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Stock overreaction to extreme market events

Pedro Piccoli [a,*], Mo Chaudhury [b], Alceu Souza [a], Wesley Vieira da Silva [a]

[a] Pontifical Catholic University of Parana, 1155, Imaculada Conceição St, Curitiba, PR, Brazil
[b] Desautels Faculty of Management, McGill University, 1001 Sherbrooke St W, Montreal, QC H3A 1G5, Canada

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ABSTRACT

The paper investigates the behavior of individual US stocks during the 21 trading days following the event of extreme movement in the market index on a day. We find that stocks tend to overreact after both positive and negative events, but in a more pronounced way in the latter case. This behavior is more intense when the market exhibits clustered extreme swings, indicating that the overreaction and market volatility are related. We also identify that the overreaction is driven by the performance of loser stocks that revert more strongly, even as they exhibit a lower market beta than winners.

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. The common method in the literature (see Amini, Gebka, Hudson, & Keasey, 2013) is to investigate such behavior by observing the reaction of a particular security after experiencing a positive/negative shock, such as 5% or 10%. There are some drawbacks to this design. First, the one-size-fits-all threshold (e.g. 5% or 10%) biases the sample towards illiquid stocks since such major shocks are more easily found in less liquid securities (Cox & Peterson, 1994; Liang & Mullineaux, 1994). Second, according to the psychology

* Corresponding author.
E-mail addresses: pedro.guilherme@pucpr.br (P. Piccoli), mo.chaudhury@mcgill.ca (M. Chaudhury), alceu.souza@pucpr.br (A. Souza), welsey.silva@pucpr.br (W.V. da Silva).

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literature, the sentiment of surprise to an outcome is not only attributed to the magnitude of the event, but also to the way it contrasts with common expectations (Teigen & Keren, 2003). Therefore, a given movement such as 5% would be more surprising during a calm period than during a financial turmoil, for example. On the other hand, a less pronounced price move (such as 2%) in a placid market could be seen as surprising, leading to overreaction. This last type of event is completely lost in the common research design. Third, the stock specific focus, by definition, introduces idiosyncratic issues (size, earnings, book to market ratios, analyst coverage, uninformed events) that can bias the result toward over/underreaction.

Our research design aims to avoid these handicaps in two ways. First, by focusing on market-level events, comparing loser and winner portfolios during the following days, microstructure effects, such as bid-ask bounce (Cox & Peterson, 1994; Liang & Mullineaux, 1994) and event-coverage (Savor, 2012; Baule & Christian, 2014; Choi & Hui, 2014), have negligible effects in our results. Second, by employing a moving-window Value-at-Risk approach to define an extreme event, we take into account the contrast dimension of a surprising event, as recommended by the psychology literature.

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 the same or opposite signals (signs) of extreme market movements, since the clustering of events can influence investor's behavior. We find an economically and statistically significant overreaction in all cases, even when the overlapping events are of the same sign what is quite puzzling since the portfolio should exhibit momentum once the subsequent event reinforces the earlier one.

The overreaction is of course stronger when the overlapping events are of opposite signals, with the contrarian strategy earning a Carhart 4 factor 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.

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 (De Bondt & 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 & Moskowitz., 2013; Barroso and Santa-Clara, 2015). However, the overreaction of stocks cannot be explained by their systematic risk. Information based hypotheses such as the Uncertain Information Hypothesis (Brown, Harlow, & Tinic, 1988) or the Information Hypothesis (Baule & Tallay, 2014; Chan, 2003; Kang, Palmon, & Yezegel, 2015; Savor, 2012) are not supported either by our results. A more appealing explanation is the behavioral bias (Griffin & 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

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.[1]

Brown et al. (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 et al. (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

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

more than 10%. Also, they did not find this phenomenon to be related to market movements. Further studies for distinct stock sets (Akhigbe, Thomas, & Harikumar, 1998; Atkins & Dyl, 1990), thresholds (Howe, 1986; Madura & Richie, 2004; Sturm, 2003) and markets (Atanasova & Hudson, 2007; Nguyen, Pham, & To, 2008) also documented a short-term reversal pattern.

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 et al. (1988). In contrast, although adopting the same threshold, Ising, Schiereck, 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, Tevfik, 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 (Benou & Richie, 2003; Lasfer, Melnik, & 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 (Baule & Tallay, 2014; Chan, 2003; Kang et al., 2015; Savor, 2012) 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).[2]

This paper improves the event study methodology in question in, at least, five ways. 1) 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; 2) 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; 3) 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; 4) We examine whether 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; 5) 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 very extreme depending on the prevailing market circumstances. This is an important point when studying responses to extreme events. According to the psychology literature, surprise at a phenomenon depends on how it contrasts with the expectations of those involved (Teigen & Keren, 2003). Therefore, the dominant approach of setting a fixed percentage as a filter for extreme returns will end up either excluding events that are considered surprising in periods of less volatility or including events that are not very surprising in times of greater turbulence. The proposed approach for this article is intended to overcome this bias.

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[3]. This represents tail events that are more extreme than the Basel 99% Value at Risk based regulatory capital requirement for trading portfolios.

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

[3] In a set of tests not reported in this paper, we used 99% VaR and 98% VaR thresholds and still found overreaction, albeit in a less pronounced way since these filters contain lower magnitude events. We would like to thank an anonymous referee for raising this point.

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 (De Bondt & 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, & 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, while negative if the market underreacts or exhibits delayed overreaction.

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.

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

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

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:

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

In Fig. 1, we plot the event threshold (99.5% VaR) throughout our sample period. It is clear that the magnitude of a market move that is considered a shock in our methodology changes substantially over time. This approach is consistent with the psychology literature, which attests that a given outcome is considered surprising not only based on its magnitude, but also by the way it contrasts with common expectations (Teigen & Keren, 2003). In this regard, the threshold peaks after financial crises such as the one that occurred in 1928 and the recent subprime crises. The vertical lines represent the events, which are clustered during some notably turbulent years e.g. 1928–1929; 1944–1946; 1987; 1996–1998; and 2007–2009.

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.

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%). 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. We then analyze whether the results are intended for a specific period, such as a financial crisis. This is followed by the results for distinct groups that were formed regarding the sign of overlapping events resulting in four subsamples: 1. Non-overlapping (no other event in the

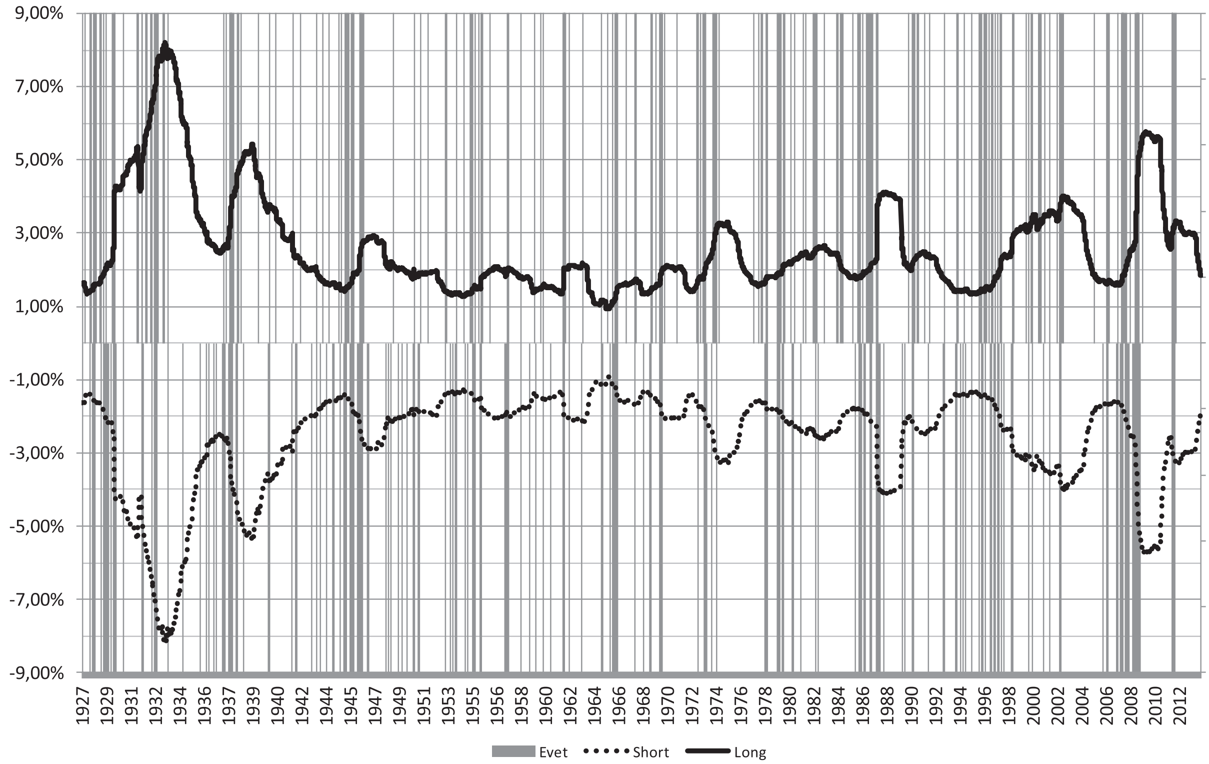

Fig. 1. Extreme event thresholds. The figure shows the 99.5% VaR on the market index for a long (short) position. The vertical lines are the events retained in our study.

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.

Statistics	Event Day (n = 663)			Post-event window (n = 6.460)			Out of sample (n = 15.636)
	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
Variation coefficient	−27.464	−0.884	1.251	43.953	13.989	50.488	20.034
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

post-event window); 2. Momentum (one or more events of same sign in a given post-event window); 3. Reversal (one event of the opposite sign in the post-event window) and 4. Mixed (more than one event of either sign in the post-event window). We then analyze the relationship between overreaction and volatility. 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 days of the window, ending the period with an annualized CAR of approximately 40%. For brevity, we only report the CAR of contrarian strategy for D1, D5, D9, D13, D17 and D21. The complete data is available upon request.

Table 2
Overreaction to extreme events.

Day	Panel A: All events (N = 663)			Panel B: Positive (N = 310)			Panel C: Negative (N = 353)		
	$ACAR_L$-$ACAR_W$	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*
5	2.62%	0.20%	*12.34*	1.59%	0.29%	*5.58*	3.52%	0.13%	*11.58*
9	2.82%	0.27%	*11.51*	1.79%	0.55%	*5.43*	3.73%	0.02%	*10.63*
13	2.91%	0.51%	*10.58*	1.97%	0.78%	*5.25*	3.74%	0.27%	*9.57*
17	3.12%	0.66%	*10.23*	2.18%	0.90%	*4.99*	3.96%	0.45%	*9.43*
21	3.33%	0.92%	*10.37*	2.38%	0.80%	*5.04*	4.17%	1.02%	*9.63*

The table reports the cumulative returns of the contrarian strategy ($ACAR_L$ – $ACAR_w$) during the 21 days post-event window. 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). For brevity, we only report the CAR of contrarian strategy for D1, D5, D9, D13, D17 and D21. The complete data is available upon request. All returns are significant at 1% level.

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 & Dyl, 1990; Corrado & Jordan, 1997; Madura & Richie, 2004), but in a more pronounced way in the latter case (Corrado & Jordan, 1997; Liang & Mullineaux, 1994; Nam, Pyun, & Avard, 2001). Although the intensity differs, both Positive and Negative subsamples exhibit similar behavior over time, which is consistent with the understanding that this reaction is related to the feeling of surprise, given that psychology affirms that this emotion is linked to both positive and negative news (Teigen & Keren, 2003).

In Fig. 2 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 should also be mentioned 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.

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 the set of Carhart (1997) risk factors[4]:

$$R_{L,t} - R_{W,t} = \alpha + b_{i,t}MRP + s_{i,t}SMB + h_{i,t}HML + m_{i,t}MOM + \varepsilon_t \tag{1}$$

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 French's website. The size (SMB), book-to-market (HML) and Momentum (MOM) factors are also from the same source.

The results displayed in Panel A of Table 3 are related to an estimation of Eq. (1) over the post-event window and are thus based on risk adjustment for the ex-post beta(s) of the contrarian portfolio. We do not measure the expected return by estimating the coefficients from the "pre-event" window since that could contain an event itself, distorting the estimation[5]. Therefore, contrarian portfolio returns and the contemporaneous risk factor values are pooled over all the pertinent events and a single regression is then run for the pooled data to generate the Jensen's alphas. The results show that the contrarian strategy generates statistically positive alphas in all the groups, but more sharply after negative events (annualized alpha of 46.5% against 30.6% after positive events), indicating that the documented overreaction cannot be attributed to the difference in the systemic risk of the winning and losing assets.

[4] We also ran tests for the five-factor Fama-French (2015) model and for a four-factor model that included the Pastor and Stambaugh (2003) liquidity factor and the three-factor Fama-French (1993) model. In the first case, the analysis began in 1963, as the daily factors available on the website of Kenneth French begin that year. The portfolio generated a positive alpha of 32.2% in annual terms (t-stat.: 6.13). In the case of the liquidity factor, as it is supplied on a monthly basis on the website of Lubos Pastor, we interpolated between business days of two subsequent months to generate a factor with daily values. In this case, we also obtained a positive alpha (21% in annual terms) and a significant one (t-stat.: 3.13). Furthermore, the coefficient of the liquidity factor was negative and significant, indicating that the high liquidity shares directed the performance of the contrarian portfolio. We would like to thank Prof. Andy Puckett for raising this issue.

[5] Alternatively, we have also run Eq. (1) over the 126 trading days prior to the event day (about six months), $t = -10, -11, \ldots, -135$ to generate ex-ante coefficients as proxies to coefficients for the post-event window, and then determine the contrarian Jensen's alpha. The results are virtually the same.

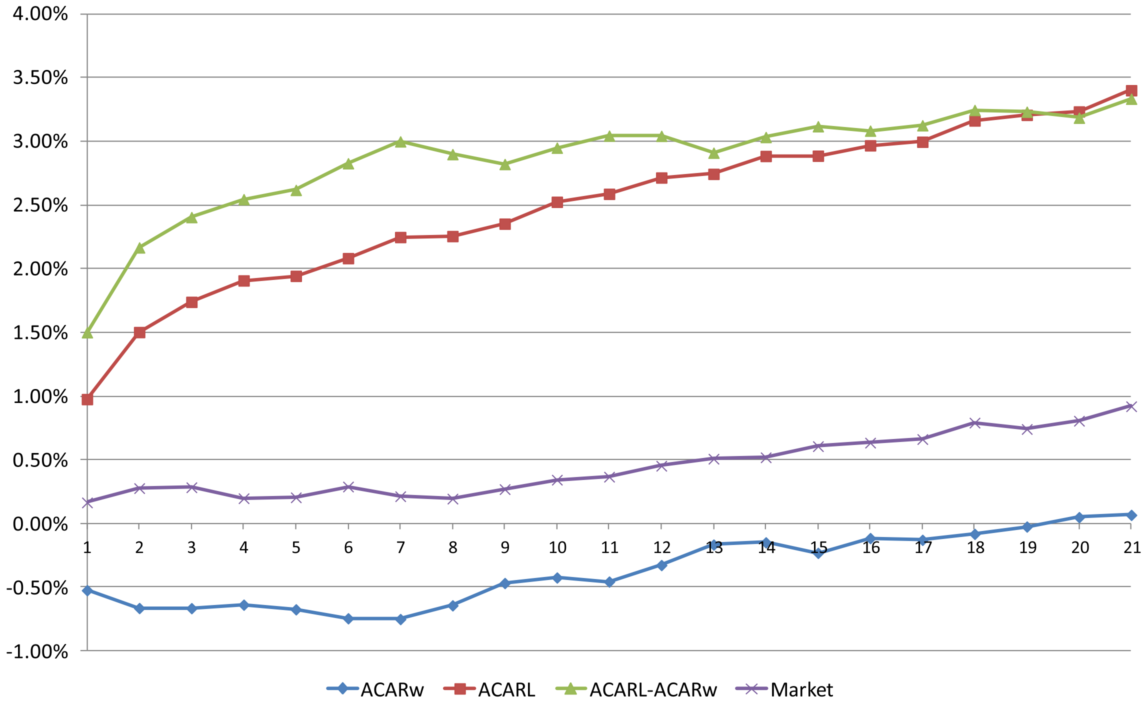

Fig. 2. Average cumulative returns of the loser and winner portfolio as well as of the contrarian strategy for all events. The average cumulative return of the market index (CRSP Value Weighted Index) was calculated employing the same methodology used to obtain the ACAR for the winner and loser portfolios.

Table 3
Contrarian profits after controlling for risk factors.

	All Events	Positive	Negative
N	13,923	6,510	7,413
Raw return	0.16	0.11	0.20
Alpha	0.14	0.12	0.18
(t-stat)	*(7,62***)*	*(5,33***)*	*(7,92***)*
MRP	0.31	−0.54	0.75
(t-stat)	*(28,80***)*	*(−34,10***)*	*(67,96***)*
SMB	0.14	0.25	−0.06
(t-stat)	*(6,45***)*	*(8,54***)*	*(−2,84***)*
HML	0.16	0.06	0.18
(t-stat)	*(6,03***)*	*(1,72**)*	*(6,14***)*
MOM	0.21	0.28	−0.11
(t-stat)	*(11,14***)*	*(11,26***)*	*(−5,41***)*
R^2	5.7	25.3	41.1

The table shows the coefficients of the regression of the contrarian strategy returns on the Carhart four-factor model for All events, Positive and Negative events during the 21-day window.
$R_{L,t} - R_{W,t} = \alpha + b_{i,t}MRP + s_{i,t}SMB + h_{i,t}HML + m_{i,t}MOM + \varepsilon_t$
The t-statistics are in parentheses, and N is the number of observations (N) used in the regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events, and a single regression (Eq. (1)) is then run for the pooled data to generate the alphas. This alpha is thus based on the ex-post beta (post-event window) of the contrarian portfolio. All daily factors were downloaded from French's website. The alphas are given in percentage form and on a daily basis.
Significant at the 10% level, **at the 5% level, *** at the 1% level.

To gauge whether these findings are directed by a specific sample period,[6] Table 4 shows the results for the overreaction test (Panel A) and for the regression of the return of the contrarian portfolio in relation to the risk factors (Panel B) for four sub-periods of the sample window. In all the groups, the hypothesis of overreaction in the short term was confirmed, with the contrarian portfolio generating statistically and economically significant alphas, varying from 13.7% (2nd period) to 56.4% (1st

[6] We would like to thank Professor Newton C.A. da Costa Jr for raising this question.

Table 4
Overreaction to extreme events for subperiods.

	1st Period (1926–1947) N = 198		2nd Period (1948–1969) N = 139		3rd Period (1970–1991) N = 149		4th Period (1992–2013) N = 177	
Panel A: Overreaction test for subsamples								
Day	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat
1	2.79%	(8,861***)	1.49%	(8,977***)	0.53%	(3,079***)	0.89%	(4,963***)
5	3.94%	(7,829***)	1.76%	(6,883***)	2.18%	(5,840***)	2.18%	(5,425***)
9	4.08%	(7,217***)	1.97%	(6,449***)	2.94%	(6,206***)	1.98%	(4,319***)
13	4.26%	(6,685***)	2.15%	(6,473***)	2.95%	(5,951***)	1.96%	(3,644***)
17	4.83%	(6,831***)	2.12%	(5,908***)	3.09%	(5,738***)	2.04%	(3,343***)
21	4.91%	(6,918***)	2.30%	(5,266***)	3.26%	(5,379***)	2.44%	(3,815***)
Panel B: Regression 4-factor model								
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Alpha	0.22	(4,73***)	0.05	(2,36***)	0.15	(5,89***)	0.12	(3,25***)
MRP	0.37	(16,10***)	0.42	(17,30***)	0.18	(7,15***)	0.27	(13,42***)
SMB	0.24	(5,95***)	−0.20	(−3,60***)	0.12	(3,87***)	0.00	(−0,08)
HML	−0.09	(−1,59*)	0.20	(3,52***)	−0.06	(−1,07)	0.44	(8,85***)
MOM	0.23	(5,82***)	0.25	(6,54***)	0.31	(9,28***)	0.23	(6,21***)
R^2	5.99		12.60		7.41		6.22	
N	4,158		2,906		3,126		3,733	

The table shows the cumulative returns of the contrarian strategy ($ACAR_L$ – $ACAR_W$) during the 21-day analysis window in Panel A and the control for the Carhart risk factors in Panel B. The t-statistics are in parentheses. Our sample period, ranging from 1926 to 2013 was divided into 4 subgroups of 21 years each. For the purposes of brevity, we only report the CAR of contrarian strategy for D1, D5, D9, D13, D17 and D21. The complete data are available upon request.

$R_{L,t} - R_{W,t} = \alpha + b_{i,t}MRP + s_{i,t}SMB + h_{i,t}HML + m_{i,t}MOM + \varepsilon_t$

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 a single regression (Eq. (1)) is then run for the pooled data to generate the alphas. This alpha is thus based on the ex-post beta (post-event window) of the contrarian portfolio. All daily factors were downloaded from French's website. The alphas are given in percentages and on a daily basis.

*Significant at the 10% level, **at the 5% level, *** at the 1% level.

period) in annual terms. The low explanatory power of the four-factor model for returns on this portfolio should also be observed, showing that the observed behavior cannot be attributed to the risk factors of the contemporaneous models.

The large sample period in question covers a number of financial crises. As there is evidence that the prices of assets vary more sharply at such times because of the heightened perception of risk on the part of economic agents, it is convenient to test whether the overreaction that was identified cannot be caused by the crises, ceasing to exist in less turbulent times. To address this issue, we divided the sample into two groups: during and outside of times of crisis. We used the database of the National Bureau of Economic Research (NBER) to identify these periods. Table 5 summarizes the results of the regression of the returns on the portfolio for the four-factor model in both subgroups.

In both groups, the LMW portfolio generated significant alphas, indicating that the short-term overreaction to unexpected events is present even when such events occur outside times of crises. The magnitude of this phenomenon, however, is heightened during a financial crisis, given that the annualized alpha for this group is double that of the second (56.5% and 23.3% in annual terms, respectively). These results are in keeping with the findings of Daniel and Moskowitz. (2013) and Barroso and Santa-Clara (2015), who reported that momentum portfolios (by construction, the opposite of the LMW portfolio) suffer crashes during financial crises. This behavior is also backed by the behavioral explanation of a feeling of surprise, as under these circumstances the market shows events of a higher magnitude and consequently with a greater effect on investors' feelings. Another item of data that arouses attention is the significance of the momentum factor coefficient for the "Outside of Crises" subgroup. As the phenomenon in question is, by definition, the opposite of the Momentum phenomenon, a low significant was expected for this factor. The following section helps to explain this apparent puzzle.

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 D_0 is followed by an extreme rebound on the following day D_1. Thus, D_0 and D_1 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 D_0 due to their higher (lower) betas. When the market rebounds with an extreme magnitude on D_1, 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 D_0, the outperformance of the loser portfolio over the winner would reflect returns warranted by the CAPM beta differential instead of overreaction of stocks on D_0.

Table 5
Contrarian profits after controlling for risk factors in and out-of-crisis periods.

	During Crises		Out-of-crises	
	Coefficient	t-stat	Coefficient	t-stat
Alpha	0.22	(5,21***)	0.09	(5,72***)
MRP	0.37	(17,44***)	0.15	(11,54***)
SMB	0.23	(6,06***)	0.00	(0,09)
HML	0.09	(1,89**)	0.20	(6,80***)
MOM	0.17	(4,73***)	0.47	(20,95***)
R^2	6.2		8.3	
N	5,097		8,826	

The table shows the coefficients of the regression of the contrarian strategy returns on the Carhart four-factor model for events that occurred during and out of financial crisis periods. Crisis periods were defined using the NBER's (National Bureau for Economic Research) classification for financial crisis periods.
$R_{L,t} - R_{W,t} = \alpha + b_{i,t}MRP + s_{i,t}SMB + h_{i,t}HML + m_{i,t}MOM + \varepsilon_t$
The t-statistics are in parentheses, and N is the number of observations (N) used in the regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events, and a single regression (Eq. (1)) is then run for the pooled data to generate the alphas. This alpha is thus based on the ex-post beta (post-event window) of the contrarian portfolio. All daily factors were downloaded from French's website. The alphas are given in percentage form and on a daily basis.
*Significant at the 10% level, **at the 5% level, *** at the 1% level.

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.

Table 6 shows the average CAR of the contrarian strategy for each subsample on days D_1, D_5, D_9, D_{13}, D_{17} and D_{21} (Panel A) and the result of the regression of the portfolio for the four-factor model (Panel B). In the Non-Overlapping subsample 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 & Jordan, 1997; Liang & Mullineaux, 1994) that aim to control for overlap, albeit of stock-specific instead of market-based events. The alpha generated by the LMW of this subgroup (Panel B) corroborates this behavior, indicating that the overreaction hypothesis remains robust, even after controlling for risk factors. This behavior also appears not to be biased by the size effect, as the SMB factor did not prove to be significant. Furthermore, the low capacity of the four-factor model for explaining the returns on the contrarian portfolio should be observed (R^2 = 4.4), indicating that this phenomenon violates the assumptions of the pricing of assets for this model.

The contrarian returns for the Momentum subsample in Panel A of Table 6 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. Even so, the contrarian portfolio generated a positive and significant alpha at 5%, although economically more modest (18.5% in annual terms). It should also be highlighted that the Momentum factor (MOM) was more significant between the subgroups, given that it alone represented an R^2 = 15% in a regression not reported in this work. This result is coherent with the expected behavior of the portfolio when overlapping extreme events have the same sign.

As expected, the Reversal subsample 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%. Part of this performance, however, is attributed to the difference in risk between the assets, given that the annualized alpha of the portfolio was 49%. The non-significance of the momentum factor for this portfolio is consistent with the fact that this sub sample is biased in favor of the overreaction phenomenon.

The results for the Mixed subsample 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. The contrarian strategy in the Mixed subsample remains highly profitable until the end of the window, with an impressive 46.92% annualized abnormal return

Table 6
Overreaction to extreme events for subsamples formed regarding the signal of the overlapping sample.

	Non-overlapping (N = 195)		Momentum (N = 103)		Reversal (N = 114)		Mixed (N = 251)	
Panel A: Overreaction test for subsamples								
Day	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat
1	1.43%	(8.189***)	0.73%	(3.274***)	1.49%	(6.195***)	1.87%	(7.578***)
5	1.95%	(7.005***)	0.87%	(2.100**)	3.39%	(7.600***)	3.50%	(8.002***)
9	2.45%	(7.254***)	1.03%	(1.837**)	3.72%	(8.372***)	3.43%	(6.854***)
13	2.58%	(6.182***)	1.21%	(2.028**)	3.93%	(7.400***)	3.39%	(6.228***)
17	2.92%	(6.089***)	0.90%	(1.316*)	4.34%	(7.291***)	3.64%	(6.167***)
21	2.77%	(5.374***)	1.31%	(1.830**)	4.85%	(7.582***)	3.91%	(6.105***)
Panel B: Regression 4-factor model								
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Alpha	0.13	(4,57***)	0.07	(1,99**)	0.19	(5,29***)	0.23	(6,27***)
MRP	−0.16	(−5,19***)	−0.15	(−5,00***)	0.32	(11,35***)	0.39	(26,11***)
SMB	0.02	(0,32)	0.61	(11,41***)	0.20	(3,87***)	0.02	(0,72)
HML	0.42	(8,76***)	0.66	(11,42***)	−0.65	(−10,96***)	0.10	(2,32**)
MOM	0.34	(9,54***)	0.68	(17,27***)	0.01	(0,23)	0.01	(0,47)
R^2	4.36		26.03		10.07		12.66	
N	4,095		2,163		2,394		5,271	

The table shows the cumulative returns of the contrarian strategy ($ACAR_L$ – $ACAR_W$) during the 21-day analysis window in Panel A and the control for the Carhart risk factors in Panel B. The t-statistics are in parentheses. The groups were formed in accordance with the signal of the overlapping events. Non-overlapping events are those 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. For brevity, we only report the CAR of the contrarian strategy for D1, D5, D9, D13, D17 and D21. The complete data are available upon request.
$R_{L,t} - R_{W,t} = \alpha + b_{i,t}MRP + s_{i,t}SMB + h_{i,t}HML + m_{i,t}MOM + \varepsilon_t$
The t-statistics are in parentheses, and N is the number of observations (N) used in the regression. The contrarian portfolio returns and the contemporaneous risk factor values are pooled over the pertinent set of events, and a single regression (Eq. (1)) is then run for the pooled data to generate the alphas. This alpha is thus based on the ex-post beta (post-event window) of the contrarian portfolio. All daily factors were downloaded from French's website. The alphas are given in percentages and on a daily basis.
*Significant at the 10% level, **at the 5% level, *** at the 1% level.

over the post-event window, although below the 58.20% performance in the Reversal subsample. The contrarian strategy of this group also had the highest alpha (57.8%) and, consequently, the lowest levels of significant for the Size, Growth and Momentum factors, being significant at 5% only for the second factor. This behavior indicates the low capacity of the contemporaneous risk factors to explain the returns on the portfolio, especially when volatility is high, and extreme events are clustered (Wu, Liu, & Chen, 2016).

To see the differential performance profile of the subsamples over the post-event days, Fig. 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 (Corrado & Jordan, 1997; Liang & Mullineaux, 1994; Madura & Richie, 2004; Tian & Hamori, 2016), this time profile indicates that the overreaction takes place shortly after the event.

The magnitude of the alpha in the Mixed subsample may be partially 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 the increased mispricing caused by aggravated asymmetry of information in an environment of heightened market volatility. 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". 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 A of Table 7.

Once again, the OH is confirmed for all the classifications in Table 7, 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 and Low Volatility 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 close to 4% mark by Day 13 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

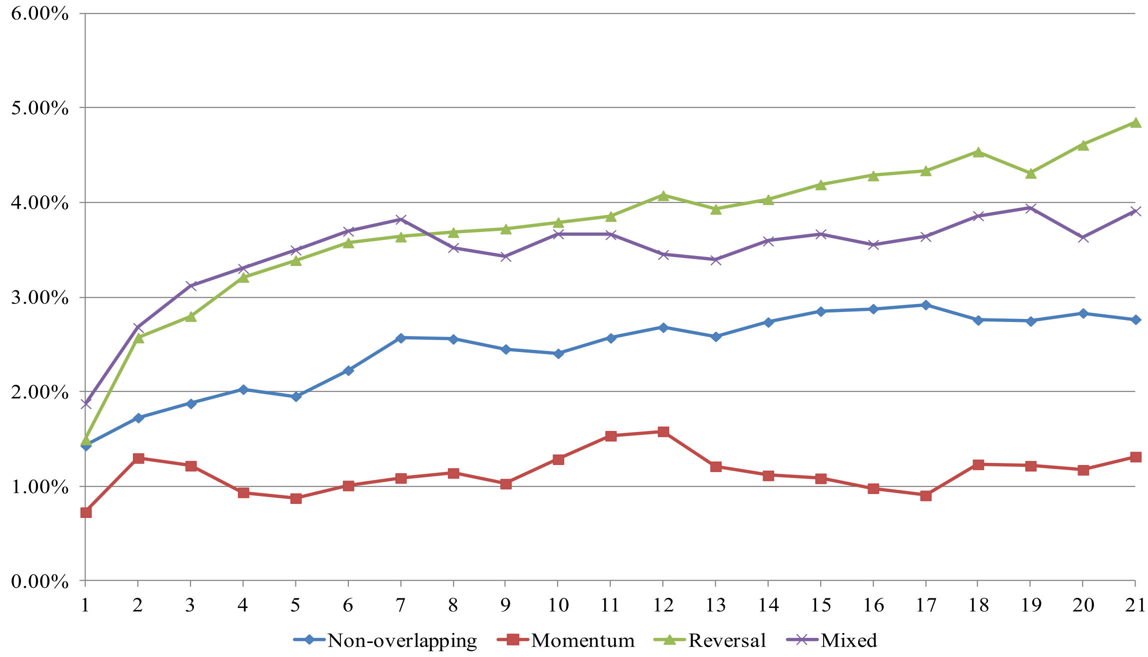

Fig. 3. Average cumulative returns of the contrarian strategy for Non-overlapping, Momentum, Reversal and Mixed subsamples.

Table 7
Overreaction to extreme events for different groups divided by volatility.

	High Volatility (N = 331)		Low Volatility (N = 331)		30% High (N = 100)		30% Low (N = 100)	
Panel A: Overreaction test for subsamples								
Day	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat	$ACAR_L$-$ACAR_W$	t-stat
1	2.09%	(9.803***)	0.91%	(8.632***)	3.49%	(6.353***)	0.97%	(4.892***)
5	3.58%	(9.415***)	1.66%	(9.191***)	5.74%	(5.838***)	1.50%	(4.947***)
9	3.64%	(8.356***)	2.01%	(9.193***)	5.85%	(5.637***)	1.71%	(4.853***)
13	3.92%	(8.082***)	1.90%	(7.715***)	6.15%	(5.210***)	1.72%	(4.518***)
17	4.40%	(8.221***)	1.85%	(6.688***)	7.61%	(5.725***)	1.90%	(4.491***)
21	4.58%	(8.261***)	2.09%	(6.821***)	7.42%	(5.297***)	1.99%	(3.94***)
Panel B: Regression 4-factor model								
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Alpha	0.21	(6,14***)	0.08	(4,84***)	0.34	(3,92***)	0.06	(2,36***)
MRP	0.30	(18,87***)	0.38	(22,26***)	0.18	(4,95***)	0.41	(13,85***)
SMB	0.14	(4,55***)	0.11	(3,73***)	0.11	(1,72**)	−0.09	(−1,61*)
HML	0.20	(5,00***)	0.10	(2,69***)	0.08	(0,94)	−0.10	(−1,30*)
MOM	0.21	(7,64***)	0.18	(7,02***)	0.04	(0,75)	0.30	(6,06***)
R^2	5.05		9.42		1.48		13.83	
N	6,951		6,951		2,100		2,100	

The table shows the cumulative returns of the contrarian strategy ($ACAR_L$ – $ACAR_W$) during the 21-day analysis window in Panel A and the control for the Carhart risk factors in Panel B. The t-statistics are in parentheses. 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 the post-event window). Events with below (above) median market standard deviation are classified as Low (High) Volatility. Events with the highest and lowest 30 percent of the cases classified as High and Low form, respectively, the 30% High and 30% Low groups. The complete data are available upon request.

$R_{L,t} - R_{W,t} = \alpha + b_{i,t}MRP + s_{i,t}SMB + h_{i,t}HML + m_{i,t}MOM + \varepsilon_t$

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 a single regression (Eq. (1)) is then run for the pooled data to generate the alphas. This alpha is thus based on the ex-post beta (post-event window) of the contrarian portfolio. All daily factors were downloaded from French's website. The alphas are given in percentage form and on a daily basis.

*Significant at the 10% level, **at the 5% level, *** at the 1% level.

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, but the CARs are lower than for the Low Volatility subsample remaining mostly below the 2% level and

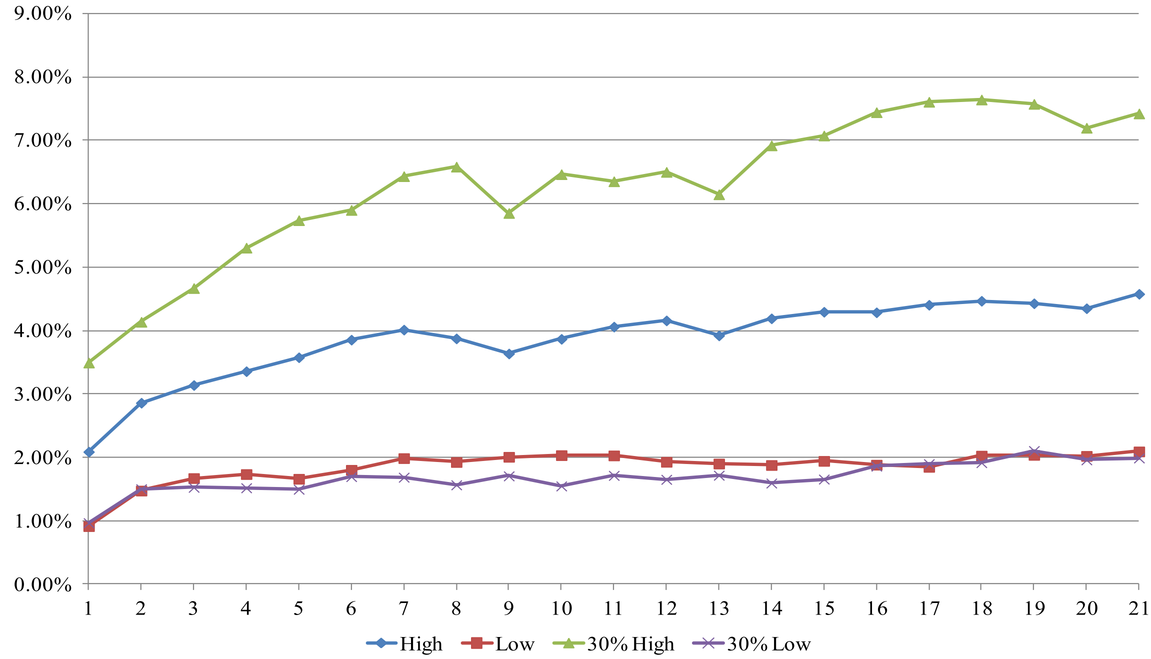

Fig. 4. Average cumulative returns of the contrarian strategy for subsamples formed basing on the standard deviation of the daily market index returns on 22 days, namely, Days 0 (event day) to 21 (last day of post-event window). Events with below (above) median market standard deviation are classified 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.

ending at 1.99% on Day 21 (annualized 23.88%). Meanwhile, the 30% High subsample exhibits pronounced CARs that are, on average, approximately 3.75 times the respective CARs of the 30% Low subsample (. 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 miss-adjustments in individual security prices at a time of extreme market movements, what is consistent with the excess volatility story (Shiller, 1981; Wang & Ma, 2014)

In Panel B, the results of the regression for the four-factor model are presented. Again, the contrarian portfolio generates statistically significant alphas in all the subgroups, but with a clear economic distinction, becoming more pronounced as the market becomes more volatile, varying in annual terms between 15.7% during times of lower volatility (30% Low) and 85% during periods of higher volatility (30% High). This asymmetry can also be seen because the alphas of the low volatility subgroups are very similar, and very different in the high volatility groups. It is interesting to note that the four-factor model loses its explanatory capacity as the volatility increases. In the "30% High" subsample, the model is highly ineffective when it comes to explaining the returns on the LMW portfolio. It is also worth mentioning that even under less stressful circumstances, stocks still overreact to extreme market movements in a way that the systematic risk models cannot explain.

To provide a better view of the distinction of the contrarian strategy's performance among the groups, Fig. 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.

In general, these results confirm that a 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 & Moskowitz., 2013; Barroso and Santa-Clara, 2015) 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.

4.4. 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:

Table 8
Testing the reversal of the winner and loser portfolios after the extreme event.

Market betas	Panel A: Non-Overlapping (N = 195)				Panel B: Momentum (N = 103)				Panel C: Reversal (N = 114)				Panel D: Mixed (N = 251)			
	Loser stocks 0.96		Winner stocks 1.08		Loser stocks 0.93		Winner stocks 1.10		Loser stocks 1.11		Winner stocks 0.87		Loser stocks 1.16		Winner stocks 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*)*		*(−5.260***)*		*(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***)*	

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.
*Significant at the 10% level, **at the 5% level, *** at the 1% level *significant at 5%; **significant at 1%.

$$CAR_{1,t2} = \gamma_0 + \gamma_1 AR_0 + \varepsilon_t \quad (2)$$

$CAR_{1,t2}$ 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 (D_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 8 presents the results for the four subsamples (Non-Overlapping, Momentum, Reversal, Mixed) defined in ection 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.

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 8), 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 4 Factors 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 (previous 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. Furthermore, this approach filters out almost 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 investigated 663 events (310 positive and 353 negative) and found strong evidence of statistically and economically significant support for the Overreaction Hypothesis (De Bondt & 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 Carhart 4 factors alpha of 30.57% after positive events and 46.49% after negative events.

The overreaction remains observable in and out of financial crisis periods and throughout the entire 87 analysis period. This behavior also keep 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 4 Factor annualized alpha of 33.02%. 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 have also documented that overreaction is particularly pronounced when the extreme market movements are clustered, implying that overreaction and market volatility circumstances may be 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 4 factors annualized alpha is an overwhelming 85%.

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 et al., 1988) or the Information Hypothesis (Baule & Tallay, 2014; Chan, 2003; Kang et al., 2015; Savor, 2012) either. We believe a more plausible explanation for the overreaction we report is the behavioral bias (Griffin & 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.

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