and losers on NYSE: A re-examination using daily closing bid-ask spreads, 21(1), 53-64, DOI: 10.1111/j.1475-6803.1998.tb00269.x

Amini, Shima; Gebka, Bartozs; Hudson, Robert; Keasey, Kevin, 2013, A review of the international literature on the shor term predictability of stock prices conditional on large prior changes: microstructure, behavioral and risk related explanations. *International Review of Financial Analysis*, 26, 1-17, DOI: 10.1016/j.irfa.2012.04.002

Atanasova, Christina V.; Hudson, R., 2007, Short term overreaction, underreaction and momentum in equity markets. *Proceedings of 2007 Annual Meeting of the Midwest Finance Association.*

Atkins, Allen B.; Dyl, Edward A., 1990, Price reversals, bid-ask spreads and market efficiency. *Journal of Financial and Quantitative Analysis*, 25, 535-547. DOI: 10.2307/2331015

Barroso, Pedro; Santa-Clara, Pedro, 2013, Momentum has its moments. *SSRN Working Paper #204142.*

Baule, Rainer; Tallay, Christian, 2014, Stocks returns following large prices changes and news releases – evidences from Germany. *SSRN Working Paper #2405373.*

Benou, Georgina; Richie, Nivine, 2003, The reversal of large stock price declines: the case of large firms. *Journal of Economics and Finance*. 27(1), 19-38. DOI: 10.1007/BF02751588

Bremer, Marc. Sweeney, Richard J., 1991, The reversal of large stock-price decreases. *Journal of Finance*, 46, 747-754. DOI: 10.2307/2328846

Brooks, Raymond M.; Patel, Ajay; Su, Tie, 2003, How the equity market responds to unanticipated events. *Journal of Business,* 76, 109-133

Brown, Keith C.; Harlow, W. V.; Tinic, Seha M.., 1988, Risk aversion, uncertain information and market efficiency. *Journal of Financial Economics*, 22, 355-385. DOI: 10.1016/0304-405X(88)90075-X

Campbell, John Y.; Lo, Andrew W.; MacKinlay, A. Craig, 1997, The econometric of financial markets. Princeton. New Jersey: Princeton University Press

Chan, Wesley S., 2003, Stock price reaction to new and no-news: drift and reversal after headlines. *Journal of Financial Economics*, 70, 223-260. DOI: 10.1016/S0304-405X(03)00146-6

Chaudhury, Mo, 2011a, The Financial Crisis and the Behavior of Stock Prices, *Working Paper, McGill University*.

Choi, Darwin; Hui, Sam K., 2014, The role of surprise: understanding overreaction and underreaction to unanticipated events using in-play soccer betting market. *Journal of Economic Behavior & Organization*, article in press. DOI: 10.1016/j.jebo.2014.02.009

Coleman, Les, 2012, Testing equity market efficiency around terrorist attacks, *Applied Economics*, 44:31, 4087-4099. DOI:10.1080/00036846.2011.587778

Corrado, Charles; Jordan, Bradford D., 1997, Risk aversion, uncertain information, and market efficiency. Reexamining the evidence. *Review of Quantitative Finance and Accounting*, 8, 51-68. DOI: 10.1023/A:1008292620583

Cox, Don R.; Peterson, David R., 1994, Stocks returns following large one-day declines: evidence on short-term reversals and longer-term performance. *The Journal of Finance,* 49 (1), 255-267. DOI: 10.1111/j.1540-6261.1994.tb04428.x

Daniel, Kent D..; Moskowitz, Tobias., 2013, Momentum crashes. *SSRN Working paper #2371227.*

De Bont, Werner F. M.; Thaler, Richard, 1985, Does the stock market overreact? *Journal of Finance*, 40, 793-805. DOI: 10.1111/j.1540-6261.1985.tb05004.x

Goyal, Amit; Wahal, Sunil, 2013, Is momentum an echo? *SSRN Working paper #1935601.*

Griffin, Dale; Tversky, Amos, 1992, The weighing of evidence and the determinants of confidence. *Cognitive Psychology*, 24, 411-435. DOI: 10.1016/0010-0285(92)90013-R

Himmelmann, Achim; Schiereck, Dirk.; Simpson, Marc W.; Zschoche, Mortiz, 2012, Long-term reactions to large stock price declines and increases in the European stock market: a note on market efficiency. *Journal of Economics and Finance*, 36, 400-423. DOI: 10.1007/s12197-010-9125-z

Howe, John S. Evidence on Stock Market Overreaction. *Financial Analyst Journal*, 42(4), 74-77. DOI: 10.2469/faj.v42.n4.74

Ising, Jan.; Schiereck, Dirk.; Simpson, Marc W.; Thomas, Thomas W., 2006, Stock returns following large 1-month declines and jumps: evidence of overoptimism in the German market. *The Quarterly Review of Economics and Finance*, 46, 598-619. DOI: 10.1016/j.qref.2006.02.005

Jegadeesh, Narasimhan, 1990, Evidence of predicable behavior of security returns. *Journal of Finance*, 45, 881-898. DOI: 10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, Narasimhan; Titman, Sheridan, 1993, Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48, 65-91. DOI: 10.1111/j.1540-6261.1993.tb04702.x

Jegadeesh, Narasimhan; Titman, Sheridan, 2001, Profitability of momentum strategies: an evaluation of alternative explanations, *Journal of Finance*, 56, 699-720.

Lasfer, M. Ameziane; Melnik, Arie; Thomas, Dylan C., 2003, Short-term reaction of stock markets in stressful circumstances, *Journal of Banking and Finance*, 27, 1959-1977. DOI: 10.1016/S0378-4266(02)00313-8

Lehmann, Bruce, 1990, Fads, martingales, and market efficiency. *Quarterly Journal of Economics*, 105, 1-28.

Liang, Youguo; Mullineaux, Donald J., 1994, Overreaction and reverse anticipation: two related puzzles? *The Journal of Financial Research,* 17(1), 31-43. DOI: 10.1111/j.1475-6803.1994.tb00172.x

Madura, Jeff; Richie, Nivine, 2004, Overreaction of Exchange-Traded Funds During the Bubble of 1998-2002. *The Journal of Behavioral Finance,* 5(2), 91-104. DOI: 10.1207/s15427579jpfm0502_3

Mehdian, Seyed; Tevfik, Nas; Perry, Marj J., 2008, An examination of investor reaction to unexpected political and economic events in Turkey. *Global Financial Journal*, 18, 337-350. DOI: 10.1016/j.gfj.2007.06.002

Nam, Kiseok; Pyun, Chong S.; Avard, Stephen L., 2001, Asymmetric reverting behavior of short-horizon stocks returns: An evidence of stock market overreaction, *Journal of Banking and Finance,* 25, 807-824. DOI: 10.1016/S0378-4266(00)00110-2

Nguyen, Tho; Pham, Vu T. L.; To, Thuy, D., 2008, Abnormal Returns After Large Stock Price Changes: Evidence from Asia-Pacific Markets. *In: Michael McKenzie, Suk-Joong Kim (eds.) Asia-Pacific Financial Markets: Integration, Innovation and Challenges. International Finance Review, vol. 8, pp.205-227.* Emerald Group Publishing Limited. DOI: 10.1016/S1569-3767(07)00010-6

Novy-Marx, Robert, 2012, Is momentum really momentum? *Journal of Financial Economics*, 103, 429-453. DOI:10.1016/j.jfineco.2011.05.003

Pastor L.; Stambaugh, Robert F., 2003, Liquidity Risk and Expected Stock Returns. *Journal of Political Economy,* 111 (3), 642-685

Pritamani, Mahesh; Singal, Vijay, 2001, Return predictability following large prices changes and information releases. *Journal of Banking & Finance,* 25, 631-656. DOI: 10.1016/S0378-4266(00)00091-1

Savor, Pavel G., 2012, Stocks Returns after major price shocks: the impact of information. *Journal of Financial Economics*, 106, 645-659. DOI: 10.1016/j.jfineco.2012.06.011

Shiller, Robert, 1981, Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review*, 71, 421-436.

Sturm, Ray R., 2003, Investor Confidence and Returns Following Large One-Day Price Changes, *Journal of Behavioral Finance,* 4(4), 201-216. DOI: 10.1207/s15427579jpfm0404_3

Table 1: Summary statistics of event and post-event windows

All daily returns and standard deviations are in percentage. An extreme market event is defined as a daily return on the CRSP Value Weight Index that exceeds a 99.50% Value at Risk for a short or long position in the index, based on the distribution of the previous 500 trading days. The top and bottom deciles of the abnormal returns of the stocks on the event day form the winner and loser portfolios. The abnormal return is defined as the excess return over the market return.

	Event day			**Post-event window**			**Out of Sample**
Statistics	Market	Loser	Winner	Market	Loser	Winner	Market
Average return	-0.144	-5.590	5.337	0.044	0.206	0.047	0.043
Standard Deviation	3.955	4.944	6.675	1.925	2.877	2.371	0.871
Skewness	0.137	-1.560	2.167	-0.279	0.741	0.180	-0.094
Minimum	-0.195	-0.310	-0.043	-0.195	-0.190	-0.191	-0.069
Maximum	0.169	0.030	0.456	0.126	0.306	0.211	0.072

Table 2: Overreaction to extreme events

The table reports the cumulative returns of the contrarian strategy ($ACAR_L$ – $ACAR_w$) during the 21 days post-event window. The t-statistics are in parentheses. The market returns are the average returns of the index during the post-event window. The analysis includes all sampled events (Panel A), only positive events (Panel B) and only negative events (Panel C). All returns are significant at 1% level.

	Panel A: All events (N=663)			**Panel B: Positive (N=310)**			**Panel C: Negative (N=353)**		
Day	$ACAR_L$-$ACAR_W$	Market	t-statistic	$ACAR_L$-$ACAR_W$	Market	t-statistic	$ACAR_L$-$ACAR_W$	Market	t-statistic
1	1.50%	0.16%	*12.50*	0.96%	0.24%	*5.79*	1.97%	0.10%	*11.69*
2	2.17%	0.28%	*13.55*	1.31%	0.21%	*6.57*	2.91%	0.33%	*12.15*
3	2.40%	0.28%	*13.70*	1.46%	0.26%	*6.65*	3.23%	0.30%	*12.30*
4	2.54%	0.20%	*13.46*	1.62%	0.25%	*6.49*	3.36%	0.15%	*12.22*
5	2.62%	0.20%	*12.34*	1.59%	0.29%	*5.58*	3.52%	0.13%	*11.58*
6	2.83%	0.29%	*12.79*	1.75%	0.29%	*5.87*	3.78%	0.29%	*11.96*
7	3.00%	0.21%	*13.82*	1.96%	0.13%	*6.83*	3.91%	0.28%	*12.46*
8	2.90%	0.19%	*12.34*	1.90%	0.34%	*6.20*	3.77%	0.07%	*10.99*
9	2.82%	0.27%	*11.51*	1.79%	0.55%	*5.43*	3.73%	0.02%	*10.63*
10	2.95%	0.34%	*11.53*	2.00%	0.58%	*5.69*	3.78%	0.13%	*10.45*
11	3.04%	0.37%	*11.60*	2.09%	0.58%	*5.95*	3.88%	0.18%	*10.27*
12	3.04%	0.45%	*11.28*	2.05%	0.69%	*5.59*	3.92%	0.25%	*10.20*
13	2.91%	0.51%	*10.58*	1.97%	0.78%	*5.25*	3.74%	0.27%	*9.57*
14	3.03%	0.52%	*10.58*	2.10%	0.72%	*5.30*	3.85%	0.35%	*9.55*
15	3.12%	0.61%	*10.80*	2.22%	0.77%	*5.49*	3.91%	0.46%	*9.71*
16	3.08%	0.63%	*10.37*	2.14%	0.87%	*5.09*	3.91%	0.43%	*9.51*
17	3.12%	0.66%	*10.23*	2.18%	0.90%	*4.99*	3.96%	0.45%	*9.43*
18	3.24%	0.79%	*10.27*	2.27%	0.81%	*4.96*	4.10%	0.77%	*9.55*
19	3.23%	0.74%	*10.16*	2.31%	0.68%	*5.03*	4.04%	0.79%	*9.33*
20	3.18%	0.81%	*9.85*	2.23%	0.81%	*4.72*	4.02%	0.80%	*9.23*
21	3.33%	0.92%	*10.37*	2.38%	0.80%	*5.04*	4.17%	1.02%	*9.63*

Table 3: Contrarian profits after controlling for risk factors

The table reports the Jensen's alpha of the contrarian strategy for the All events, Positive and Negative events during the 21 days window. The t-statistics are in parentheses and N is the number of observations (N) used in regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events and then a single regression (Equation 1) is run for the pooled data to generate the Panel A alphas. This alpha is thus based on ex-post beta (post-event window) of the contrarian portfolio. For Panel B, we first run regression Equation 1 with the market risk premium as the sole risk factor for each pertinent event using the contrarian portfolio returns and the market returns over the 126 trading days prior to the event day. For each pertinent event, the pre-event beta of the contrarian portfolio from this regression is taken to be its ex-ante expected beta for the post-event window. Using this ex-ante beta estimate and the average market risk premium and the average contrarian portfolio returns during the post-event window, the alpha is estimated for each pertinent event. The alpha in Panel B is the average of these event alphas and the t-statistic is based on the standard deviation of the alphas of the pertinent events. The alphas are given in percentage and on a daily basis. All alphas below are significant at 1% level.

	All events	**Positive**	**Negative**
N	13,923	6,510	7,413
Average raw return	0.16	0.11	0.20
Panel A: Ex-post beta (conditional) regression			
CAPM alpha	0.15	0.13	0.17
(t-statistic)	*7.971*	*5.566*	*7.918*
Fama-French alpha	0.15	0.12	0.17
(t-statistic)	*8.032*	*5.402*	*8.022*
Panel B: Ex-ante beta (rolling) regression			
CAPM alpha	0.16	0.13	0.18
(t-statisic)	*9.996*	*5.860*	*8.184*

Table 4: Overreaction to extreme events for subsamples formed regarding the signal of the overlapping sample

The table reports the cumulative returns of the contrarian strategy (ACARL – ACARw) during the 21 days analysis window. The t-statistics are in parentheses. The groups were formed in accordance to the signal of the overlapping events. Non-overlapping are those events with no other event during their window analysis. Momentums are those events with equal signal events in the same window. Reversals are those with contrarian signal events in the same window. Mixed are those with multiple equal/contrarian signal in the same window.

	Panel A: Non-overlapping (N=195)		**Panel B: Momentum (N=103)**		**Panel C: Reversal (N=114)**		**Panel D: Mixed (N=251)**	
Day	$ACAR_L$-$ACAR_W$	t-statistic	$ACAR_L$-$ACAR_W$	t-statistic	$ACAR_L$-$ACAR_W$	t-statistic	$ACAR_L$-$ACAR_W$	t-statistic
1	1.43%	(8.189**)	0.73%	(3.274**)	1.49%	(6.195**)	1.87%	(7.578**)
2	1.73%	(8.999**)	1.30%	(4.270**)	2.57%	(7.846**)	2.68%	(7.827**)
3	1.88%	(8.696**)	1.22%	(3.408**)	2.80%	(7.486**)	3.12%	(8.528**)
4	2.03%	(8.296**)	0.94%	(2.588**)	3.21%	(7.544**)	3.30%	(8.527**)
5	1.95%	(7.005**)	0.87%	(2.100*)	3.39%	(7.600**)	3.50%	(8.002**)
6	2.23%	(7.535**)	1.01%	(2.253*)	3.58%	(7.947**)	3.70%	(8.143**)
7	2.57%	(8.783**)	1.09%	(2.328*)	3.64%	(8.216**)	3.82%	(8.708**)
8	2.56%	(8.397**)	1.14%	(2.330*)	3.69%	(8.009**)	3.53%	(7.197**)
9	2.45%	(7.254**)	1.03%	(1.837*)	3.72%	(8.372**)	3.43%	(6.854**)
10	2.41%	(6.752**)	1.29%	(2.161*)	3.79%	(7.980**)	3.67%	(7.092**)
11	2.57%	(7.102**)	1.53%	(2.518**)	3.86%	(7.461**)	3.66%	(6.932**)
12	2.68%	(6.711**)	1.58%	(2.600**)	4.08%	(7.734**)	3.45%	(6.445**)
13	2.58%	(6.182**)	1.21%	(2.028*)	3.93%	(7.400**)	3.39%	(6.228**)
14	2.74%	(6.262**)	1.12%	(1.845*)	4.04%	(6.883**)	3.59%	(6.377**)
15	2.85%	(6.678**)	1.08%	(1.729*)	4.19%	(7.238**)	3.67%	(6.428**)
16	2.88%	(6.239**)	0.98%	(1.487)	4.29%	(7.156**)	3.56%	(6.180**)
17	2.92%	(6.089**)	0.90%	(1.316)	4.34%	(7.291**)	3.64%	(6.167**)
18	2.76%	(5.598**)	1.23%	(1.710*)	4.54%	(7.298**)	3.86%	(6.325**)
19	2.75%	(5.646**)	1.22%	(1.745*)	4.31%	(6.835**)	3.94%	(6.323**)
20	2.83%	(5.616**)	1.17%	(1.671*)	4.61%	(6.961**)	3.63%	(5.810**)
21	2.77%	(5.374**)	1.31%	(1.830*)	4.85%	(7.582**)	3.91%	(6.105**)

*Significant at the 5% level, ** at the 1% level

Table 5: Contrarian profits after controlling for risk factors

The table reports the Jensen's alpha of the contrarian strategy during the 21 days window. The t-statistics are in parentheses and N is the number of observations (N) used in regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events and then a single regression (Equation 1) is run for the pooled data to generate the Panel A alphas. This alpha is thus based on ex-post beta (post-event window) of the contrarian portfolio. For Panel B, we first run regression Equation 1 with the market risk premium as the sole risk factor for each pertinent event using the contrarian portfolio returns and the market returns over the 126 trading days prior to the event day. For each pertinent event, the pre-event beta of the contrarian portfolio from this regression is taken to be its ex-ante expected beta for the post-event window. Using this ex-ante beta estimate and the average market risk premium and the average contrarian portfolio returns during the post-event window, the alpha is estimated for each pertinent event. The alpha in Panel B is the average of these event alphas and the t-statistics is based on the standard deviation of the alphas of the pertinent events. The alphas are given in percentage and on a daily basis. All alphas are significant at 1% level.

	Non-overlapping	**Momentum**	**Reversal**	**Mixed**
N	4,095	2,163	2,394	5,271
Average raw return	0.13	0.06	0.23	0.19
Panel A: Ex-post beta (conditional) regression				
CAPM alpha	0.15	0.10	0.20	0.22
(t-statistic)	*(5.051**)*	*(2.463**)*	*(5.142**)*	*(6.107**)*
Fama-French alpha	0.15	0.08	0.19	0.23
(t-statistic)	*(5.138**)*	*(1.919*)*	*(5.298**)*	*(6.271**)*
Panel B: Ex-ante beta (rolling) regression				
CAPM alpha	0.13	0.18	0.10	0.20
(t-statisic)	*(5.186**)*	*(5.32**)*	*(2.961**)*	*(6.436**)*

*Significant at the 5% level, ** at the 1% level

Table 6: Overreaction to extreme events for different groups divided by volatility

The table reports the cumulative returns of the contrarian strategy ($ACAR_L - ACAR_w$) during the 21 days post-event window. The t-statistics are in parentheses. The market returns are the average returns of the index during the post-event window. The subsamples are formed based on the standard deviation of the daily market index returns on 22 days, namely, Days 0 (event day) to 21 (last day of post-event window). Events with below (above) median market standard deviation are classified as Low (High) Volatility. Events with the higher and lower 30 percent of the cases classified as High and Low form, respectively, the 30% High and 30% Low groups.

	Panel A: High Volatility (N=331)		**Panel B: Low Volatility (N=331)**		**Panel C: 30% High (N=100)**		**Panel D: 30% Low (N=100)**	
Day	$ACAR_L$-$ACAR_W$	t-statistic	$ACAR_L$-$ACAR_W$	t-statistic	$ACAR_L$-$ACAR_W$	t-statistic	$ACAR_L$-$ACAR_W$	t-statistic
1	2.09%	(9.803**)	0.91%	(8.632**)	3.49%	(6.353**)	0.97%	(4.892**)
2	2.86%	(9.975**)	1.47%	(10.782**)	4.14%	(5.771**)	1.50%	(6.268**)
3	3.14%	(10.087**)	1.67%	(10.664**)	4.67%	(5.762**)	1.53%	(5.521**)
4	3.36%	(10.042**)	1.73%	(10.169**)	5.31%	(5.986**)	1.52%	(5.278**)
5	3.58%	(9.415**)	1.66%	(9.191**)	5.74%	(5.838**)	1.50%	(4.947**)
6	3.85%	(9.777**)	1.80%	(9.412**)	5.90%	(5.630**)	1.70%	(5.371**)
7	4.01%	(10.609**)	1.99%	(9.729**)	6.43%	(6.856**)	1.69%	(5.266**)
8	3.87%	(9.340**)	1.93%	(9.065**)	6.58%	(6.491**)	1.57%	(4.599**)
9	3.64%	(8.356**)	2.01%	(9.193**)	5.85%	(5.637**)	1.71%	(4.853**)
10	3.87%	(8.524**)	2.03%	(8.934**)	6.46%	(5.811**)	1.55%	(4.267**)
11	4.06%	(8.725**)	2.03%	(8.737**)	6.35%	(5.569**)	1.71%	(4.755**)
12	4.16%	(8.752**)	1.93%	(7.952**)	6.50%	(5.562**)	1.65%	(4.552**)
13	3.92%	(8.082**)	1.90%	(7.715**)	6.15%	(5.210**)	1.72%	(4.518**)
14	4.19%	(8.266**)	1.88%	(7.442**)	6.92%	(5.572**)	1.59%	(4.010**)
15	4.29%	(8.494**)	1.94%	(7.390**)	7.07%	(5.719**)	1.66%	(4.203**)
16	4.29%	(8.208**)	1.88%	(6.992**)	7.44%	(5.799**)	1.86%	(4.709**)
17	4.40%	(8.221**)	1.85%	(6.688**)	7.61%	(5.725**)	1.90%	(4.491**)
18	4.47%	(8.055**)	2.03%	(7.106**)	7.64%	(5.494**)	1.92%	(4.376**)
19	4.43%	(7.999**)	2.04%	(6.912**)	7.57%	(5.436**)	2.11%	(4.589**)
20	4.35%	(7.738**)	2.02%	(6.723**)	7.20%	(5.152**)	1.96%	(4.120**)
21	4.58%	(8.261**)	2.09%	(6.821**)	7.42%	(5.297**)	1.99%	(3.94**)

*Significant at the 5% level, ** at the 1% level

Table 7: Contrarian profits after controlling for risk factors

The table reports the Jensen's alpha of the contrarian strategy during the 21 days window. The t-statistics are in parentheses and N is the number of observations (N) used in regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events and then a single regression (Equation 1) is run for the pooled data to generate the alphas. These alphas are thus based on ex-post beta (post-event window) of the contrarian portfolio. The alphas are given in percentage and on a daily basis.

	High	**Low**	**30% High**	**30% Low**
N	6,951	6,972	2,079	2,100
Average raw return	0.22	0.10	0.35	0.09
CAPM alpha	0.21	0.09	0.34	0.09
(t-statistic)	*(6.165**)*	*(5.479**)*	*(3.947**)*	*(3.442**)*
Fama-French alpha	0.21	0.09	0.34	0.09
(t-statistic)	*(6.16**)*	*(5.586**)*	*(3.893**)*	*(3.543**)*

*Significant at the 5% level, ** at the 1% level

Table 8: Contrarian profits of the investment strategy after controlling for risk factors

The table reports the Jensen's alpha of a contrarian investment strategy that aims to trade only after events during more volatile periods, named "High" events. The column "30% High" brings the results for a more rigorous filter while the column "30% Low", for a matter of comparison, shows the results if the strategy was employed during less volatile periods. The t-statistics are in parentheses and N is the number of observations (N) used in regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events and then a single regression (Equation 1) is run for the pooled data to generate the alphas. These alphas are thus based on ex-post beta (post-event window) of the contrarian portfolio. The alphas are given in percentage and on a daily basis. The Sharpe ratio is calculated using the market index as a benchmark.

	High	**30% High**	**30% Low**
Variance threshold	> 1.666%	> 2.750%	< 0.510%
N	2,100	882	945
Average raw return	0.35	0.41	0.07
CAPM alpha	0.33	0.40	0.06
(t-statistic)	*(3.919**)*	*(2.718**)*	*(1.759*)*
Fama-French alpha	0.33	0.38	0.07
(t-statistic)	*(3.864**)*	*(2.538**)*	*(1.907*)*
Sharpe ratio	5.23	5.29	3.05

*Significant at the 5% level, ** at the 1% level

Table 9: Testing the reversal of the winner and loser portfolios after the extreme event

The table reports the coefficient γ_1 for the regression:

$$CAR_{1,t2} = \gamma_0 + \gamma_1 AR_0 + \varepsilon_t$$

$CAR_{1,t2}$ is the cumulative return of the stock over the holding periods ranging between 1 and 20 days and AR_0 is the abnormal return on Day 0, the event day. The t-statistics are in parentheses.

	Panel A: Non-Overlapping (N=195)				**Panel B: Momentum (N=103)**				**Panel C: Reversal (N=114)**				**Panel D: Mixed (N=251)**			
	Loser stocks		Winner stocks		Loser stocks		Winner stocks		Loser stocks		Winner stocks		Loser stocks		Winner stocks	
Market betas	0.96		1.08		0.93		1.10		1.11		0.87		1.16		0.93	
	AR_0	R^2	AR_0	R^2	AR_0	R^2	AR_0	R^2	AR_0	R^2	AR_0	R^2	AR_0	R^2	AR_0	R^2
CAR_1	-0.387	24.9%	-0.037	1.0%	-0.246	14.1%	-0.073	2.2%	-0.294	19.8%	0.036	0.5%	-0.470	24.8%	0.019	0.1%
(t-statistic)	*(-7.990)***		*(-1.421)*		*(-4.066)***		*(-1.506)*		*(-5.26)***		*(0.747)*		*(-9.055)***		*(0.585)*	
$CAR_{1,5}$	-0.019	0.1%	0.105	8.0%	-0.093	3.4%	0.046	1.1%	-0.082	2.8%	-0.026	0.6%	-0.037	0.3%	0.036	0.8%
(t-statistic)	*(-0.487)*		*(4.108)***		*(-1.872)**		*(1.047)*		*(-1.791)**		*(-0.848)*		*(-0.911)*		*(0.025)*	
$CAR_{1,10}$	-0.015	0.1%	-0.042	2.6%	-0.114	3.6%	-0.035	0.8%	-0.061	2.4%	0.007	0.0%	-0.091	2.0%	-0.047	1.3%
(t-statistic)	*(-0.479)*		*(-2.275)***		*(-1.951)**		*(-0.916)*		*(-1.655)**		*(0.185)*		*(-2.277)***		*(-1.792)**	
$CAR_{1,15}$	0.041	0.9%	-0.084	14.1%	0.139	8.8%	0.100	6.1%	0.000	0.0%	0.003	0.0%	0.014	0.1%	-0.040	1.1%
(t-statistic)	*(1.290)*		*(-5.618)***		*(3.118)***		*(2.567)***		*(0.007)*		*(0.084)*		*(0.415)*		*(-1.667)**	
$CAR_{1,20}$	0.017	0.2%	0.105	14.2%	-0.007	0.0%	0.005	0.0%	-0.201	16.2%	0.060	4.4%	0.064	1.4%	0.061	2.8%
(t-statistic)	*(0.600)*		*(5.644)***		*(-0.163)*		*(0.162)*		*(-4.658)***		*(2.257)**		*(1.846)**		*(2.679)***	

*Significant at the 5% level, ** at the 1% level

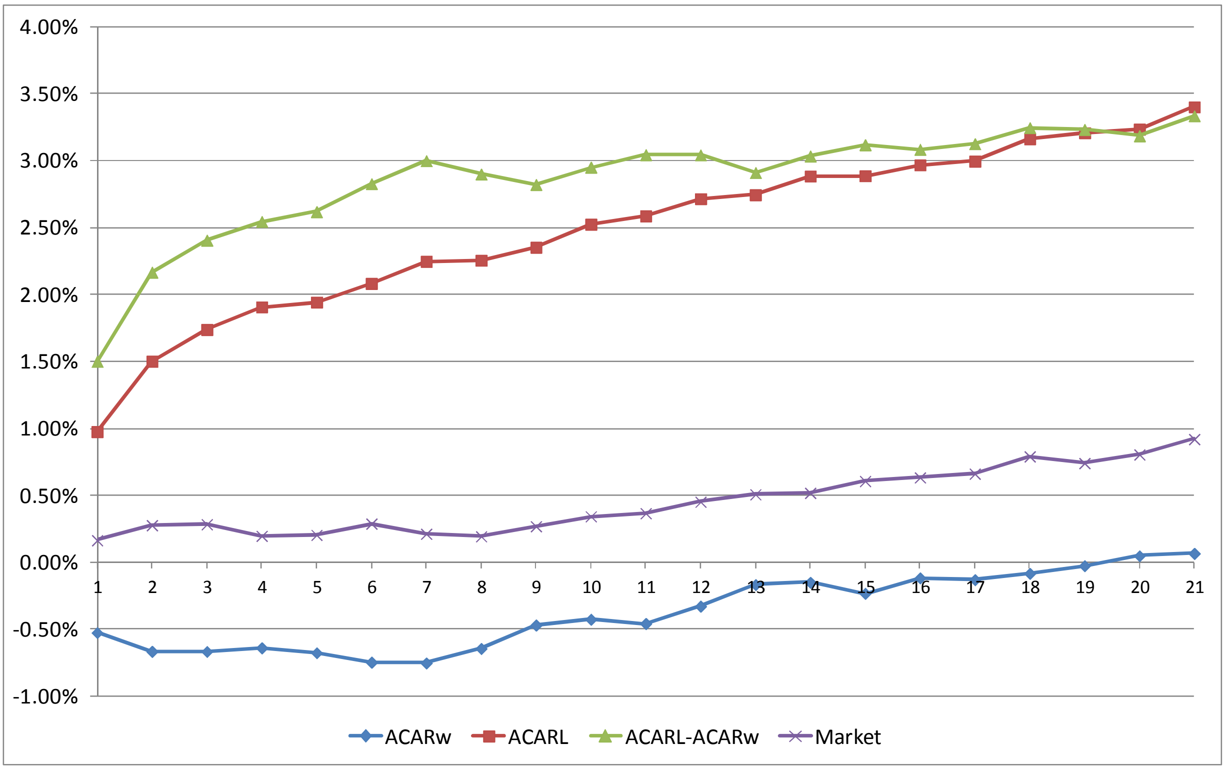

Figure 1: Average cumulative returns of the loser and winner portfolio as well as of the contrarian strategy for all events. The average cumulative return of the market index (CRSP Value Weighted Index) was calculated employing the same methodology used to obtain the ACAR for the winner and loser portfolios.

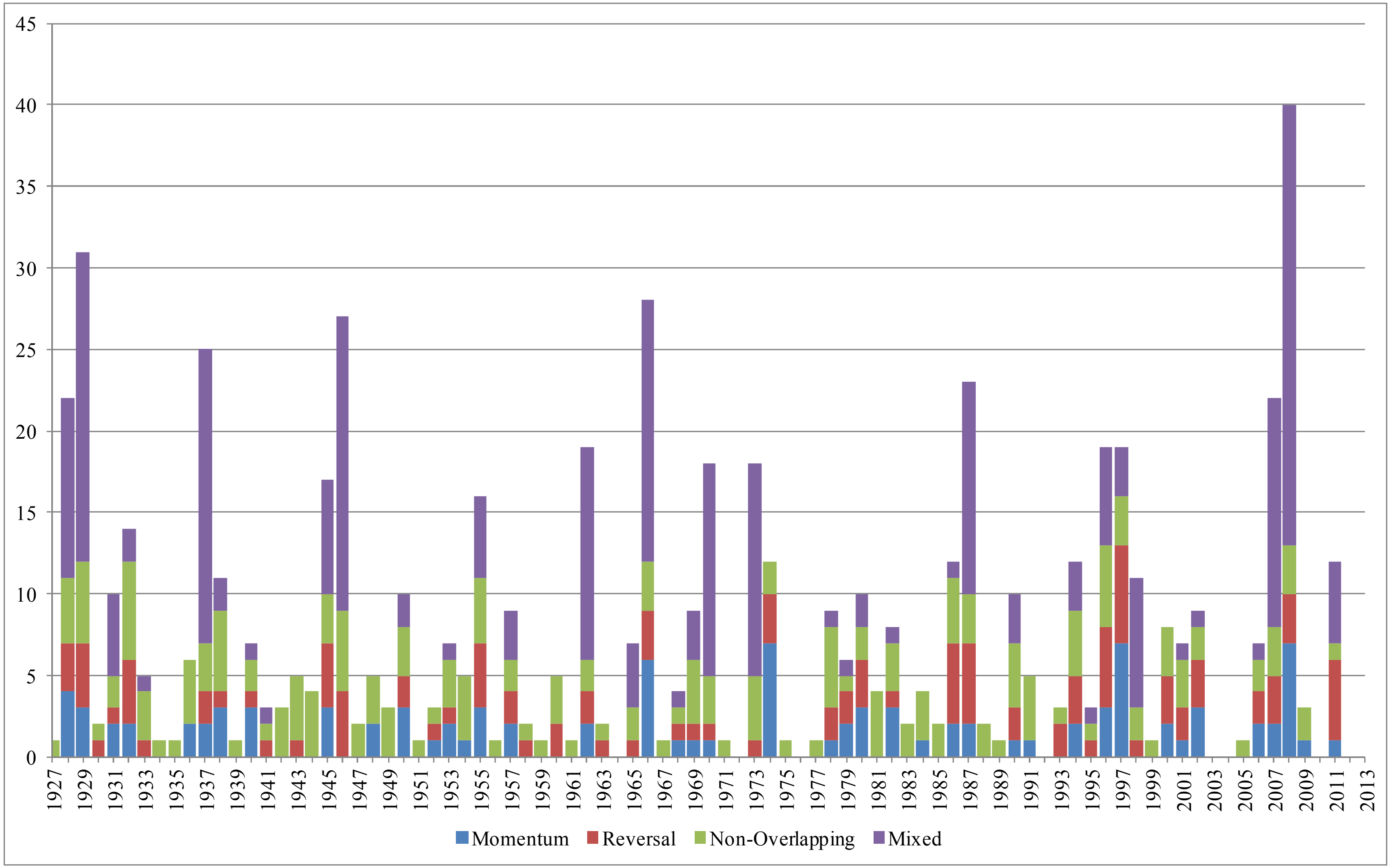

Figure 2: Distribution of events throughout the time series. The groups were formed in accordance to the signal of the overlapping events. Non-overlapping are those events with no other event during their window analysis. Momentums are those events with equal signal events in the same window. Reversals are those with contrarian signal events in the same window. Mixed are those with multiple equal/contrarian signal in the same window.

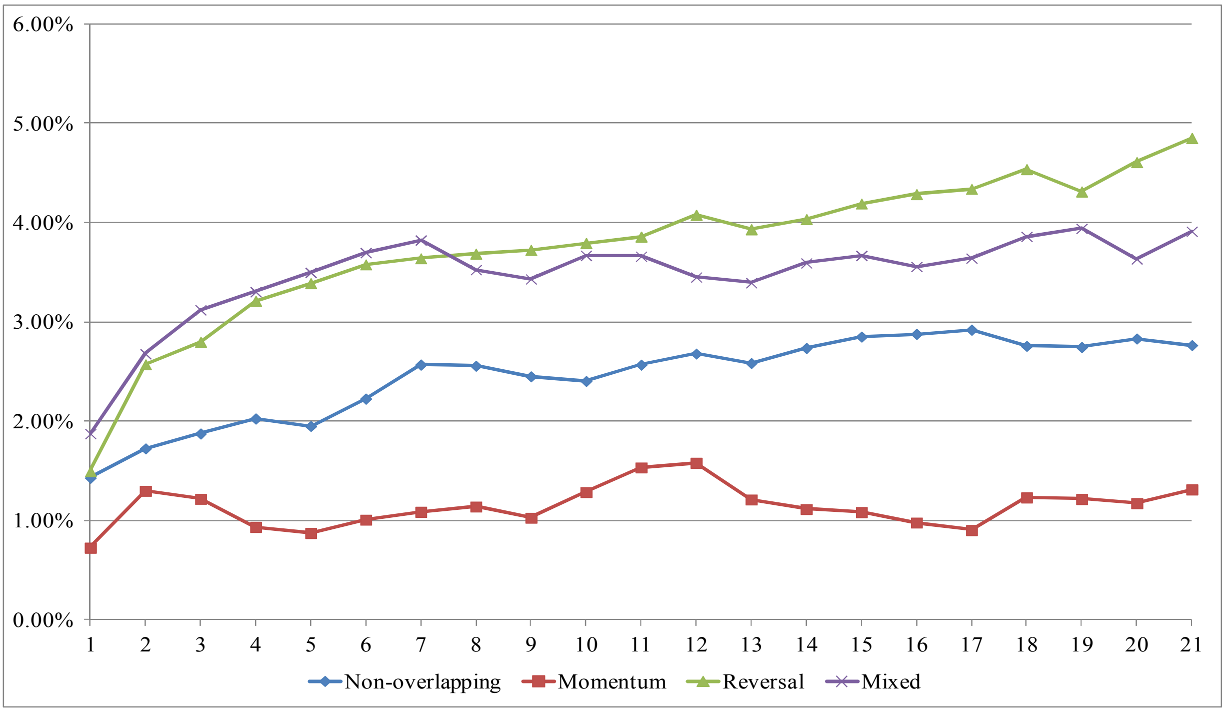

Figure 3: Average cumulative returns of the contrarian strategy for Non-overlapping, Momentum, Reversal and Mixed subsamples.

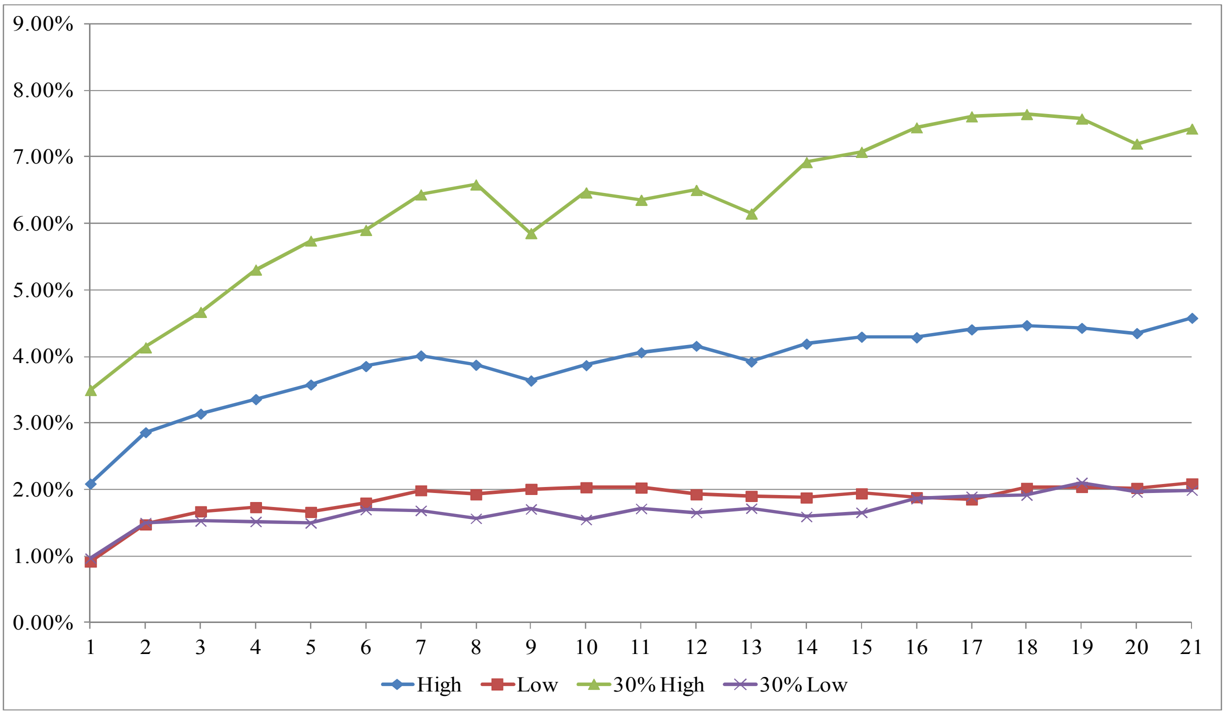

Figure 4: Average cumulative returns of the contrarian strategy for subsamples formed basing on the standard deviation of the daily market index returns on 22 days, namely, Days 0 (event day) to 21 (last day of post-event window). Events with below (above) median market standard deviation are classified as Low (High) Volatility. Events with the higher and lower 30 percent of the cases classified as High and Low form, respectively, the 30% High and 30% Low groups