Taming Momentum Crashes: A Simple Stop-loss Strategy

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Abstract

In this paper, we propose a simple stop-loss strategy to limit the downside risk of the well-known momentum strategy. At a stop-level of 10%, we find empirically with data from January 1926 to December 2011 that the monthly losses of the equal-weighted momentum strategy can go down substantially from −49.79% to within −11.34%. For the value-weighted momentum strategy, the losses reduce from −65.34% to within −23.69% (to within -14.85% if August 1932 is excluded). At the same time, the average returns and the Sharpe ratios with use of the stops are more than doubled. We also provide a general equilibrium model of stop-loss traders and non-stop traders and show that the market price differs from the price in the case of no stop-loss traders by a barrier option. The greater the volatility, the greater the value of the option, and the greater chance for the stop-loss strategy to outperform a buy-and-hold strategy.

JEL Classification: G11, G14

Keywords: Momentum, crashes, downside risk, stop-loss orders

So, it is a bigger than 10% stop, because intra-month it can go up 20%, then drop -30%, when my stop loss is activated

1. Introduction

Since the seminal work of Jegadeesh and Titman (1993), it is well-known that a momentum strategy of buying past winners and selling losers simultaneously in the cross-section of stocks can yield abnormal returns of about 1% per month, with the winners and losers defined as the top and bottom decile portfolios ranked by the returns over the past six months or a year. There are hundreds of studies that examine and explain similar momentum strategies across assets and markets, and there are today many active quantitative portfolio managers and individual investors who employ various momentum strategies in the real world. Schwert (2003) finds that the momentum profitability is the only implementable anomaly that is still persistent after its publication. Interestingly, even after the publication of Schwert (2003), the momentum strategy remains profitable with a high Sharpe ratio, which cannot be explained by risks measured from standard asset pricing models. Recently, however, the extreme downside risk of the momentum strategy receives some attention (see, e.g., Daniel and Moskowitz, 2013; Daniel, Jagannathan, and Kim, 2012; Barroso and Santa-Clara, 2012). For example, the four worst monthly drops of the momentum strategy are as large as −49.79%, −39.43%, −35.26% and −34.46% for the equal-weighed momentum strategy (with value-weighting, the worst loss goes up to −65.34%). Does this extreme downside risk explain the high abnormal returns of the momentum strategy?

In this paper, we provide a simple stop-loss strategy that limits substantially the downside risk of the momentum strategy. The key idea of our paper is that for the stocks in the momentum portfolio we have at the beginning of a month, we do not have to hold all of them to the end of the next month. We can sell some of them whenever a certain loss level is reached due to perhaps some fundamental changes unknown to us. Consider a simple 10% stop-loss rule.[1] For stocks in our winners portfolio, we automatically sell any one of them when it drops 10% below the beginning price of the month (which is the close price of the previous month used for forming the momentum portfolio). Similarly, for any stock in our losers portfolio, we cover the short position as soon as the stock bounces back 10% from its beginning price of the month. Since it is unlikely that we sell all our winners or cover all of our shorts, the stop-loss momentum strategy is likely to limit the monthly losses of the momentum strategy, if any, to about −10% most of the time except, as explained below, on

In an 10% stop loss case, it is likely that we both sell the Longs, and Cover the shorts, if there is a market movement of 10%, which happened many times. With 5% stop loss, it is guaranteed to have many months when are stop lost on all shorts and all longs. Remeber days in 2008, when market moved -+6% daily.

SPX Buy&Hold is Sharpe 0.5. Why he cites so low Sharpe? bug in his system?

But that artificially boost the return? investing in bonds

days when the open or close price jumps from the previous day.[2]

The important question is whether the stop-loss trading strategy reduces the average return of the original momentum strategy and the associated Sharpe ratio. Surprisingly, it raises the average return of the original momentum strategy from 1.01% per month to 1.73% per month, while reduces the standard deviation from 6.07% per month to 4.67%. Hence, the Sharpe ratio of the stop-loss momentum strategy is 0.371, more than double the level of the original momentum strategy (0.166).

Disagree!!!

A stop-loss strategy of selling an asset instantly when its price drops to a certain pre-set level is widely used in practice for risk control. Most brokerages allow customers to place stop-loss orders that automatically execute the trades when a certain stop level is triggered. In practice, almost all professional traders use stop strategies (see, e.g. Schwager, 1989), which is in contrast with individual investors who tend to hold losers too long (see, e.g. Odean, 1998). To see clearly how we implement the stop-loss strategy, consider our winner portfolio at the 10% stop level. On any day after the beginning of the month, if a stock price drops 10% below its beginning month price, we sell it and invest the proceeds into the risk-free T-bill for the reminder of the month. The 10% drop day is determined by either the open price or the close price of the day. If the 10% level is between the open price and the close price, it is reasonable to assume that we sell the stock at the stop level. If the open price is already below the 10% level due to perhaps overnight news, we assume that the stock is sold at the open. In practice, opening trades are active and many stocks trade at the open price with high volume. However, since the open price can be below the previous day close, the worst loss of the 10% stop-loss strategy will not necessarily be capped at the 10% level. Indeed, the worst monthly return of the equal-weighted stop-loss momentum strategy is −11.34%, below the −10% level. For the value-weighted stop-loss momentum strategy, the loss even reaches −23.69% that occurred in 1932. After 1932, however, the maximum loss is bounded by −14.85%.

The stop-loss momentum strategy seems to avoid the crash risks of the original momentum strategy completely. For example, in those four months when the original momentum strategy has its worst losses, −49.79%, −39.43%, −35.26% and −34.46%, the stop-loss momentum has returns 2.75%, 2.53%, −5.85% and −3.95%. Note that two of which are even

[2] The stop-loss strategy, rarely seen in empirical asset pricing, may also be applied to limit market crashes and to improve market timing decisions.

Something is wrong. How can it be positive? If we are in profit intra-month, we never lock in that, because stop losses are considered to the beginning of the month.

hardly believable that after we stop-lost on half of the stock with -10% loss, the other half will produce +12% profit.

positive! This is driven by good performance of the remaining stocks (which are not stopped out) in those months. It is hence clear that a bad month for the original momentum strategy is not necessarily a bad month for the stop-loss momentum strategy. Indeed, the four worst monthly drops of the stop-loss momentum strategy occur in different months, with losses of −11.34%, −10.97%, −10.61%, and −9.49%. These values are compared very favorably with the losses of the four worst months of the stock market, −28.95%, −23.69%, −22.64%, and −21.88%.

Our paper is related closely to recent studies on the crash risk of the momentum strategy. Daniel and Moskowitz (2013) point out, for example, in July and August of 1932, the original momentum strategy suffers a brutal crash. Indeed, the (equal-weighted) momentum strategy has a cumulative return of −70.24% for the two months. In practice, this magnitude of loss almost surely leads to the closure of any fund. Moreover, Daniel and Moskowitz (2013) find that momentum crashes are partially predictable and propose a dynamic strategy that can lower the risk substantially while nearly doubling the Sharpe ratio. Daniel et al. (2012) further propose a state-dependent model to provide high ex-ante probabilities for predicting crashes. Barroso and Santa-Clara (2012) find that the realized variance of daily momentum returns can forecast future momentum substantially, which can also yield a downside risk controlled momentum strategy that nearly doubles the Sharpe ratio of the original momentum strategy. Our paper adds a new perspective to this "crash-proof" literature by providing a simple and yet effective strategy in minimizing the crash risk. For the above most notable crash period, the stop-loss momentum has a return of 10.91%! Overall, the remarkable feature of our strategy is that it can cap the loss of the momentum strategy to within −12% for the entire sample period. With value-weighting, the cap is, however, much greater, at −24% over the entire sample period. Excluding August 1932, the cap reaches a quite acceptable level of −14.85%.

He says: "for the entire sample period". So, this is the maxDD. No

In this paper, we also provide a theoretical model for understanding the role of stop-loss trades in a general equilibrium setting. While the stop-loss strategy is popular and is a built feature in many trading softwares, there is a lack of theory analyzing its pricing impact. In a complete market with both stop-loss traders and non-stop traders, we show that the rational equilibrium price exists if there is only stop-loss price that is of common knowledge.[3] Interesting, we find that the equilibrium market price differs from the price of the case of

[3]The analysis of multiple stop-loss levels is too complex and goes beyond the scope of this paper.

http://en.wikipedia.org/wiki/Barrier_option

no stop-loss traders by a barrier option. Moreover, as the price approaches the stop-loss level, the greater the volatility, the greater the difference. In practice, the number of stop-loss traders are unknown, neither known the stop-loss price. Then unforseen volatility and unforseen stop-loss selling are likely to imply a lower than anticipated stop-loss price and hence more downward price pressure. This helps to understand why the momentum strategy with stops performs better empirically than the one without stops.

The rest of the paper is organized as follows. Section 2 discusses the data and methodology for constructing the original momentum portfolios as well as the stop-loss momentum portfolios. Section 3 reports the superior performance of the stop-loss momentum strategy relative to the original momentum strategy. Section 4 investigates the performances of the strategies in crash periods. Section 5 provides a theoretical analysis. Section 6 examines the robustness of the stop-loss momentum. Section 7 concludes.

So, no small cap filter. Bad, because 95% of the stocks in the portfolio will be small caps. Those that gained most, and those that lost most.

2. Data and Methodology

We use both daily and monthly stock data from the Center for Research in Security Prices (CRSP). We include all domestic common stocks listed on the NYSE, AMEX, and Nasdaq stock markets, and exclude closed-end funds, real estate investment trusts (REITs), unit trusts, American depository receipts (ADRs), and foreign stocks (or stocks that do not have a CRSP share code of 10 or 11).

Following the vast literature, we form momentum strategies using cumulative past returns. Specifically, we first calculate cumulative returns over previous six months, use the past six-month cumulative returns to sort stocks into ten deciles and form an equal-weighted decile portfolio for each decile. The decile portfolios are then held for one month. As additional robustness tests, we also examine the performance of the value-weighted momentum and the momentum sorted on past cumulative returns of other lag length such as 12-month, etc. Following Jegadeesh and Titman (1993) and others, we form momentum decile portfolios with one-month waiting period between the stock ranking period and the portfolio holding period, and also exclude stocks with prior price less than \$5 and stocks in the smallest size decile sorted by NYSE breakpoints. Our sample period covers the period from January 1926 to December 2011, however, the returns on the momentum portfolios start from August 1926 because of skipping one month. Moreover, since we use daily prices to make stop-loss

Ok. That it is good. They try to exclude small caps.

Value weighting is probably price-value weigthed, which is silly. Like buying 1 stock each. Because I hardly believe they have sharesoutsnanding info from 1926.

!That is the problem. They should use Highprice too. Which was not available in 1926, I guess. Because this is the reason why they don't have too many simulated stop-losses. If they do only End-of-the-day stoploss. Imagine: stock loses -20% on a day, but comes back to 0% at the close. An honest stop loss would stop-out at -10%, but this simulation is not. >So, it favours their simulation.
-On the other hand imagine stock end value is -40% on a day. They say they are stop-lost, but instead of using the End-ofThe day -40% price, they will say, they simulated with the -10% intraday price.> It again favours their result.
-Wowww! I firmly believe that is the reason this paper show profits.

decisions and compute returns and for holding periods less than a month, the prices are carefully calculated by accounting for dividends and stock splits.

For the stop-loss momentum strategy, we focus on the decile portfolios of the Losers and Winners as these two decile portfolios are the long (Winners) and short (Losers) arms of the momentum spread portfolio (WML). We use the daily open and close prices to determine whether or not the stop-loss trade is triggered for each stock in either portfolios on each trading day. Consider, for example, a stock in the winner portfolio, and a loss level of $L = 10\%$. Let P_0 be its price at the beginning of the month (which in implementations is the close price of the end of the previous month when we form the momentum portfolio). On each trading day before the end of the next month, we compute the return

$$R_t^X = \frac{P_t^X - P_0}{P_0}, \qquad X = O, C \tag{1}$$

where P_t^X is either the open or close price of the day. If both $R_t^O > -L$ and $R_t^C > -L$, we keep the stock in the portfolio for the next day. However, if $R_t^O > -L$ and $R_t^C \leq -L$, we close out the position and assume that we sold the stock at exactly $L = 10\%$ loss during the day. If $R_t^O \leq -L$, we also close out the position and assume that we sold the stock at the open with return R_t^O.

Once the stop-loss trade is triggered on any day, the stock is either sold (Winners) or bought (Losers) to close the position. The proceeds are invested in the risk-free asset (T-bill) until the end of the month. Therefore, the return over the month is the return on the stock until the position is closed plus the return on the risk-free asset for the remaining trading days of the month.

3. Performance of Stop-Loss Momentum

In this section, we report the performance summary statistics of the equal-weighted stop-loss mentum strategy, its properties and alphas.

3.1. Summary Statistics

Table 1 provides the average excess return (*Avg Ex.Ret*), standard deviation, Sharpe ratio, Skewness, Kurtosis, minimum and maximum returns of various strategies for data from

January 1926 to December 2011. There is one data issue here. The daily stock open prices are available from the CRSP except for the period from July 1, 1962 to June 30, 1992. For this period, since there are no open prices, we make the simplifying assumption that the stop-loss strategy can be close positions at the given level. This will over-state the results over this period and the entire period. Subsequent subperiod results of Table 2 show that this will not have significant impact on the qualitative conclusions of the paper. If this period is ignored, the results barely changed.

As shown in Panel A of Table 1, the average return of 0.62% per month on the CRSP index is the reward on the strategy of buy-and-hold the market. In contrast, the average return of the original momentum strategy (Winners-Losers) is 1.01% per month, which is much greater. The standard deviation of 6.07% per month, not much different from 5.45% of the market. Since standard asset pricing models are primarily driven by the first two moments, it is not terribly surprising that the return on the original momentum strategy cannot be explained by them. However, the original momentum strategy has a large negative skewness of −1.18, which is manifested by its many large negative returns. For example, the worse month of the market is only −28.98%, but the momentum suffers from a loss level of −49.79%.

Panel B of Table 1 reports the summary statistics for the stop-loss momentum strategy with a stop level of 10%. It has an average return of 1.73%, which is about 70% over what the original momentum strategy can achieve. Moreover, the standard deviation is 4.67%, smaller than 6.07% of the original momentum strategy. Hence, the Sharpe ratio is more than doubled from 0.17 to 0.37. Mostly strikingly, the worst loss is now capped at −11.34% for the entire sample period, which contributes to a positive skewness (1.86) for the stop-loss momentum strategy instead of the negative one (−1.18) for the original momentum strategy. Interestingly, the loss reduction seems coming from both the winners and losers portfolios.

For better understanding of the role of the stop level, we also consider two additional loss levels, $L = 5\%$ and 15%. Panels C and D report the results. The 5% loss level appears performing the best. However, in terms of the overall Sharpe ratio and loss control, performances of all the stop levels are quite similar and they all seem to work well in reducing the downside risk of the original momentum strategy.

In what follows, we will focus on results on $L = 10\%$, while the conclusions are similar with either $L = 5\%$ or 15%. Figure 1 plots the times series of returns on the original and the stop-loss momentum strategies. It is seen that they are highly correlated in general (with correlation 67.32%), but the extreme values have little correlations. When the returns of the original momentum strategy are down sharply, the returns of the stop-loss momentum strategy are tamed, due to the use of the stops. Sometime while the returns of the original momentum strategy are normal, those of the stop-loss momentum strategy can be high. In short, while the returns of the two strategies are correlated, their extreme values may not occur at the same time.

Now, to address the missing data problem, we analyze the performances of the stop-loss strategy over three subperiods: before, during and after the missing data period. Table 2 reports the summary statistics. In the period prior, both the original and the stop-loss momentum strategies do not perform as well as the latter periods. Nevertheless, the stop-loss momentum strategy still outperforms the original momentum strategy by a large margin, with about 42% ($= (1.05 - 0.74)/.74$) more average return and doubling of the Sharpe ratio. During the latter two periods (missing data period and the period after), the results are quite similar to each other. The stop-loss momentum strategy doubles both the average returns and Sharpe ratios. Hence, the bias caused by the missing open prices does not seem to affect the overall results as reported in Table 1. The subperiod results are consistent with the early evidence on the value of the stop-loss momentum strategy.

From an economic modeling perspective, one can perhaps design some optimal mixture of various stop levels that can potentially improve substantially the performance of the above plain-vanilla stop strategy. Moreover, with predictability insights from Daniel and Moskowitz (2013), Daniel et al. (2012) and Barroso and Santa-Clara (2012), among others, one can also set stop trades that are conditional on various economic variables. However, our paper focuses on simple stop strategies only. Given that they have already yield remarkable performance, we leave the search for optimal stop strategies as future research.

3.2. Stopped Percentages and Transaction Costs

The superior performance of the stop-loss momentum is clearly attributable to the loss control of the stop-loss trades. In this subsection we examine how frequently the stop-loss strategy closes positions. Figure 2 plots the time-series of the percentage of closed positions for the Losers and Winners, respectively, over the entire sample period. It is clear that the percentage of closed positions fluctuates widely month by month. In several months, nearly 100 percent of the positions are closed, while in a few months no positions are closed. This is true for both the Losers and Winners. At the bottom of Figure 2, we plot the market volatility estimated from the daily returns each month. It appears that the high volatility periods tend to be also the periods when the percentage of closed positions is high, notably, the Great Depression period, the World War II period, the Internet Bubble Burst period, and the most recent Great Recession period. The correlation between the percentage of closed positions and the market volatility is 17.42% for the Losers portfolio and 58.82% for the Winners portfolio. The percentage of closed positions is more closely related to the monthly market returns - the correlation is 59.37% for the Losers portfolio and –63.20% for the Winners portfolio.

Table 3 reports the summary statistics of the percentage of closed positions, which are similar between the Losers and Winners. For example, on average, about 31.97% stocks in the Losers portfolio are bought back in any given month, whereas about 30.37% stocks are sold in the Winners portfolio in any given month. For the stocks in the Losers portfolio, we would expect that their returns would have been higher if there were no stop buy backs, whereas for the stocks in the Winners portfolio, we would expect that their returns would have been lower if there were no stop sell orders.

An interesting question is how many stocks we sold during the month will still be in the winner's portfolios, and how many we bought will still be in the losers portfolio. The answer is about 20% for each of them. Therefore, the stop-loss momentum strategy increase the trading activity about 40% relative to the standard momentum strategy. Korajczyk and Sadka (2004) show that the standard momentum strategy survives in the presence of transaction costs in real implications. Since its return increases about 70% while the transaction rises only 40%, the stop-loss momentum clearly can be more profitable than the standard momentum strategy even after accounting for transaction costs.

3.3. Alphas

The simple summary statistics clearly show that the stop-loss strategy performs well. The stop-loss momentum outperforms the original momentum with much higher Sharpe ratios by having higher average returns and lower standard deviations. Furthermore, in a sharp contrast to the original momentum, the stop-loss momentum has a rather large and positive skewness, which suggests that more often than not the stop-loss strategy generates large positive returns. However, it is unclear whether the extra returns are due to more risk-taking.

Consider first the capital asset pricing model (CAPM) regression of the stop-loss momentum spread portfolio on the market portfolio,

$$r^{sl}_{mom,t} = \alpha + \beta_{mkt} r_{mkt,t} + \epsilon_t, \tag{2}$$

where $r^{sl}_{mom,t}$ is the monthly return on the stop-loss momentum spread portfolio, and $r_{mkt,t}$ is the monthly excess return on the market portfolio. The left-hand side columns of Table 4 reports the results of the monthly CAPM regressions of the original momentum (Panel A) and the stop-loss momentum (Panel B). The alphas or risk-adjusted returns are slightly larger than but essentially unchanged from the average returns reported in Table 1. This is due to the small negative market beta. For example, the market beta of the original momentum is only -0.23, but highly significant, while the market beta of the stop-loss momentum is even smaller, about -0.03, and statistically insignificant. The insignificant market beta suggests that the stop-loss momentum is market neutral - has virtually no market risk exposure.

Consider further the alphas based on the Fama and French (1993) three-factor model,

$$r^{sl}_{mom,t} = \alpha + \beta_{mkt} r_{mkt,t} + \beta_{smb} r_{smb,t} + \beta_{hml} r_{hml,t} + \epsilon_t, \tag{3}$$

where $r_{mkt,t}$, $r_{smb,t}$, and $r_{hml,t}$ are the monthly market excess return, monthly return on the SMB factor, and monthly return on the HML factor, respectively. The right-hand side columns of Table 4 reports the results. Again, the alpha of the original momentum is now 1.27% pre month, slightly greater than the CAPM alpha and the average returns reported in Table 1, while the alpha of the stop-loss momentum is the same as the CAPM alpha, about 1.75% per month. Not surprisingly, the market beta and the beta of the HML factor are both significantly negative for the original momentum, whereas the betas of the stop-loss momentum are all insignificant, further showing that stop-loss momentum has no risk exposure to the market risk and the risks proxied by the SMB and HML factors.

4. Crash Periods

Daniel and Moskowitz (2013) show that there are a few "crash periods" when the original momentum suffers big losses. In this subsection, we examine the performance of the stop-loss momentum in the crash periods as well as other months when the original momentum has a loss exceeding 20% a month.

Daniel and Moskowitz (2013) identify three crash periods: July and August of 1932, April and May of 1933, and March and April of 2009. For these three periods, the cumulative returns of the original momentum are −70.24%, −54.06%, and −39.52%. In contrast, the cumulative returns of the stop-loss momentum strategy are 10.91%, 16.16%, and −11.82%. It is interesting and important that all the crashes are tamed or even disappeared completely with the use of the stop trades.

To provide further insights on the downside risk of the momentum strategy, Panel A of Table 5 provides all the big losses (greater than 20%) of the original momentum strategy. There are twelve of them, 1.17% out of all the months. The extreme downside risks are rare but not rare enough. Panel B provide the returns of the stop-loss momentum strategy in the same months. It is remarkable that all the losses are tamed to within −9.07%. In fact, in three of the big loss months, the stop-loss momentum strategy even earns positive returns. The results seem to speak loudly about using the stop-loss strategy for controlling for the downside risk of the original momentum strategy.

5. A General Equilibrium Model

Assumption 1. The market is endowed with a certain amount of one risky asset, each unit of which provides a dividend flow given by

$$dD_t = \kappa(\bar{D} - D_t)dt + \sigma dB_t, \tag{4}$$

where $\bar{D}$ is the mean level of dividend flow, σ is the volatility and dB_t is the shocks. The supply of the risky asset is normalized to be 1.

Assumption 2. The claim on the risky asset is infinitely divisible and all shares are held by the investors in the economy. Shares are traded in a competitive stock market with no transaction costs. The stock is the only security traded in the market.

Assumption 3. There is a risk-free asset to all investors with a constant rate of return $1 + r$ ($r > 0$). This can be a risk free bond with perfect elastic supply.

Assumption 4. There are two types of investors, the usual investors and stop-loss investors. Both are rational utility optimizers and are informed about the dividend process of the risky asset, except that the stop-loss investors use a stop-loss strategy to manage their risk for exogenous reasons, such as financial constraints, value protection, etc. Specifically, when the price of the stock drops to certain pre-set stop-loss level p_b, the stop-loss investors sell the stock at the market clearing price and disappear from the market. We denote w as the fraction of stop-loss investors in the economy.

Assumption 5. Both types of investors have an expected additive utility with constant absolute risk aversion (CARA),

$$u(c(t), t) = -e^{-\rho t - c(t)}, \tag{5}$$

where ρ is the discount parameter and $c(t)$ is the consumption rate at time t.

Assumption 6. The structure of the market is common knowledge.

Assumption 7. There is limited outside liquidity.

This assumption is consistent with Brunnermeier and Pedersen (2008) who provide the economic rationale why investors's capital can have impact on market liquidity and risk premiums. Empirically, Lou, Yan, and Zhang (2013) document that Treasury security prices in the secondary market decrease significantly in the few days before Treasury auctions and recover shortly thereafter, even though the time and amount of each auction are announced in advance. They further attribute the abnormal return to limited risk-bearing capacity and the imperfect capital mobility of investors, which is also consistent with assumption 7.

5.1. Equilibrium Price

The key idea in deriving the equilibrium price is to link the stop-loss strategy to a contingent claim. Carr and Jarrow (1990) find a connection between the stop-loss strategy and options. Jouini and Kallal (2001) provide a link between stop-loss strategy and option replication under short-selling or lending frictions. In our context, we connect the stop-loss strategy to a barrier option. The equilibrium price is characterized as follows.

Theorem 1 Given Assumptions 1-7, the equilibrium price is

$$p_t = p_t^* - \frac{w\sigma^2}{(1-w)(r+\kappa)^2} \cdot E[e^{-r\tau_b}|D_t], \tag{6}$$

where

$$p_t^* = \frac{\bar{D}}{r} + \frac{D_t - \bar{D}}{r+\kappa} - \frac{\sigma^2}{(r+\kappa)^2}\theta \tag{7}$$

is the equilibrium price in the absence of the stop-loss investors, and τ_b is the first random time the stock price hits the stop-sell level p_b.

Proof. See the Appendix.

Since p_t^* is determined by the dividends and has nothing to with the stop-loss strategy, it can be interpreted as the fundamental value. When there are stop-loss investors in the economy, Theorem 1 says that the equilibrium price will be below its fundamental value, which allows non-stop investors to rationally absorb the selling by the stop-loss investors. Their difference is captured by the second term in (6), which is the payoff on a barrier option (whose explicit formula is given in the Appendix.) It is clear that the greater the volatility of the stock which is reflected here by the dividend volatility σ, the greater the option value. In addition, the greater proportion of the stop-loss investors, w, the greater the option value. In the special case of $w = 0$ when there are no stop-loss investors, then the equilibrium price reduces to the fundamental value p_t^*.

To see how the value of the barrier option varies near the boundary of the stop-loss price level, Figure 3 plots the function of $E[e^{-r\tau_b}|D_t]$ versus the distance between D_t and D_b in terms of number of unconditional standard deviation $\sigma_D = \frac{\sigma}{\sqrt{2\kappa}}$, where

$$D_b = \bar{D} + (p_b + p_L\frac{1}{1-w} - \frac{\bar{D}}{r})(r+\kappa).$$

The option value is a convex function of the distance to the boundary. As the distance approaches one standard deviation in terms of σ_D, the slope becomes very deep. The option value quickly goes up to 0.1 and to 1 eventually as the distance hits zero. This means that, holding the fundamental value constant, the market price should decline quickly as the price approach to the stop-loss level.

Our model studies a case where information is symmetric and the stop-loss strategy is exogenously used by short-term investors to manage their risk. Gennotte and Leland (1990) provides an asymmetric information model where the asset price plays a role not only in allocation, but also in shaping the expectation. Hence, the market price is prone to big crashes even with very limited amount of stop-loss traders. Empirically, Osler (2003) documents that in foreign exchange market, the exchange rates tend to continue their trend after stop-loss trades are triggered. In our setting, both the fraction of stop-loss traders and the asset volatility have impact on the equilibrium price. Since data on w are available, we focus on the implication of σ. In our model, the greater the volatility, the greater the price drop near the sell-stop. Similar conclusion should be true for the buy-stop. Therefore, a testable prediction from our model is that the greater the volatility, the better the performance of the momentum portfolio with stops as long as the stop-loss level to not too high (not higher than the last stop-loss perceived by the market). In other words, at a given stop-loss level of our choice, if the market stop level is below it, it is likely that the stock price will continue to drop after we sell at the sell stop or continue to rise after we buy at the buy stop. Then the use of the stop-loss strategy in the momentum will outperforms more the buy-and-hold momentum as the volatility goes up.

To test the model prediction, we sort stocks into quintile volatility portfolios. For each of the quintiles, we examine the performance of the standard momentum strategy and the one with stops at the 10% stop-loss level. Table 6 provides the results. For the lowest quintile portfolio, the average return on the buy-and-hold momentum is 0.49% per month with a Sharpe ratio of 0.126. In contrast, the one with the stop has an average of 0.56% and a Sharpe ratio of 0.129. As the volatility goes up, the buy-and-hold momentum performs better, but the momentum with the stop improves even more. For example, for the highest quintile volatility portfolio, the difference in the average returns of the two momentum strategies reaches 0.71% per month.

In practice, the number of stop-loss traders are unknown. Moreover, there are likely multiple stop-price levels and they are unknown to other investors. When the volatility variations and stop-loss sellings are unanticipated by the market, their impact will be even greater than predicted by our simple theoretical models. This helps to understand our major results in Section 2 as to why the momentum strategy with stops performs better empirically than the one without stops.

6. Robustness

In this section, we examine the robustness of the stop-loss strategy with either value-weighting or a momentum lag period of twelve months instead of six months.

6.1. *Value-weighting*

When momentum strategies are based on value-weighted decile portfolios, the performances are generally different from those of equal-weighting. Parallel to Table 1, Table 7 reports the summary statistics for the value-weighted momentum strategies. Let us focus on the results with $L = 10\%$. The average return of the original momentum is now 0.78% per month, lower than the equal-weighting case. The minimum is lowered too, from -49.79% to -65.34%. However, the Sharpe ratio is quite close. The stop-loss momentum strategy now also has a lower average return of 1.18% instead of 1.73%. Nevertheless, the Sharpe ratio is double as before. The greatest difference of the results is about the minimum return. Instead of -11.34%, it has a value of -23.69% that occurred in August, 1932 due to jumps of stock prices from one day to another during that time. However, once the month August of 1932 is excluded, the minimum return is -14.85%, much closer to the pre-set stop-level of $L = 10\%$.

Analogous to Table 5, we also examine how well the value-weighted stop-loss momentum strategy performs over crash months in Table 8. Except the large loss of -23.69% in August, 1932, all other losses are within -14.85%, taming immensely from the huge losses of the original momentum strategy. Overall, it is clear that our earlier conclusions remain valid qualitatively for the value-weighted strategies that the stop-loss strategy tams the crash risk of the original momentum strategy substantially.

6.2. *Twelve-Month Momentum*

In this subsection, we examine the robustness of the conclusions when the momentum portfolios are formed based on past twelve-month performances instead of six.

Table 9 provides the results. As expected, they are very similar to those reported in Table 1 for the six-month momentum. For example, the original momentum yields an excess return of 1.12% per month on average for the Winners-Losers spread portfolio, whereas the stop-loss momentum yields 2.47%, 1.83%, and 1.37% per month on average with a stop-loss levels of 5%, 10%, and 15%, respectively. Similarly, the stop-loss momentum has smaller volatility than the original momentum, which results in much higher Sharpe ratios for the stop-loss momentum spread portfolio. Once again, the stop-loss momentum Winners-Losers portfolio has a positive skewness in contrast to the negative skewness of the original momentum. The maximum loss of the original momentum spread portfolio is −55.10%, whereas it is only −8.96%, −11.78%, and −14.08% with the three stop-loss levels, respectively.

7. Concluding Remarks

The momentum strategy of buying winners and selling losers is of great interest to both academic research and practical investing. However, Daniel and Moskowitz (2013), among others, document that the momentum strategy has significant crash risks. In this paper, we propose a simple stop-loss strategy to limit the downside risk. At a stop-level of 10%, we find empirically with data from January 1926 to December 2011 that the monthly losses of the equal-weighted momentum strategy can go down substantially from −49.79% to within −11.34%. For the value-weighted momentum strategy, it reduces from −65.34% to within −23.69% (to within −14.85% if August 1932 is excluded). At the same time, the average returns and the Sharpe ratios are more than doubled. Our results indicate that the crash risk explanation for the profitability of the momentum strategy may deserve a new examination. In addition, we also provide a general equilibrium model of stop-loss traders and non-stop traders and show that the market price differs from the price in the case of no stop-loss traders by a barrier option. Our model helps to understand the economic rationales why the stop-loss strategy works empirically.

Academic studies on the stop-loss strategy is rare. It will be valuable to design optimal stop strategies with mixture of stop levels and with conditional information. In the vast literature of empirical asset pricing and risk control, the analysis is usually carried out at the monthly frequency. Our paper highlights the importance of using daily information and stops which can drastically alter the risk profiles at the monthly frequency. Hence, the methodology might have greater implications on asset pricing beyond the scope of this paper. These issues will be of interest for future research.

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Appendix

In this Appendix, we provide proofs for the theoretical results.

A. Proof of Equation (7)

Equation (7) characterizes the equilibrium price in the absence of the stop-loss investors. To show it, we conjecture a linear pricing rule,

$$p^* = \phi_0 + \phi_1 D_t. \tag{A.1}$$

Given the dividend process, the investment opportunity satisfies the following stochastic differential equation

$$dQ = (D - rp^*)dt + dP = e_Q \Psi dt + \sigma_Q dB_t, \tag{A.2}$$

where $e_Q \in R^{1\times 2}$ and $\sigma_Q \in R^{1\times 2}$, and are given by

$$\begin{aligned} e_Q &= (\phi_1\kappa\bar{D} - r\phi_0, 1-(\kappa+r)\phi_1), \\ \sigma_Q &= (0, \phi_1\sigma), \end{aligned}$$

and $\Psi = (1, D_t)^T$, whose dynamics can be written as

$$d\Psi = e_\Psi \Psi dt + \sigma_\Psi dB_t, \tag{A.3}$$

with

$$e_\Psi = \begin{pmatrix} 0 & 0 \\ \kappa\bar{D} & -\kappa \end{pmatrix}, \tag{A.4}$$

and

$$\sigma_\Psi = \begin{pmatrix} 0 & 0 \\ 0 & \sigma \end{pmatrix}. \tag{A.5}$$

Then, the investors' optimization problem is

$$\max_{\eta,c} E\left[-\int_t^\infty e^{-\rho s - c(s)} ds | \mathcal{F}_t\right] \ s.t.\ \ dW_t = (rW_t - c_t)dt + \eta dQ. \tag{A.6}$$

Let

$$J(W;t) = -e^{-\rho t - rW} \tag{A.7}$$

be the value function, then it must satisfy the HJB equation

$$0 = \max_{c,\eta}[-e^{-\rho t - c} + J_W(rW - c + \eta e_Q \Psi) + \frac{1}{2}\sigma_Q^T\sigma_Q\eta^2 J_{WW}]. \tag{A.8}$$

Differentiating the HJB equation with respect to η, we have

$$\eta = \frac{1}{r}(\sigma_Q^T\sigma_Q)^{-1} e_Q \Psi = \frac{1}{\phi_1^2\sigma^2}[(\phi_1\kappa\bar{D} - r\phi_0) + (1-(\kappa+r)\phi_1)D_t]. \tag{A.9}$$

The market clearing condition requires

$$\eta = \theta. \tag{A.10}$$

It follows that

$$\begin{aligned} \phi_1 &= \frac{1}{\kappa + r}, \\ \phi_0 &= \frac{\sigma^2}{(\kappa+r)^2}\theta - \frac{\kappa\bar{D}}{r(r+\kappa)}, \end{aligned}$$

which completes the proof of Equation (7).

B. Proof of Theorem 1

To understand better the role of the stop-loss, we provide a more general proposition, and then apply it to the stop-loss trading strategy case to obtain the theorem.

B.1. A General Case

For the general case, we replace the Assumption 4 by the following:
Assumption 4b. there are two types of investors, defined as type I and type II, with fraction $1-w$ and w, respectively. Type I investors are rational, and Type II investors trade to replicate a contingent claim with payoff defined as $B(T)$ at some future stopping time T.

It is easy to see that Assumption 4 is a special case of the Assumption 4b. We provide the characterization of the equilibrium in the proposition below.

Proposition 1 Given Assumptions 1-3, 5-7 and Assumption 4b, there exists an equilibrium price

$$p_t = p_t^* - p_c = p_t^* - \exp(-rT)E[Z(T)B(T)], \tag{A.11}$$

where p_t^* is given in Equation (7), $Z(T)$ is the pricing kernel with respect to p_t, and the second term in Equation (A.11) is the risk-neutral price of the contingent claim.
Proof. The idea to prove the equilibrium price of Equation (A.11) is to construct a price path such that both types of investors are indifferent to invest in the contingent claim. We follow the method in Davis (1997).

Assume that the two types of investors have a general concave utility function U and cash endowments x_1 and x_1. They choose dynamic portfolio whose cash value at time t is $X_x^\pi(t)$ with trading strategy $\pi \in \mathcal{T}$, where $\mathcal{T}$ denotes the set of admissible trading strategies. Type II investors replicate a contingent claim with payoff $B(T)$, while type I investors rationally anticipate the trading strategy of Type II investors. To clear the market, type I investors are replicating a short position in the same contingent claim. Both investors' objective is to maximize expected utility of wealth at τ, dented as

$$V(x) = \sup_{\pi \in \mathcal{T}} E[U(X_x^\pi(\tau))]. \tag{A.12}$$

The equilibrium price p_c of the contingent claim is reached when both investors are indifferent to purchasing or selling the contingent claim at price p_c. Specifically, given the price $p_c(t)$ of the contingent claim at time $t < \tau$, for both investors, they will buy (or sell) the option only if their maximum utility in (A.12) can be increased. Otherwise, they can always replicate the contingent claim by using dynamic hedging since market is complete. Hence $p_c(t)$ is an equilibrium price for the contingent claim if investing a little funds in it will have neutral effect for maximal achievable utility for both investors. Denote

$$W(\delta, x, p_c) = \sup_{\pi \in \mathcal{T}} EU(X^{\pi}_{x-\delta}(\tau) + \frac{\delta}{p_c} B). \tag{A.13}$$

p_c solves for

$$\frac{\partial W}{\partial \delta}(0, p_c, x) = 0 \tag{A.14}$$

Since the market is complete, p_c is given by the risk-neutral pricing formula independent from utility function and initial wealth.

To prove that the equation (A.11) is an equilibrium price, we show the market clears under the pricing. For type I investors, since they anticipate the trading strategy by type II investors, the price of the asset is adjusted by the fair value of the synthetic contingent claim, the p_c offset the short position in contingent claim and the demand for asset by type I investors is 1-w, the same as in Proposition 1. For type II investors, due to price has already fully adjusted for the effect on exercising the contingent claim, there will be no price jump when they exercise it. So they do not need to synthetically replicate it, and demand for the asset is w, and hence the market clears. This completes the proof of Proposition 1. QED.

There are a few comments on the above proposition. First, the equilibrium is constructed by decomposing the price into fundamental value plus the short position in the option. The equilibrium price is set in a way that both types of investors are indifferent to whether divest fund to invest in the contingent claim or not. Hence under the equilibrium price (A.11), the demand for the contingent claim is zero. Second, due to market completeness, the option can be priced in the risk-neutral framework. Third, Equation (A.11) is a functional equation on the price process p_t, and is generally hard to solve.

B.2. Application to Theorem 1

In this subsection, we present the proof of Theorem 1. In light of Proposition 1, the rational investor in our setting is type I investor, and the stop-loss investor is type II investor, with the contingent claim being the binary "down-and-out" barrier option. We show that due to the special feature of our model, we can solve for p_t explicitly.

First, we show that even though in Theorem 1, the investment horizon for rational investors is infinite, the Proposition still applies to our model setting if we assume the equilibrium price shock B at the stop-loss time τ. Given Assumption 7 and due to backward induction, the investment problem for investor with infinite horizon can now be reduced to that of a finite horizon with stopping time τ. There are a lot of factors that can have impact on the equilibrium price shock B. For example, it could depend on the stop-loss investor population, the risk preference of investors, the speed of outside capital to move into the asset market, etc. In this paper, we only provide a simplified derivation of B that comes only from the liquidity shock due to the stop-loss trading, and there is no outside capital moving in to buy the asset. Other assumptions can apply, but it does not alter our main result.

According to Equation (7), the liquidity shock B due to stop-loss selling can be characterized by

$$B = p_L \Delta\theta = \frac{w}{1-w} p_L, \tag{A.15}$$

where $\Delta\theta = 1 - \frac{1}{1-w}$ is the change in supply of per capita risky asset before and after the stop-loss trading, and

$$p_L \equiv \frac{\sigma^2}{(r+\kappa)^2}. \tag{A.16}$$

In Equation (A.15), we assume rational investors bear the full loss. To the extent that the stop-loss investors cannot always get the stop-loss price, they share the price loss with rational investors, but the shock would still be proportional to B in Equation (A.15), which will not change our main result.

In light of Proposition 1, the contingent cash flow due to stop-loss strategy is equivalent to the payoff structure of a binary "down-and-out" option. The rational investors short the option, while stop-loss investors long such an option. Further, the price of the binary barrier option can be written as

$$B \cdot E[e^{-r\tau_b} | p_t],$$

where τ_b is the first hitting time of the stop-loss boundary p_b,

$$\tau_b \equiv \inf\{t > 0 : p_t = p_b\}, \tag{A.17}$$

and B is defined in Equation (A.15).

Let p_b be the stop-loss investors trigger price when stop-loss order comes effective. The first hitting time for the price to hit the boundary p_b is defined as

$$\tau_b \equiv \inf\{t > 0 : p_t = p_b\}, \tag{A.18}$$

which is the trigger time for stop-loss order. A key step in solving the functional equation (A.11) is to observe that there is a one-to-one monotonic correspondence between D_t and p_t, hence we can denote

$$\tau_b \equiv \inf\{t > 0 : p_t = p_b\} = \inf\{t > 0 : D_t = D_b\}, \tag{A.19}$$

where D_b, corresponds to the hitting boundary of D_t when p_t hits p_b. The option price can be written as

$$f(D_t, D_b) = B \cdot E[e^{-r\tau_b}|D_t]. \tag{A.20}$$

This equation much simplifies the analysis because the option now becomes a contingent claim on dividend process rather than the price, which is endogenous in the model.

The stock price can be written as the fundamental value of equation (7) minus a "down-and-out" option which pays out a value of B in Equation (A.15) when the price first hits the boundary p_b. Let

$$g(p_t, p_b) = E_t[e^{-r\tau_b}], \tag{A.21}$$

hence the value of the "down-and-out" option can be written as

$$f(p_t, p_b) = B \cdot g(p_t, p_b). \tag{A.22}$$

The stock price now consists of the fundamental value subtracting the option value of (A.22):

$$p_t = \hat{p}_t - B \cdot g(p_t, p_b). \tag{A.23}$$

Since there is a one-to-one monotonic correspondence between D_t and p_t, we can denote

$$\tau_b \equiv \inf\{t > 0 : p_t = p_b\} = \inf\{t > 0 : D_t = D_b\}, \tag{A.24}$$

where D_b corresponds to the hitting boundary of D_t when p_t hits p_b. Hence the option price can be written as $g(D_t, D_b)$ as well, with D_b solves

$$\frac{\bar{D}}{r} + \frac{D_b - \bar{D}}{r + \kappa} - p_L - B \cdot g(D_b, D_b) = p_b. \tag{A.25}$$

Since $g(D_b, D_b) = 1$ we have

$$D_b = \bar{D} + (p_b + p_L \frac{1}{1-w} - \frac{\bar{D}}{r})(r+\kappa). \tag{A.26}$$

Then, once we know the function $g(D_t, D_b)$ explicitly, we can obtain the equilibrium price explicitly. It is clear that $g(D_t, D_b)$ is a simple algebraic function of $E(e^{-\lambda\tau_b}|X_0 = x)$. Note that the dividend process is an Ornstein-Uhlenbeck Process, we can, based on Alili, Patie, and Pedersen (2004), solve the expected hitting time explicitly,

$$E(e^{-\lambda\tau_b}|X_0 = x) = \begin{cases} \frac{e^{\frac{\kappa}{2\sigma^2}(x-\bar{X})^2} D_{-\lambda/\kappa}(-\frac{\sqrt{2\kappa}}{\sigma}(x-\bar{X}))}{e^{\frac{\kappa}{2\sigma^2}(b-\bar{X})^2} D_{-\lambda/\kappa}(-\frac{\sqrt{2\kappa}}{\sigma}(b-\bar{X}))}, & \text{if } x < b; \\ \frac{e^{\frac{\kappa}{2\sigma^2}(x-\bar{X})^2} D_{-\lambda/\kappa}(\frac{\sqrt{2\kappa}}{\sigma}(x-\bar{X}))}{e^{\frac{\kappa}{2\sigma^2}(b-\bar{X})^2} D_{-\lambda/\kappa}(\frac{\sqrt{2\kappa}}{\sigma}(b-\bar{X}))}, & \text{if } x > b, \end{cases} \tag{A.27}$$

where $D_\nu(x)$ is the parabolic cylinder function given by

$$D_\nu(x) = \left\{ \begin{array}{ll} \sqrt{\frac{2}{\pi}} \exp\left(\frac{x^2}{4}\right) \int_0^\infty t^\nu \exp\left(-\frac{t^2}{2}\right) \cos\left(xt - \frac{\nu\pi}{2}\right) dt, & \text{if } \nu > -1; \\ \frac{1}{\Gamma(-\nu)} \exp\left(-\frac{x^2}{4}\right) \int_0^\infty t^{-\nu-1} \exp\left(-\frac{t^2}{2} - xt\right) dt, & \text{if } \nu < 0. \end{array} \right\} \tag{A.28}$$

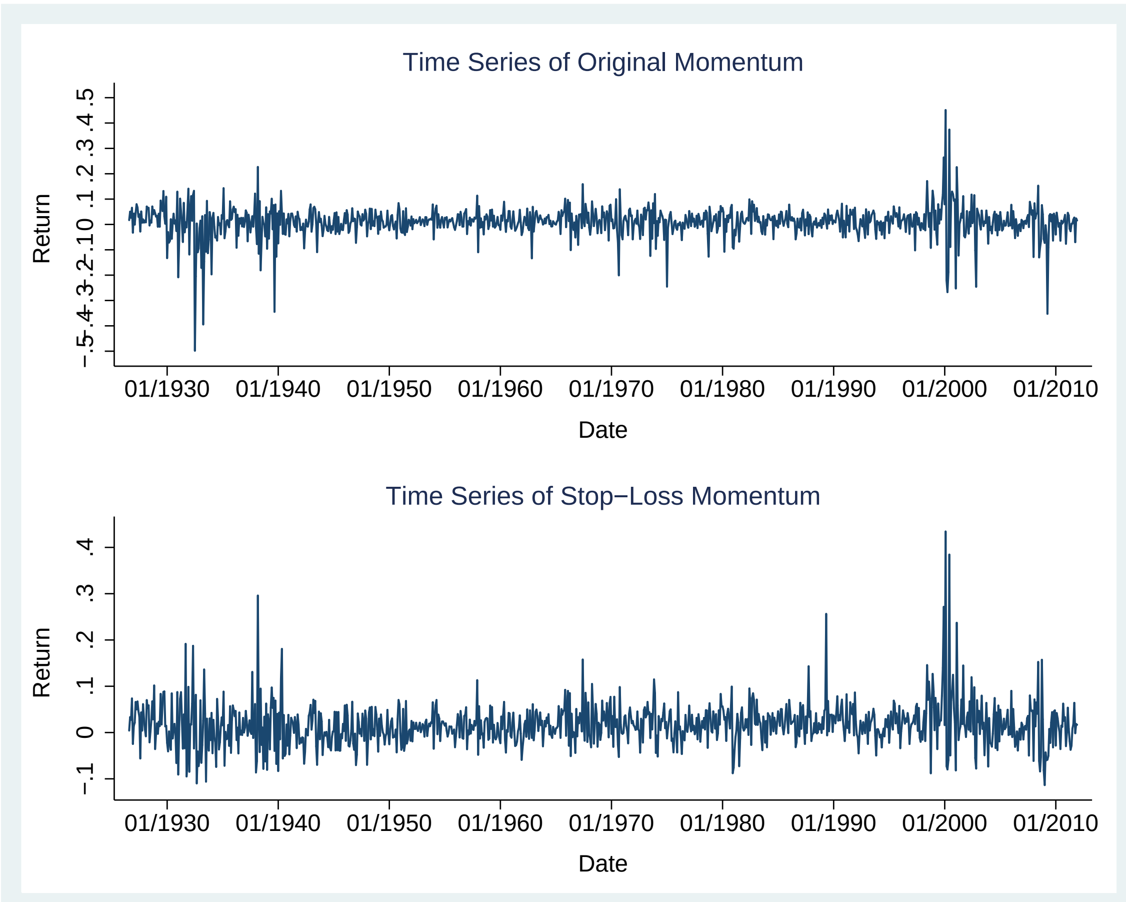

Figure 1: Comparison of the Original and Stop-Loss Momentum Strategies.

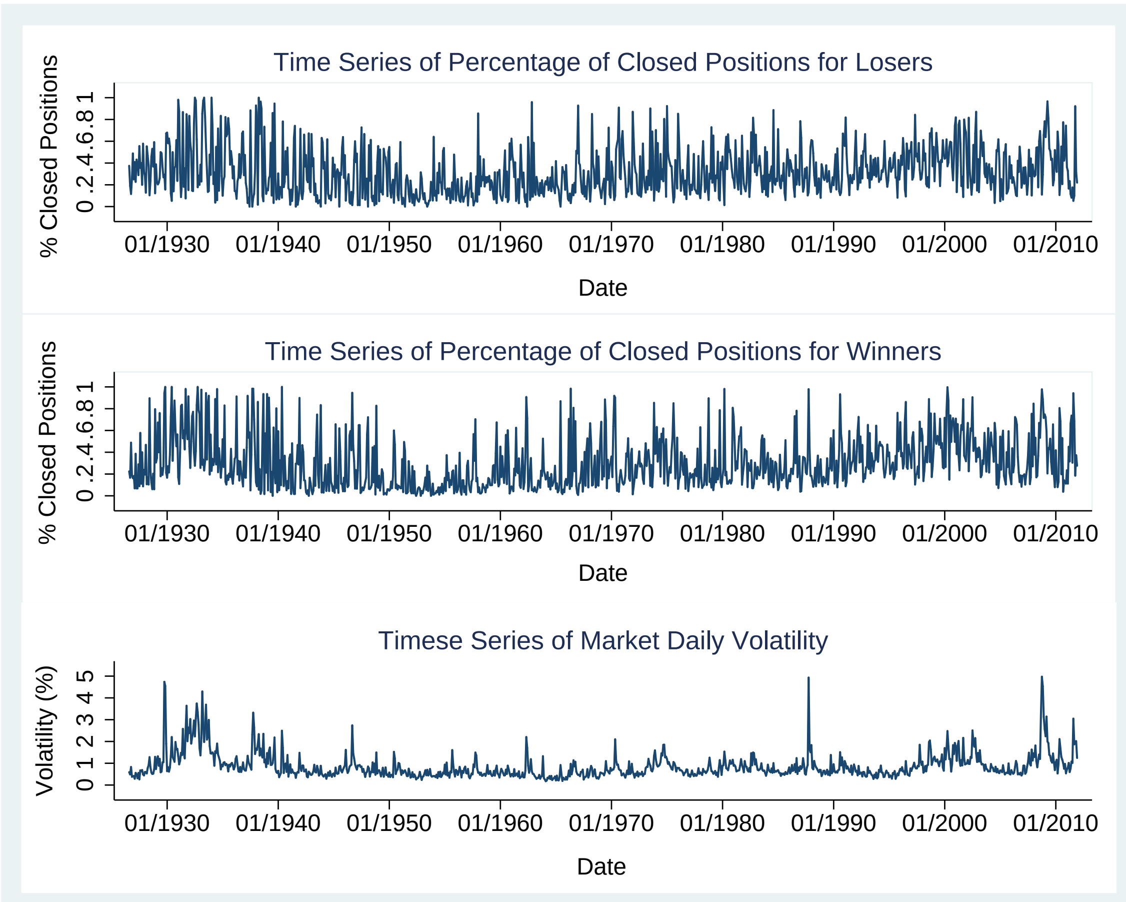

Figure 2: Time-Series of the Percentage of Closed Positions.

This figure shows the impact of the stop-loss boundary (in terms of the unconditional standard deviation of price) on stop-loss option value $E[e^{-r\tau_b}|D_t]$ when $B = 1$. The shape is convex which means the uncertainty in the distance to the boundary perceived by the investors will increase the option value, hence decrease the price.

Figure 3: Stop-loss Option Value versus Boundary

Table 1: Summary Statistics of Stop-Loss Momentum

We compare the summary statistics of the monthly returns on the original momentum portfolios (Losers, Winners, and Winners-Losers) with those on the corresponding stop-loss momentum portfolios. The original momentum portfolios are formed using the last six month cumulative returns from $t-7$ to $t-2$ as described in the text. To form the stop-loss momentum portfolios, each month a stock in the original momentum portfolio is liquidated and the proceeds are invested in the risk-free treasury bill if the stop loss trade is triggered. For the losers portfolio, the trade is triggered once the stock price is above the triggering price, while for the winners portfolio, the trade is triggered once the stock price is below the triggering price. The triggering price is set to be 5% (Panel B), 10% (Panel C), or 15% (Panel D) above (below) the last month-end closing price for the losers (winners) portfolios. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*SRatio*), Skewness, Kurtosis, minimum and maximum returns. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

Variable	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	Minimum(%)	Maximum(%)
	Panel A: Market and Original Momentum						
Market	0.62*** (3.62)	5.45	0.114	0.17	7.31	-28.98	37.77
Losers	0.20 (0.71)	8.88	0.023	1.18	10.07	-39.43	66.10
Winners	1.20*** (4.93)	7.82	0.153	-0.28	3.66	-33.06	44.86
Winners-Losers	1.01*** (5.31)	6.07	0.166	-1.18	14.47	-49.79	45.11
	Panel B: Stop Loss at 10%						
Losers	-0.49*** (-2.68)	5.90	-0.083	-1.37	4.26	-39.19	12.73
Winners	1.24*** (6.44)	6.14	0.202	0.74	3.40	-12.91	42.08
Winners-Losers	1.73*** (11.87)	4.67	0.370	1.86	12.79	-11.34	43.43
	Panel C: Stop Loss at 5%						
Losers	-0.93*** (-6.38)	4.68	-0.199	-1.97	7.01	-35.59	8.28
Winners	1.46*** (9.49)	4.92	0.297	1.51	7.27	-8.58	40.01
Winners-Losers	2.39*** (17.81)	4.30	0.556	2.26	14.28	-9.01	40.41
	Panel D: Stop Loss at 15%						
Losers	-0.21 (-1.02)	6.66	-0.032	-0.95	3.05	-39.06	17.04
Winners	1.02*** (4.79)	6.83	0.149	0.29	2.46	-16.86	42.78
Winners-Losers	1.23*** (8.14)	4.86	0.253	1.40	11.36	-13.77	44.23

Table 2: Performance of Stop-Loss Momentum in Three Periods

We compare the performance of the original momentum portfolios (Losers, Winners, and Winners-Losers) with that of the corresponding stop-loss momentum portfolios in three subperiods. The original momentum portfolios are formed using the last six month cumulative returns from $t-7$ to $t-2$ as described in the text. The stop-loss momentum portfolios are described as in Table 1. The stop-loss triggering price is set at 10% above or below the last month-end closing price. In the first (Panel A) and third (Panel C) periods, we use both open price and close price to determine whether the stop-loss trades are triggered and the trade prices, whereas in the second period (Panel B) when the open price is not available, we use the closing prices to determine whether the stop-loss trades are triggered. The details of the construction of the stop-loss momentum portfolios are discussed in the text. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

	Original Momentum			**Stop-Loss (10%) Momentum**		
Variable	Avg Ret(%)	Std Dev(%)	Skewness	Avg Ret(%)	Std Dev(%)	Skewness
			Panel A: August 1926 to June 1962			
Losers	0.55	10.33	1.63	-0.09	6.58	-1.59
	(1.11)			(-0.30)		
Winners	1.29***	8.15	-0.52	0.95***	6.23	0.11
	(3.28)			(3.17)		
Winners-Losers	0.74***	6.18	-2.63	1.05***	4.44	0.95
	(2.47)			(4.89)		
			Panel B: July 1962 to June 1992			
Losers	-0.14	6.94	0.34	-0.81***	4.94	-0.77
	(-0.40)			(-3.12)		
Winners	1.08***	6.79	-0.82	1.40***	5.56	0.41
	(3.01)			(4.79)		
Winners-Losers	1.22***	4.41	-1.09	2.21***	3.57	0.92
	(5.25)			(11.77)		
			Panel C: July 1992 to December 2011			
Losers	0.07	8.64	0.09	-0.74*	5.92	-1.42
	(0.12)			(-1.91)		
Winners	1.25**	8.64	0.51	1.50***	6.80	1.90
	(2.21)			(3.38)		
Winners-Losers	1.18**	7.81	0.30	2.24***	6.18	2.56
	(2.30)			(5.55)		

Table 3: Average Percentage of Closed Positions

The table reports the percentage of stocks whose positions are closed through stop-loss trades, averaged over the entire sample periods. Also reported are the median, skewness, kurtosis, minimal and maximal percentage of closed positions. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

Momentum	Average(%)	Median	Skewness	Kurtosis	Minimum(%)	Maximum(%)
Losers	31.97	0.27	0.86	0.20	0.00	100.00
Winners	30.37	0.23	1.03	0.31	0.00	100.00

Table 4: CAPM and Fama-French Alphas

We compare abnormal return and risk loadings with respect to the CAPM and Fama-French three-factor model, respectively between the original momentum portfolios (Panel A) and the stop-loss momentum portfolios (Panel B). The original momentum portfolios are formed using the last six month cumulative returns from $t-7$ to $t-2$. The stop-loss triggering price is set at 10% above or below the last month-end closing price. The abnormal returns (α) are in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

	CAPM		**Fama-French**			
Rank	α(%)	β_{mkt}	α(%)	β_{mkt}	β_{smb}	β_{hml}
	Panel A: Original Momentum					
Losers	-0.69***	1.45***	-0.83***	1.28***	0.70***	0.19**
	(-5.54)	(35.1)	(-8.51)	(36.0)	(7.04)	(2.19)
Winners	0.45***	1.22***	0.43***	1.10***	0.77***	-0.24***
	(3.61)	(21.3)	(4.05)	(28.9)	(5.96)	(-2.66)
Winners-Losers	1.15***	-0.23***	1.27***	-0.18***	0.07	-0.43***
	(6.70)	(-2.67)	(6.95)	(-2.69)	(0.36)	(-2.64)
	Panel B: Stop-Loss (10%) Momentum					
Losers	-1.05***	0.90***	-1.07***	0.83***	0.41***	-0.10
	(-9.39)	(13.9)	(-10.3)	(18.4)	(4.55)	(-1.10)
Winners	0.70***	0.87***	0.68***	0.78***	0.62***	-0.20***
	(5.53)	(15.8)	(5.85)	(20.1)	(6.55)	(-2.68)
Winners-Losers	1.75***	-0.03	1.75***	-0.05	0.21	-0.10
	(10.7)	(-0.50)	(10.1)	(-1.06)	(1.52)	(-0.87)

Table 5: Crash Months

This table reports the performance of the stop-loss momentum for the crash months, periods when the original momentum performs poorly - the Winners-Losers portfolio experiences losses exceeding 20%. We report the returns for the Losers, Winners and Winners-Losers for both the original momentum and the stop-loss momentum, respectively. Returns are in percentage.

Date	Losers(%)	Winners(%)	Winners-Losers(%)	Losers(%)	Winners(%)	Winners-Losers(%)
	Panel A: Original Momentum			**Panel B: Stop-Loss (10%) Momentum**		
01/1931	24.51	3.68	-20.83	10.43	1.36	-9.07
07/1932	61.94	12.15	-49.79	9.54	12.29	2.75
08/1932	60.43	39.98	-20.45	11.78	19.94	8.16
04/1933	66.20	26.77	-39.43	11.37	13.90	2.53
09/1939	46.23	11.78	-34.46	12.74	8.79	-3.95
09/1970	24.15	4.08	-20.07	9.28	4.00	-5.28
01/1975	32.07	7.57	-24.50	9.06	7.79	-1.27
03/2000	7.34	-14.72	-22.06	3.23	-4.02	-7.25
04/2000	-1.22	-27.91	-26.69	-1.93	-9.91	-7.98
01/2001	29.02	3.78	-25.24	7.10	-1.07	-8.17
11/2002	26.37	1.79	-24.57	8.89	1.11	-7.77
04/2009	39.22	3.98	-35.24	10.01	4.16	-5.85

Table 6: Performance of Stop-loss for Volatility Sorted Momentum Portfolios

We first sort stocks into five quintiles according to their volatility, and then within each quintile we construct decile momentum portfolios. We compare the summary statistics of the monthly returns on the original momentum portfolios (Losers, Winners, and Winners-Losers) with those on the corresponding stop-loss momentum portfolios in each volatility quintile. The original momentum portfolios are formed using the last six month cumulative returns from $t-7$ to $t-2$ as described in the text. To form the stop-loss momentum portfolios, each month a stock in the original momentum portfolio is liquidated and the proceeds are invested in the risk-free treasury bill if the stop loss trade is triggered. For the losers portfolio, the trade is triggered once the stock price is above the triggering price, while for the winners portfolio, the trade is triggered once the stock price is below the triggering price. The triggering price is set to be 10% above (below) the last month-end closing price for the losers (winners) portfolios. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*SRatio*) and Skewness. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

Vol Rank	Winners-Losers			
	Avg Ret(%)	Std Dev(%)	SRatio	Skew
	Original Momentum			
Low	0.49***	3.88	0.126	-0.33
	(4.08)			
2	0.75***	4.48	0.167	-0.20
	(5.33)			
3	0.89***	5.41	0.165	-1.37
	(5.29)			
4	0.98***	6.32	0.155	-1.04
	(4.95)			
High	1.64***	7.77	0.211	-0.58
	(6.76)			
	Stop Loss Momentum at 10%			
Low	0.59***	3.49	0.169	1.18
	(5.38)			
2	1.09***	3.86	0.282	0.08
	(9.06)			
3	1.59***	4.58	0.347	0.46
	(11.13)			
4	1.60***	5.37	0.298	0.93
	(9.52)			
High	2.35***	6.64	0.354	0.94
	(11.33)			

Table 7: Value-Weighted Stop-Loss Momentum

We compare the summary statistics of the monthly returns on the original momentum portfolios (Losers, Winners, and Winners-Losers) with those on the corresponding stop-loss momentum portfolios. The portfolios are value-weighted by the last month-end market size. The triggering price is set to be 5% (Panel B), 10% (Panel C), or 15% (Panel D) above (below) the last month-end closing price for the losers (winners) portfolios. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*SRatio*), Skewness, Kurtosis, minimum and maximum returns. Newey and West (1987) robust *t*-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

Variable	Avg Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	Minimum(%)	Maximum(%)
	Panel A: Original Momentum						
Losers	0.23	8.38	0.027	1.32	14.08	-39.28	78.28
	(0.88)						
Winners	1.01***	7.24	0.140	-0.49	2.43	-33.62	37.70
	(4.45)						
Winners-Losers	0.78***	7.03	0.111	-1.73	17.05	-65.34	44.41
	(3.53)						
	Panel B: Stop Loss at 10%						
Losers	-0.17	5.94	-0.029	-1.34	4.54	-39.04	15.05
	(-0.92)						
Winners	1.01***	6.20	0.163	0.63	3.36	-22.60	43.82
	(5.24)						
Winners-Losers	1.18***	5.57	0.212	1.22	8.34	-23.69	43.12
	(6.81)						
	Panel C: Stop Loss at 5%						
Losers	-0.55***	4.75	-0.116	-2.10	8.18	-38.07	8.67
	(-3.69)						
Winners	1.23***	5.18	0.237	1.37	6.70	-19.06	42.85
	(7.61)						
Winners-Losers	1.78***	5.03	0.354	1.73	10.43	-18.17	40.99
	(11.32)						
	Panel D: Stop Loss at 15%						
Losers	-0.01	6.58	-0.002	-0.93	3.23	-38.90	17.08
	(-0.03)						
Winners	0.83***	6.80	0.122	0.20	2.60	-26.02	43.82
	(3.93)						
Winners-Losers	0.84***	5.88	0.143	0.71	7.42	-27.26	43.40
	(4.58)						

Table 8: Performance of Value-Weighted Stop-Loss Momentum in Crash Months

This table reports the performance of the stop-loss momentum for the crash months, periods when the original momentum performs poorly - the Winners-Losers portfolio experiences losses exceeding 20%. We report the returns for the Losers, Winners and Winners-Losers for both the original momentum and the stop-loss momentum, respectively. All portfolios are value-weighted by last month-end market size. Returns are in percentage.

Date	Losers(%)	Winners(%)	Winners-Losers(%)	Losers(%)	Winners(%)	Winners-Losers(%)
	Panel A: Original Momentum			**Panel B: Stop-Loss (10%) Momentum**		
07/1932	62.94	4.96	-57.98	9.64	12.59	2.95
08/1932	55.76	17.18	-38.58	11.80	-11.90	-23.69
11/1932	-2.23	-26.02	-23.79	-5.19	-8.81	-3.62
04/1933	78.38	13.04	-65.34	11.48	15.50	4.02
06/1938	37.76	13.44	-24.33	8.95	13.25	4.30
09/1939	29.70	4.23	-25.46	15.06	1.81	-13.26
09/1970	21.96	1.35	-20.61	9.24	1.33	-7.90
01/1975	23.64	1.21	-22.43	9.57	1.73	-7.84
03/2000	14.09	-13.17	-27.26	6.99	-4.52	-11.51
05/2000	7.40	-16.97	-24.37	4.39	-9.62	-14.01
01/2001	29.45	-6.46	-35.91	7.54	-7.31	-14.85
11/2002	22.77	-0.72	-23.50	10.17	-0.96	-11.13
04/2009	35.49	-1.03	-36.51	11.03	-0.19	-11.22

Table 9: Stop-Loss Momentum Based on Past Twelve-Month Returns

We compare the summary statistics of the monthly returns on the original momentum portfolios (Losers, Winners, and Winners-Losers) with those on the corresponding stop-loss momentum portfolios. The original momentum portfolios are formed using the last twelve month cumulative returns from $t-13$ to $t-2$ as described in the text. To form the stop-loss momentum portfolios, each month a stock in the original momentum portfolio is liquidated and the proceeds are invested in the risk-free treasury bill if the stop loss trade is triggered. For the losers portfolio, the trade is triggered once the stock price is above the triggering price, while for the winners portfolio, the trade is triggered once the stock price is below the triggering price. The triggering price is set to be 5% (Panel B), 10% (Panel C), or 15% (Panel D) above (below) the last month-end closing price for the losers (winners) portfolios. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*SRatio*), Skewness, Kurtosis, minimum and maximum returns. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5% , or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January, 1926 to December, 2011.

Variable	Avg Ex.Ret(%)	Std Dev(%)	SRatio	Skewness	Kurtosis	Minimum(%)	Maximum(%)
	Panel A: Market and Original Momentum						
Market	0.62***	5.46	0.114	0.17	7.27	-28.98	37.77
	(3.60)						
Losers	0.14	8.78	0.016	1.46	14.34	-38.79	84.84
	(0.52)						
Winners	1.26***	8.12	0.155	-0.16	3.79	-33.96	50.50
	(4.96)						
Winners-Losers	1.12***	6.27	0.179	-1.20	13.82	-55.10	41.76
	(5.70)						
	Panel B: Stop Loss at 10%						
Losers	-0.52***	5.89	-0.088	-1.44	5.00	-37.98	13.07
	(-2.84)						
Winners	1.31***	6.32	0.207	0.74	3.09	-12.27	39.72
	(6.61)						
Winners-Losers	1.83***	4.90	0.373	1.66	10.05	-11.78	41.32
	(11.93)						
	Panel C: Stop Loss at 5%						
Losers	-0.93***	4.66	-0.200	-2.13	8.61	-35.10	7.77
	(-6.38)						
Winners	1.53***	5.01	0.305	1.36	5.64	-8.61	38.79
	(9.78)						
Winners-Losers	2.47***	4.40	0.561	2.04	11.64	-8.96	38.27
	(17.90)						
	Panel D: Stop Loss at 15%						
Losers	-0.28	6.60	-0.042	-0.98	3.41	-37.83	17.14
	(-1.34)						
Winners	1.09***	7.04	0.155	0.34	2.25	-16.10	40.07
	(4.96)						
Winners-Losers	1.37***	5.10	0.269	1.22	8.27	-14.08	42.08
	(8.57)						