Article

Equity Returns Around Extreme Loss: A Stochastic Event Approach

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ABSTRACT

We define an extreme loss event as a daily return at the left tail of negative two standard deviations of all daily returns for a specific stock. Prior studies focus on the relationship between extreme losses and specific anticipated announcements. Our study identifies the extreme loss events after they are randomly realized, and examines the return patterns of the equities in question on stochastic event setups. We investigate the daily returns of 2,651 stocks traded in the U.S. equity markets and identified 217,990 extreme loss events from the 1950s to early 2019. Our findings show that after an extreme loss, an asset realizes, on average, a daily return of 0.8459% on the first day, and 1.8099% cumulatively in the following 5-day window. We attribute the fast recovery to the investors' overreaction. This suggests an extreme loss reversal trading strategy. Our confirmation suggests that behavioral bias may not be corrected or eliminated through arbitrage.

KEYWORDS

Trading Strategy, Mean Reversion, Momentum, Equity Return, Loss

JEL Classification: G11, G14, G17

INTRODUCTION

Many stocks have experienced extreme loss events. This research defines an extreme loss as a daily return at the left tail of negative two standard deviations of all daily returns for a specific stock, or worse than 97.5 % of all daily returns. While extreme negative events have attracted much attention in the literature, most of the studies focus on the relationship between the loss event and specific events occurring before the loss at a specific point in time, such as earnings announcements or interest rate decisions. In contrast, this study identifies the extreme loss events which are market-driven after they are realized on random days and examines equities' return patterns before and after.

When an event and the information flow regarding specific equities are scheduled to arrive at the market, the market expects a certain degree of abnormal volatility around the event. Therefore, the trading strategies around the event focus on interpreting the nature and the impact of the event. In contrast, an extreme loss event may not be anticipated but may only be observed after it is realized. The trading strategies focus on interpreting the reason for the loss and the behavior of the peer investors. The reason may largely be categorized as market-based or intrinsic-value-based. A market-based extreme loss may be triggered by the change of some fundamental factors such as interest rate or maybe sentiment based. The intrinsic value-based extreme loss may be led by the unexpected disclosure of negative information regarding the asset.

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Among the sentiment-driven extreme loss events, inadvertent losses are widely observed. The price of an asset may be altered due to market panic or margin call though the asset has not experienced a significant change in its fundamental factors or pattern of future cash flows. The price of such an asset is expected to recover quickly in this case. In this study, we attempt to address (1) the definition of extreme loss and explore the application of a trading strategy that makes use of the extreme loss; (2) distinguish the extreme loss due to market sentiment and overaction versus due to fundamental factor changes, and understand the difference between the loss recovery processes; and (3) provide the numerical value of the expected excess return with the loss recovery trading strategy for investors to gauge the feasibility after the impact of transaction cost is taken into account.

By exploring these topics, we contribute to the current literature regarding equities' extreme loss in the following ways that have not been conducted in the past to our knowledge. First, this study identifies each equity's extreme loss events to analyze whether any return patterns foreshadow the upcoming event. Second, this study looks at return patterns after an event to determine whether the loss can be attributed to the market's overreaction. Finally, the post-loss return patterns suggest a robust and implementable trading strategy that takes advantage of a specific stock's extreme loss.

However, the focus of this study is to examine the return reversal and the relation between its cause and its magnitude rather than provide a trading strategy. Our confirmation of the persisting return reversal and long-existing excess return makes a significant theoretical contribution: behavioral bias, in our context the overreaction bias, may not be corrected or eliminated through arbitrage. Thus, the investment actions of rational investors do not limit the market capacity for irrational actions.

The strategy explored in this study is unique because it is not an ad hoc trading rule built on expectations. It regards the investor behavior as a black box, and the trading orders submitted follow a Brownian motion. The decision-making process of this strategy is ex-post and is based on the observed extreme loss regardless of the reason and interpretation. This strategy is also cohort-based; it is valid from a statistics perspective when a portfolio of assets suffering from extreme loss is traded and may not be valid for individual assets.

This research's organization is as follows: Section II provides a review of previous literature; Section III describes the data used and methodology; Section IV presents the results and the strategy; Section V concludes and provides some avenues for future research.

LITERATURE REVIEW

Earlier research has examined extreme returns of assets. Bali, et al. (2011) are the first to suggest the effect of extreme positive returns (MAX) and provide evidence of a preference among investors for assets with lottery-like payoffs. However, they also document a negative relation between an extremely positive daily return over the preceding month and expected stock returns. Similarly, Annaert, et al. (2013) find that stocks with an extremely positive daily return face lower-than-expected returns over a longer period. Nartea, et al. (2014) add evidence of a strong negative MAX effect in South Korea. Their results demonstrate consistency with studies from Berggrun, et al. (2019) and Piccoli, et al. (2017) on Brazil's financial market, indicating that the MAX effect is not limited to equities in the developed markets. Michail (2019) finds that the predictability of asset prices increases during the Great Recession due to extreme loss.

A significant number of studies have examined extreme loss events and equity returns around such events. However, we identify five major gaps in those studies that should be addressed regarding the reasons proposed for post-loss reversal and the implementation of possible trading strategies in the capital market.

The first gap in the literature pertains to the absence of a universal definition for extreme loss with an implementable benchmark. Kang, et al. (2018) define the price reversal with a relative benchmark.

Therefore, a price reversal may only be recognized after the reversal is realized. This approach foregoes the investment opportunity and fails to establish itself as an investment strategy.

The second gap is to neglect the connection between individual assets with the market portfolio. It is the collective plunge of individual asset prices that leads to extreme loss of the market portfolio. Several studies focus on the existence of short-term return reversal behavior in asset pricing, defined as the gain of an asset after turmoil in the market when controlling for market performance, size, value, and momentum of the asset (Nagel, 2012; Kang, et al., 2018). Thus, these studies treat market loss as an exogenous triggering factor that leaves the extreme loss of the asset as an after-effect. Existing literature does not use the extreme loss confined to the asset itself as an endogenous triggering factor to detect its consequences.

The third gap occurs between the theoretical excess return and the investment practice when the portfolio needs to be rebalanced, but the timing of rebalancing receives no specific instruction. Therefore, a trading strategy reliant on the asset weight in the portfolio is less reliable regarding profitability. Research has also examined trading strategies around extreme loss events. Traders with performance constraints or investment policy restrictions are often forced to rebalance the weights of assets in a defined portfolio after an extreme loss occurs. As a result, the timing of their investments and clearance of assets that suffer an extreme loss might be sub-optimal. Daniel and Moskowitz (2016) suggest a dynamic momentum strategy using momentum crashes and extreme negative losses. Though previous studies document that short-term reversal strategies provide positive returns theoretically (e.g., Shahzad, et al., 2018), there is no broad indication of the exact investment strategy that is implementable in brokerage practice.

Moreover, previous studies question the actual value of short-term reversal returns. Avramov, et al. (2006) argue that the returns barely cover the transaction cost incurred in the high-frequency trading activities required to capture the reversal profit. However, de Groot, et al. (2012) contend that short-term reversal returns are persistent and profitable even when the transaction cost is considered. As past studies do not attempt to quantify the size of the return following extreme loss events, this gap hampers the ability of fund managers to exploit any short-term reversal return.

The fourth gap occurs where previous studies focus on post-loss return patterns while ignoring pre-loss return patterns. These studies often use indirect forecasting factors to predict an upcoming loss event. For example, Switzer, et al. (2017) study the relationship between volatility and the probability of expected extreme returns in Canada's capital market. They find a positive relationship between a firm's idiosyncratic volatility and an extreme return in the subsequent month. However, Dong, et al. (2019) find that the link between idiosyncratic volatility and subsequent return is weak using a broad dataset with a long time series history.

The fifth gap in the literature is that past studies do not agree on the most appropriate methods for studying reversal returns. For example, Hood and Malik (2018) suggest that the best way to forecast the downside risk in the stock market is through a model that includes both time-varying volatility and structural breaks. In contrast, Dong, et al. (2019) observe that volatilities and breaks identified by trading volume need not be included in forecasting losses. Alternatively, Aboulamer and Kryzanowski (2016) and Trapin (2018) show that realized idiosyncratic volatility is positively related to asset returns in Canada's stock market, and so are the extreme positive returns (MAX) related to future returns. They also suggest that reversal to the mean after extreme daily returns is mostly limited to small stocks. This study uses a dataset covering 500 large- and mid-cap stocks and 2,151 small-cap stocks to analyze the survivorship of the short-term reversal returns.

This study builds on previous literature in four ways. First, it focuses on extreme loss events as they affect individual assets, rather than the market as a whole. Second, rather than focus on a more theoretical explanation of extreme loss events, it focuses on identifying an implementable trading strategy with timing and operation guidelines and attempts to quantify the size of any recouped losses. Third, whereas previous studies might ignore pre-loss return patterns, this study examines pre-loss return patterns to identify early warning signals. Finally, this study presents a novel stochastic event methodology to study extreme loss events.

DATA AND METHODOLOGY

This study aims to suggest a robust trading strategy for stocks that experience an extreme loss event. To ensure that the trading strategy proposed is valued, we employ the largest possible dataset with a long historical record of daily returns of the equities of the Russell 3000 Index. The trading volume of the assets included in this index represents an overwhelming fraction of the U.S. equity market trading volume.

We use adjusted closing prices of equities in the Russell 3000 Index from the Center for Research in Security Prices (CRSP) to compute daily returns and the standard deviation of daily returns for each equity. The adjusted closing price adjusts for dividends and stock splits. We remove equities with returns that are not continuous so that each equity analyzed has five continuous trading days before and after an extreme loss event identified, which leaves 2,651 equities for this analysis. Thus, the dataset covers daily returns since January 2, 1950, or their IPOs for those that began trading later.

This study assumes that equity daily returns follow a normal distribution and defines the extreme loss threshold for an equity as a daily return that is 1.96 standard deviations below the mean value, i.e.,

$$r_i^{CDF2.5} = \overline{r_i} - 1.96\sigma_i \quad (1)$$

where $r_i^{CDF2.5}$is the extreme loss threshold for equity i; $\overline{r_i}$ is the mean value of the daily returns of equity i; and σ_i denotes the standard deviation of daily return for equity i. Thus, an equity's extreme losses are its daily returns lower than 97.5% of all its daily returns. This study, using this definition, observes 217,990 extreme loss events for the 2,651 equities in the sample. The thresholds of these events are tailored for each individual asset and are fixed for each asset to ensure universal event qualifications.

For example, we calculate the extreme loss return threshold for the Standard and Poor's 500 Index as:

$$r_{sp500}^{CDF2.5} = \overline{r_{sp500}} - 1.96\sigma_{sp500} \quad (2)$$

where $r_{sp500}^{CDF2.5}$is the extreme loss threshold for the Standard and Poor's 500 Index; $\overline{r_{sp500}}$ is the mean daily return of this index; and σ_{sp500} denotes the standard deviation of the daily return of this index. Similarly, we identify an extreme loss event for the entire market when this index realizes a daily return that is lower than this threshold. These calculations use a 0.0341% average daily return and a 0.009624 standard deviation of daily returns for the Standard and Poor's 500 Index. Other return thresholds can be calculated based on the cumulative distribution function of the normal distribution of the index, which the daily return follows, as presented in Figure 1.

In the next step, we categorize the types of returns in an 11-day window around an extreme loss event. We subdivide the five trading days before an extreme loss event into three subperiods, one for the fifth and fourth day, one for the third and second day, and one for the day before the extreme loss event. Each of the three subperiods is labeled either G (Gain) if the realized return over the period is positive, or L (Loss) if negative. We do not include the data in the sample if a daily return is zero.

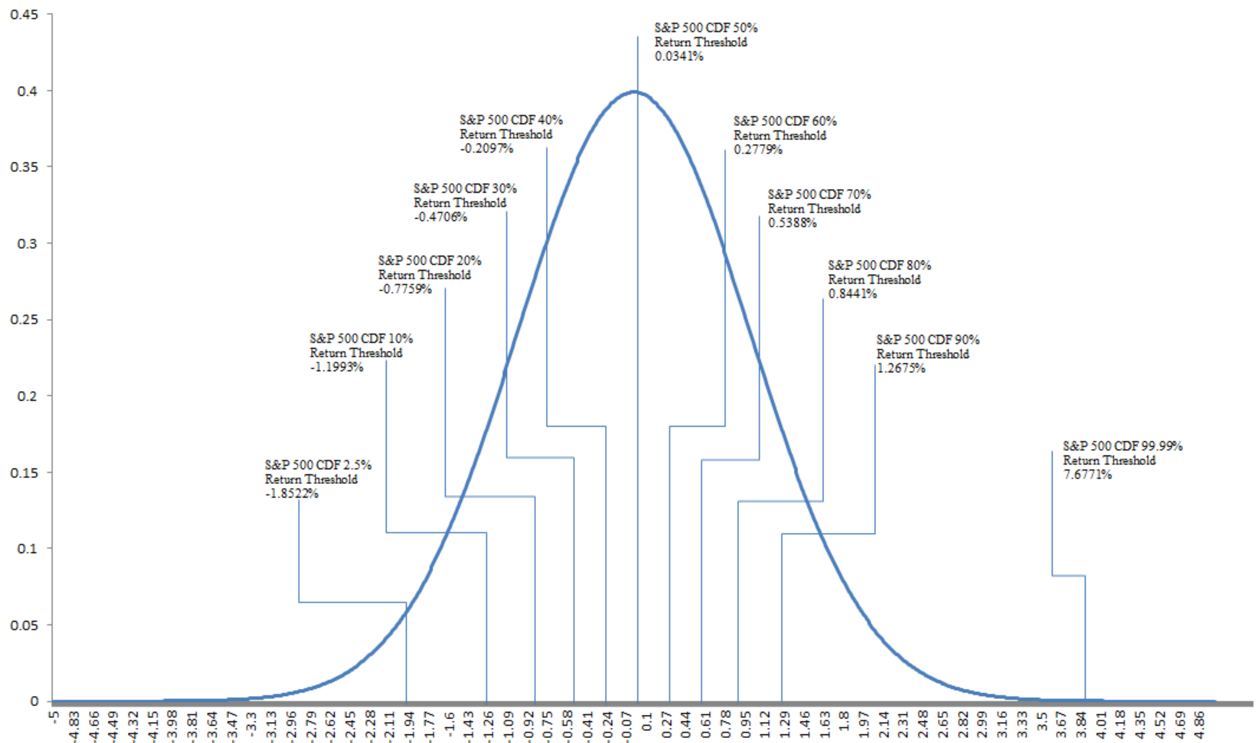

Figure 1. The Threshold Return Values of the S&P 500 Index

For example, suppose a hypothetical asset realizes daily returns of –0.10%, 0.20%, –0.15%, 0.12%, and 0.13% on each of the five days before an extreme loss event. The cumulative return from the fifth to the fourth day before the event, calculated as (1–0.10%)×(1+0.20%)–1, is positive. Therefore, the first pre-loss return pattern label for this asset is G. The return from the third to the second day before the loss event, calculated as (1–0.15%)×(1+0.12%)–1, is negative. Therefore, the second return pattern label is L. On the day before the extreme loss event, the asset's daily return, 0.13%, is positive. Therefore, the third return pattern label is G. The pre-loss pattern for this asset is thus recorded as GLG.

Similarly, we examine the asset's performance during the five days after an extreme loss event and label the three subperiods accordingly. We assign a label of G or L for an asset according to the same criteria mentioned above for the first day, from the second to the third day, and from the fourth to the fifth day after the extreme loss event.

Table 1 shows how the pre- and post-loss return patterns are mapped to different types. To illustrate this study's methodology, suppose a hypothetical asset has an average daily return of 0.03% and a standard deviation of daily returns of 0.021. According to Equation (1), the extreme loss threshold of this asset is 0.03%–1.96×0.021, or –4.09%. Therefore, this asset is considered to experience an extreme loss event if its return on a specific trading day is below –4.09%.

Suppose on a specific trading day, Day 6, the asset realizes a daily return of –4.83%, which is lower than the extreme loss threshold defined above. We identify Day 6 as an extreme loss event for this asset. Suppose the asset's daily returns within the ±5-day window around Day 6, follow the pattern presented in Table 2. According to Table 1, the pre-loss return pattern is recorded as GGL, and the post-loss return pattern is LLL. Thus, this asset's daily equity return pattern is categorized as a Type 2-7.

The next section presents the results of the empirical analysis of these events.

Table 1. The Definition of Daily Equity Return Patterns in a ± 5-Day Window

Type	Return on Days 5 and 4 Pre-loss	Return on Days 3 and 2 Pre-loss	Return on Day 1 Pre-loss	Return on Day 1 Post-loss	Return on Days 2 and 3 Post-loss	Return on Days 4 and 5 Post-loss
Type 1	*Gain*	*Gain*	*Gain*	*Gain*	*Gain*	*Gain*
Type 2	*Gain*	*Gain*	*Loss*	*Gain*	*Gain*	*Loss*
Type 3	*Gain*	*Loss*	*Loss*	*Gain*	*Loss*	*Loss*
Type 4	*Gain*	*Loss*	*Gain*	*Gain*	*Loss*	*Gain*
Type 5	*Loss*	*Gain*	*Gain*	*Loss*	*Gain*	*Gain*
Type 6	*Loss*	*Gain*	*Loss*	*Loss*	*Gain*	*Loss*
Type 7	*Loss*	*Loss*	*Loss*	*Loss*	*Loss*	*Loss*
Type 8	*Loss*	*Loss*	*Gain*	*Loss*	*Loss*	*Gain*

Table 2. A Hypothetical Asset Performance and the Return Pattern Categorization

Time	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11
Event Axis	*5 days pre extreme loss*	*4 days pre extreme loss*	*3 days pre extreme loss*	*2 days pre extreme loss*	*1 day pre extreme loss*	*extreme loss day*	*1 day post extreme loss*	*2 days post extreme loss*	*3 days post extreme loss*	*4 days post extreme loss*	*5 days post extreme loss*
Daily Return	*0.44%*	*0.09%*	*-0.38%*	*0.46%*	*-0.29%*	*-4.83%*	*-0.10%*	*-0.13%*	*-0.22%*	*-0.21%*	*0.09%*
Holding Period Return	*0.53%*		*0.08%*		*-0.29%*		*-0.10%*	*-0.35%*		*-0.12%*	
Return Pattern	*G*		*G*		*L*		*L*	*L*		*L*	
Type	2						*7*				

RESULTS AND DISCUSSION

AVERAGE MARKET PATTERNS AROUND EXTREME LOSS EVENTS

The 2,651 equities included in this study generate an average daily average return of 0.0748% with an average standard deviation of daily returns of 0.030038. While the average extreme loss threshold for the entire market is –5.8127%, the threshold for each equity differs and depends on its daily average returns and standard deviation.

The average extreme loss across all identified events is –8.2105%. Yet we observe an average daily return of 0.4450% during the five trading days before an extreme loss event, which is higher than the overall average daily returns. However, this difference is mainly due to the returns on the last day before the extreme loss events, which brings a 0.3773% capital appreciation on average. The first four trading days within the five-day window before an extreme loss event carry positive but lower-than-average return performance, resulting in a four-day-combined return of 0.0677%.

The 2,651 equities realize an average daily return of 0.8459% during the first day after an extreme loss event. The average holding period return during the five days after the event is 1.8099%, which indicates a partial recovery of the average 8.2105% loss from the event. Theoretically, an asset price that experiences an 8.2105% loss needs a return of 1/(1–8.2105%)–1=8.9445% afterward to fully recover. Therefore, the gain during the five-day window after the extreme loss event only recovers 20.23% of the loss (1.8099%/8.9445%). Table 3 presents summaries of the above-mentioned statistical results.

Table 3. The Average Equity Return Patterns around the Extreme Loss in a ± 5-Day Window

Average Daily Return	Average Standard Deviation of Returns	Average Threshold of Loss
0.0748%	*0.030038*	*-5.8127%*
Average Return 5 Days Pre-loss	*Average Return 3 Days Pre-loss*	*Average Return 1 Day Pre-loss*
0.4450%	*0.3832%*	*0.3776%*
Average Return on Identified Loss Days		
-8.2105%		
Average Return 1 Day Post-loss	*Average Return 3 Days Post-loss*	*Average Return 5 Days Post-loss*
0.8459%	*1.3406%*	*1.8099%*

The recovery of the asset return after a material loss is not necessarily evidence of market inefficiency. If the market consensus is that an asset should be priced correctly at a lower level, then no price recovery would be necessary. Conversely, an average 20.23% price recovery signifies that the extreme loss occurs previously may be an overreaction, with the market correcting it.

The statistical results suggest a trading strategy that takes advantage of an extreme loss event. Investors can buy an asset just before the market closes on the day of an extreme loss event, and then sell it just before the market closes on the fifth trading day after the event.

As Table 3 shows, the average daily return is only 0.0748% for the 2,651 equities. The average return during the five days before the extreme loss event is 0.4450%, which is about six times (0.4450%/0.0748%) greater than the average daily return. However, the average extreme loss identified, –8.2105%, represents a price change almost 110 times greater than the average daily return in absolute magnitude (|–8.2105%/0.0748%|). This study focuses on only 11 trading days around extreme loss events for the 2,671 stocks, yet it is unlikely that changes in an asset's fundamentals generate a large gain before an extreme loss event, the extreme loss itself, or the 20% recovery after the event. The dramatic change in an asset's return, from accumulating a 0.4450% gain during five days to losing 8,2105% on one day afterward, is believed to come from the investors' crowd selling behavior in response to a sudden large-scale loss. The quick recovery right after the extreme loss with a 0.8459% daily return, 11 times of average daily return (0.8459%/0.0748%), provides further evidence for this assumption. Moreover, the immensity of the quick recovery and the cumulative returns from Day 2 to Day 5 after the extreme loss rule out the explanation that the reversal return is a compensation of liquidity provision.

ABSOLUTE AND CONDITIONAL PROBABILITIES OF RETURN PATTERNS

This study identifies eight types of return patterns before and after an extreme loss event, which generates 64 possible combinations of pre- and post-loss return patterns if we look at the entire ± five-day window around the event. Table 4 shows all the type groups possible, as well as the probability of occurrence for each return pattern (among all the 64 possible patterns) which is shown as an absolute probability by type. Table 4 also shows the absolute probability pre-loss of each group type. It is the sum of the absolute probabilities by type of all return patterns that have the same pre-loss return pattern, showing the probability of a specific return pattern before the extreme loss event occurs. Conditional probability post-loss indicates the probability of a specific return pattern after the event occurs, given a specific return pattern occurring before the event.

Table 4 shows that return patterns are not identically distributed and show significant grouped differences. There appears to be no return pattern that deterministically signals an upcoming extreme loss event. Type 7, with its LLL return pattern during a five-day window and a 15.46% probability, occurs most often with extreme loss events. Conversely, the Type 1 pattern, with its 10.61% probability and GGG return pattern occurs most seldom with extreme loss events. Thus, Type 7 most likely implies an upcoming extreme loss, while Type 1 appears to be least likely to lead to an extreme loss.

Relatively speaking, Types 3 (GLL), 6 (LGL), 7 (LLL), and 8 (LLG) return patterns all have two "loss" periods and are connected to 54.76% of extreme loss events. Conversely, Types 1 (GGG), 2 (GGL), 4 (GLG), and 5 (LGG) return patterns all have two "gain" periods and precede only 45.24% of the extreme loss events. Moreover, as this study cumulates returns on Days 5 and 4 as well as the returns on Days 3 and 2 before the extreme loss, the higher probabilities of Types 3, 6, 7, and 8 before the loss imply more days of negative returns. Table 4 provides some evidence that holding period return for the days before the extreme loss is declining, from a 5-day return of 0.4450% to a 3-day return of 0.3832%, and a 1-day return of 0.3776%.

There also appears to be no deterministic return pattern after an extreme loss event. The differences among the post-loss return patterns are smaller than they are for pre-loss return patterns. We observe that Type 4 (GLG) return pattern occurs most often at 14.21% after an extreme loss event. The return pattern Type 7 (LLL) occurs least often with 10.64% of the time. Moreover, return patterns with two or more losses occur less often at 47.75% than those with two or more gains at 52.25% of the time.

THE RATIONALE OF THE RESULTS

Now the question is why do investors overreact to extreme loss events? While this is the first study to quantify the recovery of asset returns after extreme loss events, the mean reversion strategy is widely adopted in the capital market as public knowledge. Thus, it is reasonable to assume that investors understand the market may reverse even though they continue selling in an extreme loss event. Rational investors should have reflected on their actions concerning avoiding overreaction as they continue selling.

Then the question becomes more puzzling: why do investors still overact when they understand the existence of such behavioral bias? We offer two possible explanations: (1) investors believe that their behavior is rational and the executions they conduct are normal sell orders instead of an overreaction; and (2) investors who do not possess complete information regarding the price state in the next stage conduct sells to avoid possible greater loss. In both cases, the investors exhibit rationality and plan a systematic strategy based on the information available.

In the first case, investors believe that they do not overreact by placing sell orders in extreme loss events, though results show that the transaction would be categorized as overreaction. Such an understanding of the nature of the orders is only hindsight information. When investors are making decisions to sell, they follow a set of rational analyses and procedures. When they observe a cascade of sell orders from other investors, they do not regard themselves as following or herding. Instead, they believe that other sell orders confirm the appropriateness of their decisions with the joint selling behavior seeming to be no more than a coincidence on the time axis.

In other words, the market can only justify if a transaction behavior is an overreaction only after the price trend in the next stage is realized. Therefore, there is a mismatch of information when justifying the investors' overreaction if the identification is only known afterward. An overreaction identified after an extreme loss event may be conducted by investors who implement investment decisions rationally. Schadewitz et al. (2002) confirm the rationale of the investors' considerations. They document evidence that the market's reaction to a firm's announcement is delayed for one day for firms reporting lower-than-expected earnings. This delay is extended for two other days for firms reporting greater-than-expected earnings. Faced with an extreme loss, investors may regard that further delayed market reaction on the same trajectory is yet to arrive.

Table 4. The Probabilities of Return Patterns around the Extreme Loss in a ± 5-DayWindow

Type Group	Absolute Probability by Type	Absolute Probability Pre-loss	Conditional Probability Post-loss	Type Group	Absolute Probability by type	Absolute Probability Pre-loss	Conditional Probability Post-loss
1-1	1.29%		12.15%	5-1	1.31%		11.66%
1-2	1.39%		13.14%	5-2	1.50%		13.33%
1-3	1.36%		12.86%	5-3	1.47%		13.04%
1-4	1.54%	10.61%	14.53%	5-4	1.62%	11.25%	14.37%
1-5	1.29%		12.12%	5-5	1.23%		10.90%
1-6	1.43%		13.45%	5-6	1.68%		14.91%
1-7	1.14%		10.76%	5-7	1.17%		10.40%
1-8	1.17%		10.99%	5-8	1.28%		11.38%
2-1	1.62%		14.29%	6-1	1.62%		12.46%
2-2	1.51%		13.30%	6-2	1.73%		13.28%
2-3	1.40%		12.37%	6-3	1.95%		14.95%
2-4	1.73%	11.34%	15.25%	6-4	1.85%	13.02%	14.19%
2-5	1.34%		11.84%	6-5	1.51%		11.63%
2-6	1.35%		11.94%	6-6	1.49%		11.47%
2-7	1.19%		10.51%	6-7	1.33%		10.21%
2-8	1.19%		10.51%	6-8	1.54%		11.82%
3-1	1.76%		13.80%	7-1	2.09%		13.53%
3-2	1.55%		12.15%	7-2	1.82%		11.77%
3-3	1.45%		11.39%	7-3	2.02%		13.09%
3-4	1.61%	12.76%	12.62%	7-4	2.36%	15.46%	15.24%
3-5	1.78%		13.94%	7-5	1.88%		12.15%
3-6	1.79%		14.00%	7-6	1.81%		11.72%
3-7	1.39%		10.86%	7-7	1.58%		10.25%
3-8	1.43%		11.23%	7-8	1.89%		12.24%
4-1	1.29%		10.71%	8-1	1.79%		13.20%
4-2	1.62%		13.47%	8-2	1.88%		13.89%
4-3	1.62%		13.46%	8-3	1.72%		12.71%
4-4	1.56%	12.04%	12.95%	8-4	1.85%	13.52%	13.70%
4-5	1.69%		14.07%	8-5	1.64%		12.11%
4-6	1.53%		12.73%	8-6	1.58%		11.66%
4-7	1.35%		11.21%	8-7	1.49%		10.99%
4-8	1.37%		11.42%	8-8	1.59%		11.73%

In the second case, investors understand the existence of overreaction and the benefit of the reverse strategy: taking an opposite position after an extreme price movement would bring excess profit on average. However, rational investors also understand that this average benefit does not make investors fully informed about when and which event would happen: further losses versus a correction. In other words, while mean reversion would bring profit half of the time, investors possess little information about whether an extreme loss would be deterministically followed by a mean reversion.

Faced with such limited information, the investors need to plan for two opposite scenarios: execute sell orders to avoid further loss, or hold the current position to recover most of the loss. As the prospective theory suggests, a common investment behavioral bias is loss aversion: investors avoid realizing loss and control the size of the loss, while quickly realizing gain and limiting the size of the gain. Any rational and risk-averse investor should follow the sell orders in the extreme loss event and close the losing position when information is not readily available.

In both cases, that while the investors' behaviors may be regarded as overacting and irrational, their decisions during the extreme loss events may be rational and not in line with any behavioral bias. Thus, this study cautions other researchers in this field that overreaction is a hindsight judgment and may not be applied to the classification of behaviors with limited information.

Furthermore, a price reversal should not be regarded as a correction of the previous overreaction or irrationality. A reversal may represent a different view of the asset price in the capital market unless it can be proved that the reverse is caused by the same investors who participate in the selloff during the extreme loss event. The existence of such a different view does not warrant the notion that the selloff transactions are irrational per se. Furthermore, the reverse strategies are not constantly profitable, though they are on average. They should not be regarded as representing the rational side of the market.

ROBUSTNESS CHECK

The size of the firm and the stock price level may drive our conclusion. We conduct a series of robustness checks to confirm the validity of the trading strategy and the adaptivity of the findings around the extreme loss.

While market capitalization is typically used as the main indicator of equity size, we decompose our robustness check into the number of shares outstanding and the equity price. This is because the market cap is dependent on the asset price, and the categorization based on the market cap may be attributed to the price effect or liquidity issue.

We use the 25% quantile, median, 75% quantile, and maximum to categorize the assets according to their asset price and the number of shares outstanding. All the share and price data are adjusted based on the last day of the sample to take into account stock splits and reverse splits. This generates a four-by-four matrix from the smallest number of shares outstanding and the lowest price to the largest of both.

The results show that there is no consistent pattern of price reversal for stocks regarding their prices. Both stocks with high prices such as BRK and low prices such as penny stocks exhibit similar extreme losses and reversals. This result is counterintuitive, as it is commonly believed that smaller stocks are prone to large volatility changes. We argue that this is because the size refers to the market capitalization, and the higher volatility observed among the smaller stocks is not due to their price levels but due to their smaller number of shares outstanding. In fact, the recent deep loss and rapid recovery of Tesla (NASDAQ: TSLA) is an example that a higher stock price does not protect the asset from going through a deep dive. The stock price dropped by 12.24% on January 3, 2023, and recovered by 9.85% in the next five days. Our study does not include over-the-counter (OTC) stocks that are also called pink sheet stocks. The price information of the delisted firms included in this study ends on their last day of exchange-traded status.

However, we do find a consistent pattern with the number of shares outstanding. Equities with limited shares outstanding are prone to extreme loss and rapid recovery. This phenomenon occurs across stocks at different price levels. The stocks with a large number of shares outstanding still present a partial price recovery, though there are fewer extreme loss events associated with these stocks.

CONCLUDING REMARKS

This study analyzes the daily returns of 2,651 equities in the Russell 3000 Index continuously traded between January 2, 1950, or the date of the IPO, and early 2019. We examine extreme loss events for assets in our sample, which we define as a negative return lower than 97.5% of this asset's daily returns. Our sample contains 217,990 extreme loss events according to this definition.

This study finds that the average extreme loss is –8.2105%. A stock's price would increase by 8.9445% to get back to its initial level before the extreme loss. This is because (1–8.2105%)×(1+8.9445%)=1. However, on average, we observe that the equities realize a daily return of 0.8459% on the first day after an extreme loss event and a cumulative return of 1.8099% during five trading days after the event that counts for only 20.23%, i.e., 1.8099%/8.9445%, of the full recovery.

The gradual and partial recovery from the extreme loss suggests that overreaction and a panic sentiment explain approximately 20% of the loss and that extreme losses are mainly due to materialized reasons for the revaluation of the asset. If there is no role for overreaction, the asset price is expected to drop to the new price, which is on average 79.87% of the drop realized empirically, or 6.5577%, after the new information that leads to the extreme loss arrives at the market. The fact that the price drops by 8.2105% and recovers by 1.8099%, or 20.23% of the total loss, implies that the instant loss on the event day is comprised of 20.23% investor overreaction and 79.87% materialized reasons for the revaluation of the asset.

The results strongly support an extremely negative loss reversal strategy. Investors can profit if they buy an asset on the day of its extreme loss event, right before the market closes, then sell it within five trading days when the market closes. On average, this strategy can generate a daily return of 0.8459% during the first trading day, and 1.8099% in total during five trading days after entering the position.

This study can be expanded in four ways for further research. First, it is observed that many stocks realize a much higher return than normal daily returns right after an extreme loss. Then their prices decrease for multiple days. Future studies can identify all stocks that exhibit such a pattern. The goal is to determine whether this pattern indicates an extreme loss event and can be used as an early warning signal.

Second, the time window used in this analysis can be expanded. In this study, a five-day window is selected because it is a trading week. This analysis documents that selling a stock five trading days after an extreme loss event will yield better returns than selling it earlier. It is interesting to observe how the return during the five days after an event compares to later returns. However, separating the later returns that are not attributed to the extreme loss recovery would be challenging.

Third, this analysis is confined to the US equity market. The proposed trading strategy is only valid for the US equity market in which algorithm and rule-based high-frequency trading are prevalent. This analysis can be repeated for other markets that have detailed data available.

Fourth, instead of focusing on only equities, this analysis can be expanded to other asset classes, such as commodities, to determine whether similar trading strategies can be identified following extreme losses.

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APPENDIX

This derivation process presents sufficient conditions for the reverse strategy to be profitable and explains why the condition does not constantly hold.

Let p_t^i be the price of asset i at the current moment (time t) right after an extreme loss event, $p_{t+1}^{i,\gamma}$ be the projected price of asset i at time t+1 by the investors who sell off the asset during an extreme loss event, and $p_{t+1}^{i,\theta}$ be the projected price of asset i at time t+1 by the investors who hold the asset during an extreme loss event and expect a price reversal. Let ω_γ and ω_θ be the likelihood for states γ and θ, respectively. Thus, the following relations hold.

$$p_t^i > p_{t+1}^{i,\gamma} \quad (A.1)$$
$$p_t^i < p_{t+1}^{i,\theta} \quad (A.2)$$
$$p_{t+1}^i = \sum \omega_{\gamma|\theta} p_{t+1}^{i,\gamma|\theta} \quad (A.3)$$

It is obvious that investors with either belief are rational unless one of the following conditions is violated.

$$p_{t+1}^i > p_{t+1}^{i,\gamma} \quad (A.4)$$
$$p_{t+1}^i < p_{t+1}^{i,\theta} \quad (A.5)$$

As numerous past studies have confirmed that an asset price follows a random walk in an efficient market, expressed in discrete terms,

$$p_{t+1}^i = p_t^i + \sigma_i d\omega \quad (A.6)$$
$$\omega \sim N(0,1)$$

or expressed in continuous terms,

$$p^i(t) = p^i(0) + \sigma_i d\omega dt \quad (A.7)$$
$$\omega \sim N(0,1)$$

It is obvious that there exist an upper bound (M) and a lower bound (m) for p_{t+1}^i. Therefore, investors are regarded rational if

$$m \geq p_{t+1}^{i,\gamma} \quad (A.8)$$
$$p_{t+1}^{i,\theta} \geq M \quad (A.9)$$