Taming Momentum Crashes: A Simple Stop-Loss Strategy

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First Draft: January, 2014
Current version: September, 2016

*We are grateful to Pedro Barroso, Tarun Chordia, Charles Cuny, Ryan Israelsen, Fuwei Jiang, Lei Jiang, Raymond Kan, Yvonne Kreis, Pawel Maryniak, Scott Murray, Ľuboš Pástor, Matthew Ringgenberg, Ronnie Sadka, Pedro Santa-Clara, Shuai Ye, and Xiaoyan Zhang, seminar participants at Shanghai Advanced Institute of Finance, Singapore Management University, Southwestern University of Finance and Economics, University of Missouri, Washington University in St. Louis, and conference participants at the 2014 Tsinghua University Finance Workshop, 2014 International Symposium on Financial Engineering and Risk Management, 2015 Midwest Finance Association Annual Meetings, 2015 Eastern Finance Association Annual Meetings, 2015 ITAM Finance Conference, 2015 China International Conference in Finance, and 2015 World Finance Conference, for very insightful and helpful comments.
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Abstract

We propose a stop-loss strategy to limit the downside risk of the well-known momentum strategy. At a stop-level of 15%, we find, with data from January, 1926 to December, 2013, that the maximum monthly losses of the equal- and value-weighted momentum strategies go down from −49.79% to −17.43% and from −64.97% to −22.10%, respectively, while the Sharpe ratios are more than doubled. We also provide a general equilibrium model with 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.

JEL Classification: G11, G14

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

I Introduction

Since the seminal work of Jegadeesh and Titman (1993), it is well-known that a momentum strategy of buying past winners and selling past 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 momentum 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 significant attention (see, e.g., Daniel and Moskowitz, 2014; Daniel, Jagannathan, and Kim, 2012; Barroso and Santa-Clara, 2015). For example, the four worst monthly drops of the momentum strategy are as large as −49.79%, −39.43%, −35.24% and −34.46% for the equal-weighted momentum strategy (with value-weighting, the worst loss goes up to −64.97%). Does this extreme downside risk explain the high abnormal returns of the momentum strategy?

In this paper, we provide a simple stop-loss trade 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 at the beginning of each month, we do not have to hold all of them to the end of the month. We can sell some of them once a certain loss level is triggered due to perhaps some fundamental changes unknown to us. While such a stop-loss strategy is very popular in practice and every trading system today may allow stop-loss orders, there are few studies in the finance literature. Kaminski and Lo (2014) is perhaps the first theoretical study to show that stop-loss rules can be profitable in the presence of momentum behaving as an AR(1) process. Complimenting to their theoretical analysis, our paper here applies simple stop-loss rules empirically to individual stocks in the momentum decile portfolios and we show that such a strategy does control the crash risk of the momentum anomaly.

The important empirical question is whether the stop-loss trading strategy reduces the average return of the original momentum strategy and the associated Sharpe ratio due to its less risk exposure. Surprisingly, for our simple stop-loss strategy with 15% loss trigger and a 7.50% threshold, it in fact raises the average return of the original momentum strategy from 0.99% per month to 1.93% per month, while reducing the standard deviation from 6.01% per month to 4.85% per month. Hence, the stop-loss momentum strategy generates a monthly Sharpe ratio of 0.399, more than double the level , 0.165, of the original momentum strategy.

How well does the stop-loss strategy avoid the momentum crash? In those four months when the original momentum strategy has its worst losses, −49.79%, −39.43%, −35.24% and −34.46%, the stop-loss momentum returns −9.62%, 2.83%, −10.76% and −17.43%, respectively. Note that the return is even positive in one of the months! 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 only −17.43%, −14.77%, −13.85%, and −13.10%. In addition, these losses are compared very favorably even to the losses of the four worst months of the stock market, −34.46%, −10.76%, −17.14%, and −20.90%. Overall, the stop-loss momentum has much greater average return and Sharpe ratio than the original momentum and has no crash risk of a level exceeding 30%, making the momentum anomaly more anomalous than ever.

Barroso and Santa-Clara (2015) recently provide a novel approach to control the crash risk of the original momentum strategy by scaling the position. The scalar is less than one if the forecasted risk is high, and is as high as 2 if the risk is low. But their approach has two potential weaknesses. First, it is not easy to double the position in practice.[1] A manger of a billion dollar portfolio dedicated to the momentum strategy would not be able to raise another billion quickly, and, even if loans are available, the cost can be much higher than the riskfree rate given the risk involved. Second, out-of-sample forecasting is well known to be extremely difficult. When the scalar is 2 and when the original momentum strategy loses only 25%, the total investment of the leveraged position will lose 50%, which will put any fund at the risk of closure in practice. In contrast, our stop-loss strategy does not require any leverage beyond the original momentum portfolio, nor does it rely on any predictability.

To understand the role of stop-loss trades in affecting prices, we, in this paper, also provide a simple equilibrium model in the presence of both stop-loss traders and non-stop-loss traders. In traditional models with only non-stop-loss traders, the stop-loss strategy is not optimal (see, e.g., Dybvig, 1988). However, with a drawdown constraint of risk control, Grossman and Zhou (1993) show that a continuous stop-loss strategy is optimal, which maps into a series of stops in practice and simplifies to a single stop used empirically by this paper. Our model is the first to explore the pricing role played by stop-loss traders. Interestingly, we find that the equilibrium market price differs from the price when there are no stop-loss traders by a barrier option. One testable implication of the model is: the greater the volatility near the stop-loss level, the greater the value of the barrier option. This is consistent with our empirical evidence that the greater the volatility, the greater the impact of the stop-loss strategy in improving the momentum profitability.

The stop-loss strategy is very robust. It is effective across liquidity and size as well as over business cycles and other subperiods. In addition, if one constructs the stop-loss levels by using the daily volatility estimated from the previous month rather than the simple percentage loss from the beginning of the month, the stop-loss strategy performs much better.

The rest of the paper is organized as follows. Section II discusses the data and the

[1] If it were, one could always invest in the doubled position and earn double the return while controlling the downside risk using our stop-loss strategy.

construction of the original momentum portfolios. Section III describes the methodology for constructing the stop-loss momentum portfolios. Section IV reports the superior performance of the stop-loss momentum strategy relative to the original momentum strategy. Section V investigates the performance of the strategies in crash periods. Section VI provides a theoretical analysis. Section VII examines the robustness of the stop-loss momentum strategy. Section VIII explores alternative stop-loss strategies. Section IX concludes.

II Data

We use daily prices and monthly stock returns 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, each month we first calculate cumulative returns over the previous six months, and conditioning on the past six-month cumulative returns we form ten equal-weighted decile portfolios. The decile portfolios are then held for one month. As robustness checks, we also examine the performance of the value-weighted momentum and the momentum sorted on past cumulative returns of other lag lengths such as 12-month, etc. Then, following Jegadeesh and Titman (1993) and others, we activate the 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, 2013, however, the returns on the momentum portfolios start from August 1926 because of skipping one month. Since we use daily prices below to make stop-loss decisions and to compute returns for holding periods less than a month, the prices below are adjusted for dividends and stock splits.[2]

III Stop-Loss Momentum Strategy

The stop-loss idea is simple. For any stock in our long positions of the original portfolio, we sell it if it drops to a certain level. Similarly, for a stock in the short positions, we cover it or buy it back when its price rises to a certain level. However, the actual implementation requires some care.

Consider, for example, a stock in the winners portfolio, and a pre-determined loss level of $L = 15\%$. Let P_0 be its price at the beginning of the month, which is the close price at the end of the previous month when we form the momentum portfolio. On each trading day t before the end of the month, we compute the worst return

$$R_t^L = \frac{P_t^L - P_0}{P_0}, \tag{1}$$

where P_t^L is the lowest price of day t. When $R_t^L \leq -15\%$ occurs the first time, our stop order is triggered. That is, we consider to sell the stock when the lowest price passes below $SP_D = (1-L)P_0$. However, we do not execute our sell order on day t for possible overreaction of the stock price due to volatility, consistent with the common practice of practitioners who trade limit orders to use up to 3 days to establish their desired positions (Frazzini, Israel, and Moskowitz, 2012). For this same reason, we will also allow a threshold of price movements around SP_D to make sure that the initial drop of $L = 15\%$ is genuine and not due to random fluctuations. In this paper, we set the threshold level at $L/2$. Hence, in the following day after the stop-loss is triggered, we sell the stock at the stop-loss limit price $LP_D = (1 - 0.5L)SP_D$ whenever it is reached. If this price is between the highest and the lowest on this day, it is obvious that our trade is executed, and we invest the proceeds in the money market to earn

[2] Results are virtually identical if we exclude dividends.

the riskfree T-bill return for the rest of the month. If the highest is below LP_D, we sell the stock on the close and invest the proceeds the same way. However, if the lowest is above LP_D, we keep the stock for another day and do the same on the future trading days of the month. This completely defines our sell stop-loss strategy at a stop level $L = 15\%$.

For a stock in the losers portfolio, we can define similarly a stop-loss buy strategy. In this case, the initial stop-loss trigger price is $SP_U = (1 + L)P_0$ and the subsequent stop-loss buy limit price is $LP_U = (1 + 0.5L)SP_U$. Then our stop-loss momentum strategy is completely determined.

Although we report below results of using additional stop-loss levels of $L = 10\%$ and $L = 20\%$, we will, for brevity, focus on results using $L = 15\%$. Clearly, more complex and efficient stop-loss strategies may be designed to improve the performance. For example, one may allow more days to execute the stops or break down the single trades into smaller ones optimally (see, e.g., Bertsimas and Lo, 1998; Obizhaeva and Wang, 2013). However, our objective is to show that the stop-loss can help to avoid the crash risk of the momentum portfolio without sacrificing returns. Since our simple strategy works already and it makes the momentum anomaly becomes more difficult to explain, more sophisticated strategies can only strengthen the conclusion further. Given its analytical challenge, we leave the study of optimal stop strategies as future research where earning the maximum profits from stop-loss trading is of interest. In other words, our paper shows that stop-loss trading is profitable in taming large losses of the popular momentum portfolio, but does not address the question on the maximum profits.

IV Performance of Stop-Loss Momentum

Table I provides the performance summary statistics for the stop-loss strategies for data from January, 1926 to December, 2013. As shown in Panel A of Table I, the average excess return of 0.65% per month on the market index is the reward on the strategy of buying and holding the market. In contrast, the average excess return of the original momentum strategy (WML) is 0.99% per month, which is much greater. The standard deviation of 6.01% per month for the original momentum, is not much different from 5.43% 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 these models. 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 worst month of the market is only −29.13%, but the momentum suffers from a maximum loss level of −49.79%.

Panel B of Table I reports the performance for the stop-loss momentum strategy with a stop level of 15%. It has an average return of 1.93%, which is almost twice of what the original momentum strategy can achieve. Moreover, the standard deviation is 4.85%, smaller than 6.01% of the original momentum strategy. Hence, the Sharpe ratio is more than doubled from 0.165 to 0.399. Most strikingly, the worst loss is now capped at −17.43% for the entire sample period, which contributes to a positive skewness (1.28) for the stop-loss momentum strategy instead of the negative one (−1.18) for the original momentum strategy. In addition, the percentage increase in M2 is 141.38%. That is, if the stop-loss strategy is leveraged to have the same volatility as the original momentum, the average return would be 2.39% per month, about 241.38% of the average return on the original momentum. Interestingly, although both the winners and losers portfolios contribute to the loss reduction, it seems mainly coming from the losers portfolio.

For better understanding of the role of the stop level, we also consider two additional loss levels, $L = 10\%$ and 20%. Panels C and D report the results. The 10% loss level appears to perform even better. The average return is as high as 2.32% per month, the standard deviation is even smaller at 4.61%, the Sharpe ratio is thus 0.504, and the skewness is 1.54 with a worst monthly loss of −15.37%. The increase in M2 is over 204.64%.

However, in terms of the overall Sharpe ratio and loss control, performance of all the stop levels is 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 the results of $L = 15\%$, while the conclusions are similar for either $L = 10\%$ or 20%. Figure 1 plots the time series of returns on the original and the stop-loss momentum strategies at 15%. It is expected that they are highly correlated in general (with correlation of 68.75%), 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. Sometimes 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.

From an economic modeling perspective, one can perhaps design some optimal mixture of various stop-loss levels that can potentially improve substantially the performance of the above plain-vanilla stop-loss strategy. Moreover, with predictability insights from Daniel and Moskowitz (2014), Daniel, Jagannathan, and Kim (2012) and Barroso and Santa-Clara (2015), among others, one can also set stop-loss trades that are conditional on various economic variables. However, our paper focuses on simple stop-loss strategies only. Given that they have already yielded remarkable performance, we leave the search for optimal stop-loss strategies as future research.

A Stopped Percentage, Turnover Rates 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 first 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 a few months, nearly 100 percent of the positions are closed, while in many months no positions are closed at all. This is true for both the losers and winners. On average, about 10.69% stocks in the losers portfolio are bought back in any given month, whereas about 10.05% stocks are sold in the winners portfolio in any given month. At the bottom of Figure 2, we plot the market volatility estimated from the daily returns each month and the market monthly returns. 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 37.48% for the losers portfolio and 68.49% for the winners portfolio. Furthermore, the percentage of closed positions seems more closely related to the monthly market returns – the correlation is 49.04% for the losers portfolio and −55.91% for the winners portfolio.

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. However, the improved performance comes with potentially more transactions or turnovers. Panel A of Table II compares the monthly turnover rates of the original momentum and the stop-loss momentum. For the original momentum, the monthly turnover rates are 45.05% and 39.11% for the losers and winners portfolios, respectively, which are very similar to what are reported by Grundy and Martin (2001). In contrast, the stop-loss momentum has monthly turnover rates[3] of 58.57% and 49.08%, respectively, for the losers and winners portfolios. Therefore the increased turnover rates are 13.53% and 9.98%, respectively, for losers and winners. The median increases in turnover rate are even smaller, about 8.23% and 4.87%, respectively.

[3]To determine the value of the portfolios on the days with stop trades required for the calculation of turnover rates, we use close prices for stocks remaining in the portfolios, and use the traded prices for the stocks traded out of the portfolios.

To further explore the impact of additional turnovers on the performance of the stop-loss momentum strategy, we estimate the break-even transaction costs and report the results in Panel B of Table II. Following Grundy and Martin (2001) and Barroso and Santa-Clara (2015), we estimate three different break-even transaction costs. The first is the transaction costs that make the stop-loss momentum to have the same average return as the original momentum. For the stop-loss momentum (WML) portfolio, the break-even costs are 4.00%. The second is the transaction costs that make the Sharpe ratios of the two strategies the same, which are slightly higher at 4.82%. The third is the transaction costs that make the average returns of the two momentum strategies insignificantly different at 5% significance level. The costs are 3.18%. Using the medians of the increased turnover rate, the break-even transaction costs are higher, at 7.18%, 8.65%, and 5.71%, respectively. These very high break-even transaction costs confirm that the stop-loss momentum can still generate better performance even after taking into account higher transaction costs due to additional trading.

B 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 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 portfolio, and $r_{mkt,t}$ is the monthly excess return on the market portfolio. The left-hand side columns of Table III report 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 I. 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 -0.06, 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 III 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 I, while the alpha of the stop-loss momentum is almost the same as the CAPM alpha, about 2.01% 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 the stop-loss momentum has no risk exposure to the market risk and the risks proxied by the SMB and HML factors.

V Crash Periods

Daniel and Moskowitz (2014) show that there are a few "crash periods" when the original momentum suffers big losses. In this section, 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 (2014) 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 −70.25%, −54.06%, and −39.30%. In contrast, the cumulative returns of the stop-loss momentum strategy are −13.79%, 13.30%, and −12.42%. It is interesting and important that all the crashes are tamed or even disappear completely with the use of the stop trades.

To provide further insights on the downside risk of the momentum strategy, Panel A of Table IV provides all the big monthly losses (greater than 20%) of the original momentum strategy. There are twelve of them, 1.14% out of all the months. The extreme downside risks are rare but not rare enough. Panel B provides the returns of the stop-loss momentum strategy in the same months. It is remarkable that all the losses are tamed to within −17.43%, as compared to the biggest loss of −49.79% for the original momentum. The results seem to speak loudly about using the stop-loss strategy for controlling for the downside risk of the original momentum strategy.

Similarly, we compare the performance of the original and stop-loss momentum strategies for the months when the stop-loss momentum experiences the ten biggest losses in Panel C and D. As noted before, the biggest loss for the stop-loss momentum is −17.43%, while the original momentum has a loss of −34.46% in the same month. Similarly, in majority of the months, the stop-loss strategy still outperforms the original strategy by a large margin.

VI A General Equilibrium Model

In this section, we provide an equilibrium model to understand the price impact of stop-loss orders. Our assumptions are standard except that there are now both stop-loss traders and non-stop-loss traders in a typical competitive market setting.

Assumption 1. The market is endowed with a certain amount of 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.

Assumption 7 is consistent with Brunnermeier and Pedersen (2008) who provide the economic rationale why investors' 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.

A 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 standard 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 do 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 characterized by 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 behaves 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 of the value function 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 approaches 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. 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 unavailable, 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 winner (loser) combined with stops as long as the stop-loss level is not too high (low) relative to the stop-loss level perceived by the market.

To test the model prediction, we sort stocks into quintile volatility portfolios. For each of the quintiles, we examine the performance of the original momentum strategy and the one with stops at the 15% stop-loss level. Table V provides the results. For the lowest quintile portfolio, the average return on the original momentum is 0.46% per month with a Sharpe ratio of 0.120. In contrast, the one with the stops has an average of 0.57% and a Sharpe ratio of 0.160. As the volatility goes up, the original momentum performs better, but the stop-loss momentum improves even more. For example, for the highest volatility quintile, the difference in the average returns of the two momentum strategies reaches 1.12% (2.78% − 1.66%) per month, about 67.47% (1.12%/1.66%) improvement over the original momentum. If we compare the leveraged returns (M2), the increase is even higher at 86.11%. In addition, the percentage increase in M2 monotonically increases as volatility increases until the fourth quintile, which has the highest improvement at 144.75%.

In practice, the number of stop-loss traders are unknown. Moreover, there are likely multiple stop-loss levels and they are unknown to other investors. When the volatility variations and stop-loss selling are unanticipated by the market, their impact will be even greater than what is predicted by our simple theoretical model. This helps to understand further why the momentum strategy with stops performs much better empirically than the one without stops.

VII Robustness

In this section, we examine the robustness of the stop-loss strategy along several dimensions. We first examine the performance of the stop-loss momentum strategy using liquidity or size sorted stocks. We then examine the performance under business cycles and ten-year subperiods. Finally we examine the performance of value-weighting and using a momentum lag period of twelve months instead of six months.

A Liquidity and Size

Since liquidity is one of the key factors in explaining anomalies, especially momentum (see, e.g., Lesmond, Schill, and Zhou, 2004; Sadka, 2006), it is of interest to examine whether or not the stop-loss momentum strategy is effective only for illiquid stocks. To do so, we sort stocks first by Amihud (2002) illiquidity measure into five quintiles and then construct the stop-loss momentum strategy within each of the quintiles.

The results are reported in Table VI. Interestingly the performance of the original momentum increases as illiquidity increases. Specifically, the most liquid stocks yield an average return of 0.53% per month for the original momentum, while the stocks in the fourth quintile yield an average return of 1.39% per month. However, the performance of the least liquid stocks decreases to 0.97% per month. The stop-loss momentum displays a similar pattern – performance monotonically increases as illiquidity increases but declines for the least liquid quintile. However, even for the most liquid stocks, the stop-loss momentum yields an average return of 1.62%, more than twice of that of the original momentum. Indeed, the performance increase is the highest for the most liquid stocks. Moreover, the Sharpe ratios are much higher for the stop-loss momentum portfolios than for the original momentum portfolios across the five illiquidity quintiles also because of reduced volatilities of the stop-loss momentum.

Similar results in Table VII are also obtained when stocks are sorted by size. As for the liquidity case, both the original momentum and stop-loss momentum yield better performance for smaller stocks, and the performance decreases monotonically as the size increases. However, the average returns of the stop-loss momentum are always about twice of those of the original momentum across the size quintiles, and the Sharpe ratios are thus more than twice of those of the original momentum, again because of lower volatilities of the stop-loss momentum. For example, the original momentum yields an average return of 1.18% per month and a Sharpe ratio of 0.174 for the smallest stocks, whereas the stop-loss momentum yields an average return of 2.32% per month and a Sharpe ratio of 0.413 for the smallest stocks. Even for the largest stocks, the performance is 0.51% versus 1.03% per month for the average return and 0.077 versus 0.186 for the Sharpe ratio, respectively, for the original momentum and the stop-loss momentum. Furthermore, the percentage increase in M2 is all above 135% except for the second size quintile, for which the increase is slightly over 100%.

B Business Cycles

It is also of interest to examine the performance of the stop-loss momentum during recessions. Chordia and Shivakumar (2002) provide evidence that momentum payoffs are reliably positive and significant over expansionary periods, whereas they become negative and insignificant over recessionary periods. Cooper, Gutierrez, Jr., and Hameed (2004) argue that the momentum strategy is profitable only after an up market, where the up market is defined as having positive returns in the past one, two, or three years.

Table VIII confirms the cyclic performance of the original momentum. During expansions, the original momentum yields 1.13% per month with a Sharpe ratio of 0.210, compared to 0.99% per month with a Sharpe ratio of 0.165 (Table I) for the entire sample period. During recessions, on the other hand, the performance is much weaker with insignificant average return (0.47% per month) and much smaller Sharpe ratio (0.059).

In sharp contrast, the stop-loss momentum yields similar performance in recessions. The average return is 1.98% per month, and the Sharp ratio is 0.433 during the expansion periods, and they are 1.77% per month (average return) and 0.304 (Sharpe ratio) during recession periods. Because of the weak performance during recessions for the original momentum, the relative performance of the stop-loss momentum is much stronger with an increase of 413.28% in M2 relative to the original momentum.

C Subperiods

An alternative to dividing the sample period into recessions and expansions is to divide it into consecutive subperiods over time. For simplicity, we consider nine roughly ten-year periods from the beginning to the end of the data backwards. Therefore, the first subperiod is from 1926 to 1933 with only seven years, and the rest have exactly ten years with the last subperiod from 2004 to 2013. Fig 4 plots the average monthly returns of the original momentum, the stop-loss momentum, and the market within each of the nine subperiods. Clearly the stop-loss momentum drastically outperforms the original momentum in eight of the nine ten-year subperiods. Even in the third ten-year period from 1944 to 1953 when the performance difference is not that drastic, it still significantly outperforms the original momentum (1.04% versus 0.90%). Interestingly, both the original and the stop-loss momentum have their highest performance in the eighth subperiod, from 1994 to 2003, which is the ten years right after the publication of the seminal momentum work of Jegadeesh and Titman (1993). In this period, the stop-loss momentum still has excellent relative performance (4.22% versus 2.06%). It is worth noting that, in sharp contrast to the original momentum that performs much worse than the market in the first and last ten-year periods, the stop-loss momentum outperforms the market considerably in those two subperiods. Overall, the outperformance of the stop-loss momentum is quite robust to various subperiods.

D Value-weighting

When momentum strategies are based on the value-weighted decile portfolios, the performance is generally different from that of the equal-weighting. Parallel to Table I, Table IX reports the performance statistics for the value-weighted momentum strategies. Let us focus on the results with $L = 15\%$. The average return of the original momentum is now 0.74% per month, lower than the equal-weighted case. The minimum is lowered too, from −49.79% to −64.97%. Furthermore, the Sharpe ratio is lower. The stop-loss momentum strategy now also has a lower average return of 1.42% instead of 1.93%. Nevertheless, the Sharpe ratio is more than twice as high as the Sharpe ratio of the original momentum, similar to the equal-weighed case. The greatest difference of the results is about the minimum return. Instead of −17.43%, it has a value of −22.10% that occurred in January, 2001 due to jumps of stock prices from one day to another during that time.

Analogous to Table IV, we also examine how well the value-weighted stop-loss momentum strategy performs over crash months in Table X. Except for four large losses, all other losses are less than −16%, and in some months the losses are less than −1%, taming immensely from the huge losses of the original momentum strategy. In particular, when the original momentum had its biggest loss in April, 1933, the stop-loss momentum merely lost −0.99%. Overall, it is clear that our earlier conclusions remain valid qualitatively for the value-weighted strategies that the stop-loss strategy substantially tames the crash risk of the original momentum strategy.

E Twelve-Month Momentum

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

Table XI provides the results. As expected, they are very similar to those reported in

Table I for the six-month momentum. For example, the original momentum yields an excess return of 1.12% per month on average for the WML spread portfolio, whereas the stop-loss momentum yields 2.09%, 2.48%, and 1.76% per month on average with a stop-loss level of 15%, 10%, and 20%, 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 portfolios, 0.412%, 0.514%, and 0.336% versus 0.181. Once again, at each stop-loss level, the stop-loss momentum WML portfolio has a positive skewness in contrast to the negative skewness of the original momentum WML portfolio. The maximum loss of the original momentum spread portfolio is −55.10%, whereas it is only −13.48%, −12.78%, and −15.19% with the three stop-loss levels, respectively.

VIII Alternative Stop-Loss Strategies

In this section, we examine further the robustness of the results by exploring the performance of three additional alternative stop-loss strategies. The first strategy explores a modified execution of the stop-loss trades, and second strategy examines the effect of using different thresholds, and the last strategy explores a new way for setting up the stop-loss level.

Table XII reports the results of these alternative strategies. In Panel A, we changed the execution of the stop-loss trades so that the trades will only be executed when the limit prices are reached. In other words, we do not trade at the close when the limit prices are not reached as in the original stop-loss strategy. Compared to the results in Table I, the performance of this new strategy is even higher, which is not unexpected given that this strategy is more patient than the original stop-loss strategy. The average return, Sharpe ratio, and increase in M2 are 2.10%, 0.437, and 164.45% versus 1.93%, 0.399, and 141.38%, respectively. It is worth noting that the maximum loss is greater for this alternative strategy, −25.78%, which is likely due to the more stringent requirement for executing the stop-loss trades.

Panels B and C report the results of using alternative thresholds. Recall that in the original stop-loss strategy, the limit price is set so that the threshold is half of the loss level (i.e., 7.50%). Here we set the limit price so that the threshold is either smaller than the half (4% in Panel B) or larger than the half (10% in Panel C). It turns out that a smaller threshold slightly reduces the performance of the stop-loss strategy (e.g., Sharpe ratio reduced from 0.399 in Table I to 0.335), but improves the maximum loss (from −17.43% to −16.79). On the other hand, a larger threshold increases the performance of the stop-loss strategy, with higher average return (2.09% versus 1.93%), higher Sharpe ratio and percentage increase in M2 (0.432 versus 0.399, 160.99% versus 141.38%), larger skewness (1.39 versus 1.28), and even smaller maximum loss (−15.83% versus −17.43%).

Finally instead of using an arbitrary stop-loss level (e.g., 15%) we use the daily volatility in the previous month to set up the stop-loss level. First, we estimate the daily volatility at the beginning of a month based on the daily returns of the past month. Then, we set the buy- and sell-stop levels at three standard deviation away from the prior month-end close price. Other than using different stop-loss levels, the strategy implementation is the same as before (including setting the threshold as one half of the stop-loss level). This alternative stop-loss momentum strategy also delivers superior performance as shown in Panel D, with an average return of 1.81% per month, a standard deviation of merely 3.38%, a Sharpe ratio of 0.535, more than three times that of the original momentum, and thus an increase of M2 of 223.18%. The skewness remains positive and large, and the worst performance is −17.69%.

IX 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 (2014), Daniel, Jagannathan, and Kim (2012), and Barroso and Santa-Clara (2015), among others, concern about its crash risk. In this paper, we propose a simple stop-loss strategy to limit the downside risk. At a stop-level of 15%, we find empirically with data from January, 1926 to December, 2013 that the monthly losses of the equal-weighted momentum strategy can be improved substantially from −49.79% to within −17.43%. For the value-weighted momentum strategy, it reduces from −64.97% to within −22.10%. At the same time, the average returns and the Sharpe ratios are more than doubled. Our results show that the crash risk cannot explain the profitability of the momentum strategy.

Academic studies on the stop-loss strategy are rare. There are only a few related studies such as Dybvig (1988) and Grossman and Zhou (1993).[4] Although our paper provides a simple, and the first, general equilibrium model to understand the role of stop-loss traders, much remains to be done. Empirically, it will be valuable to examine alternative stop strategies with mixture of stop levels and with conditional information. While most empirical asset pricing studies are carried out at the monthly frequency, our paper highlights the importance of using daily information, such as the stop-loss strategy, that can alter the risk at the monthly frequency drastically. Hence, the methodology is likely to have greater implications on asset pricing beyond the scope of this paper. These issues will be of interest for future research.

[4]Zhou and Shang (2015) provide a recent review of the related literature.

References

Alili, L., P. Patie, and J.L. Pedersen, 2004, Representations of the first hitting time density of an Ornstein-Uhlenbeck process, *Stochastic Models* 21, 967–980.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Barroso, Pedro, and Pedro Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111–120.

Bertsimas, Dimitris, and Andrew W. Lo, 1998, Optimal control of execution costs, *Journal of Financial Markets* 1, 1–50.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2008, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Carr, Peter P., and Robert A. Jarrow, 1990, The stop-loss start-gain paradox and option valuation: A new decomposition into intrinsic and time value, *Review of Financial Studies* 3, 469–492.

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985–1019.

Cooper, Michael J., Roberto C. Gutierrez, Jr., and Allaudeen S. Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345–1365.

Daniel, Kent, Ravi Jagannathan, and Soohun Kim, 2012, Tail risk in momentum strategy returns, Unpublished working paper, Columbia University and Northwestern University.

Daniel, Kent, and Tobias Moskowitz, 2014, Momentum crashes, Unpublished working paper, Columbia University and University of Chicago.

Davis, M., 1997, Option pricing in incomplete markets, in *Mathematics derivative securities* (Cambridge University Press, Cambridge, UK).

Dybvig, Phillip H., 1988, Inefficient dynamic portfolio strategies or how to throw away a million dollars in the stock market, *Review of Financial Studies* 1, 67–88.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Frazzini, Andrea, Ronen Israel, and Tobias J. Moskowitz, 2012, Trading costs of asset pricing anomalies, Working paper, University of Chicago.

Grossman, Sanford J., and Zhongquan Zhou, 1993, Optimal investment strategies for controlling drawdowns, *Mathematical Finance* 3, 241–276.

Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Economics* 14, 29–78.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jouini, Elyes, and Hedi Kallal, 2001, Efficient trading strategies in the presence of market frictions, *Review of Financial Studies* 14, 343–369.

Kaminski, Kathryn M., and Andrew W. Lo, 2014, When do stop-loss rules stop losses?, *Journal of Financial Markets* 18, 234–254.

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics* 71, 349–380.

Lou, Dong, Hongjun Yan, and Jinfan Zhang, 2013, Anticipated and repeated shocks in liquid markets, *Review of Financial Studies* 26, 1891–1912.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Obizhaeva, Anna A., and Jiang Wang, 2013, Optimal trading strategy and supply/demand dynamics, *Journal of Financial Markets* 16, 1–32.

Sadka, Ronnie, 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309–349.

Schwert, G. William, 2003, Anomalies and market efficiency, in G. M. Constantinides, M. Harris, and R. M. Stulz, eds.: *Handbook of the Economics of Finance* (Elsevier, Amsterdam, Netherlands).

Zhou, Joe, and James Shang, 2015, Drawdown control with a risk floor, *Journal of Alternative Investments* 17, 79–94.

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.

A 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

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

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 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

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

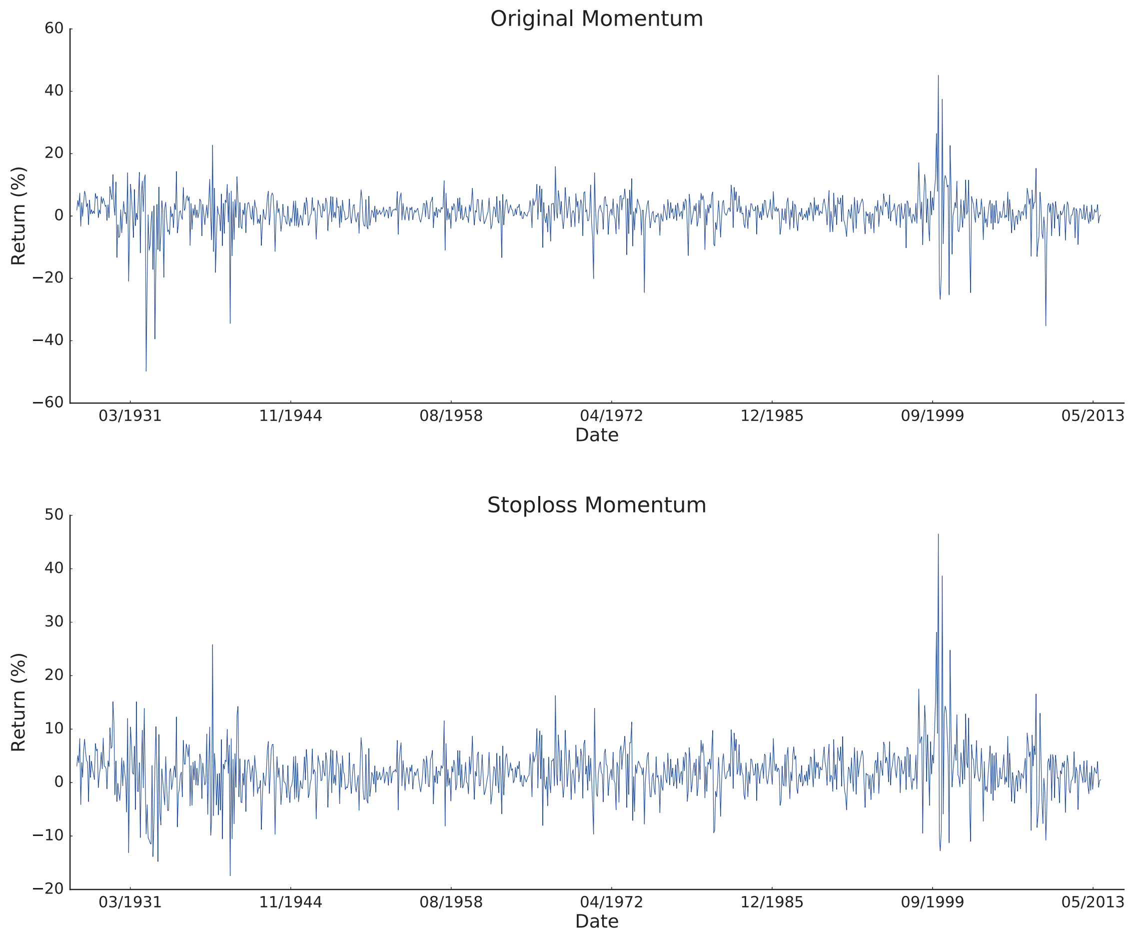

Figure 1: Comparison of the Original and Stop-Loss Momentum Strategies. This figure plots the time-series of the original momentum portfolio and the stop-loss momentum portfolio with a stop-loss level of 15%. The sample period is from August, 1926 to December, 2013.

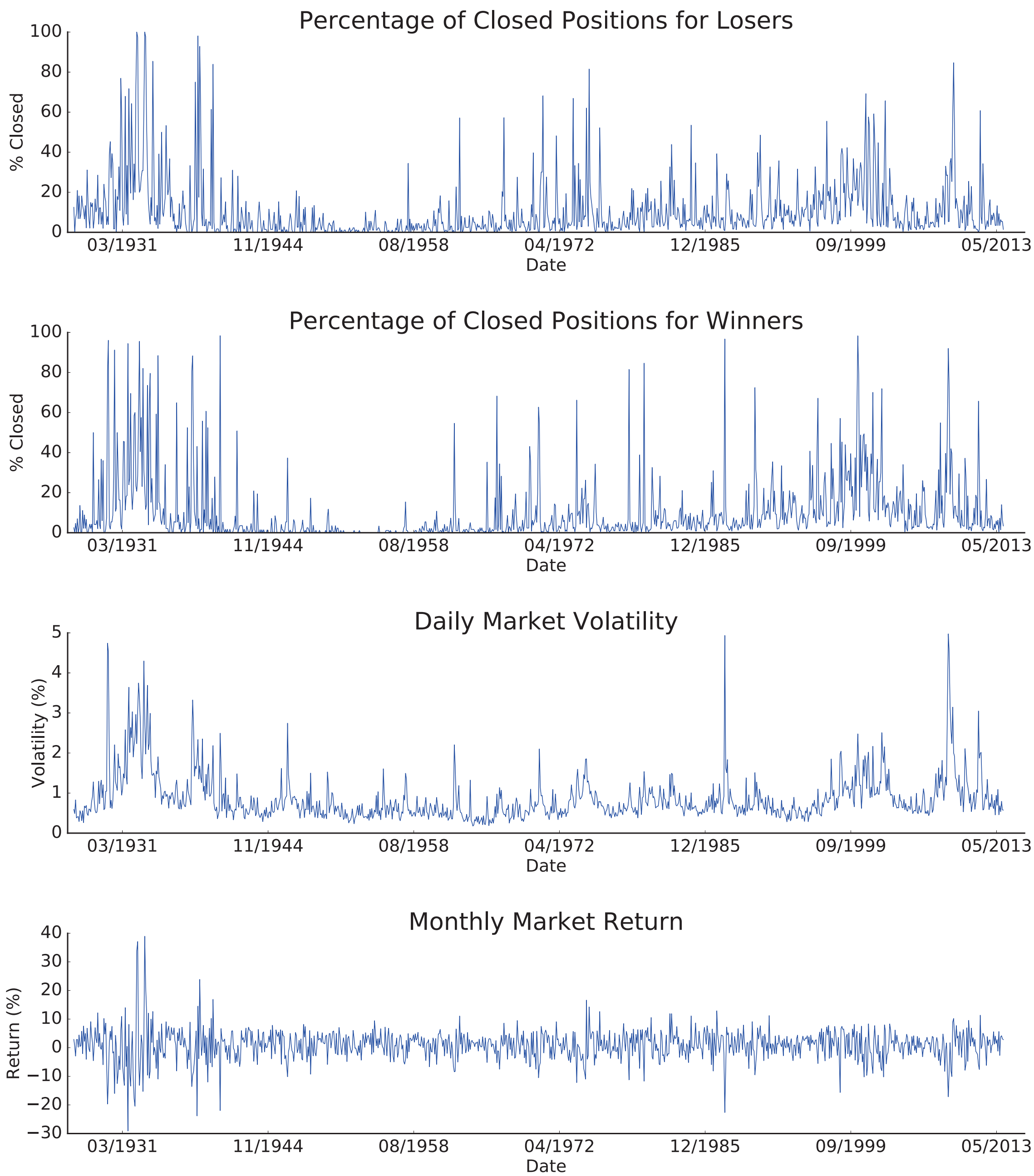

Figure 2: Time-Series of the Percentage of Closed Positions.
This figure plots the time-series of the percentage of closed positions for the losers and winners and compare them with the time-series of the market volatility and returns. The sample period is from August, 1926 to December, 2013.

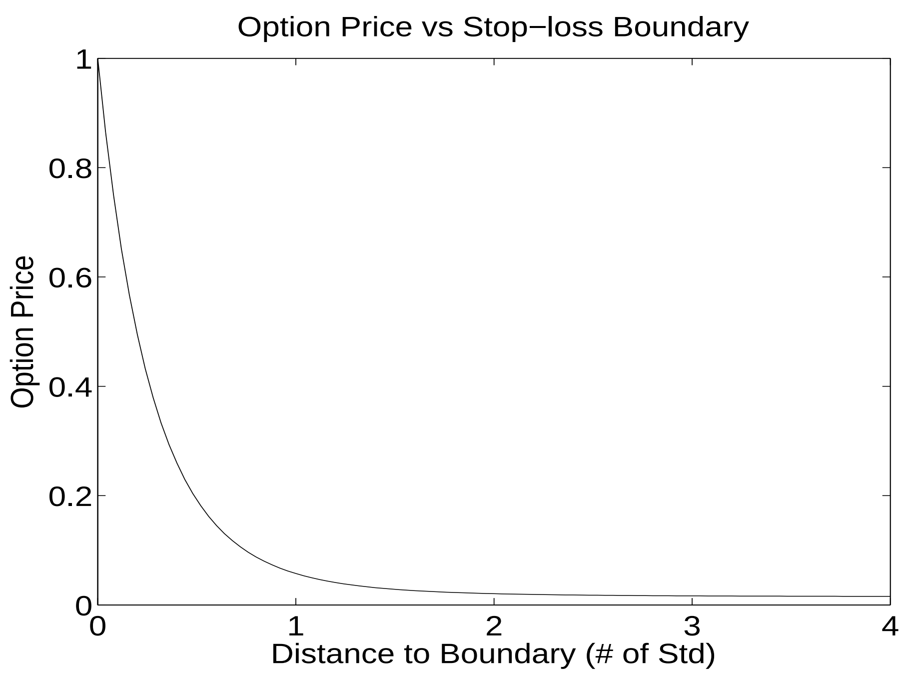

Figure 3: Stop-loss Option Value versus Boundary.
This figure shows the impact of the stop-loss boundary (in terms of the unconditional standard deviation of price) on stop-loss option value $E[e^{-r\tau_b}|D_t]$ when $B = 1$. The shape is convex which means the uncertainty in the distance to the boundary perceived by the investors will increase the option value, hence decrease the price.

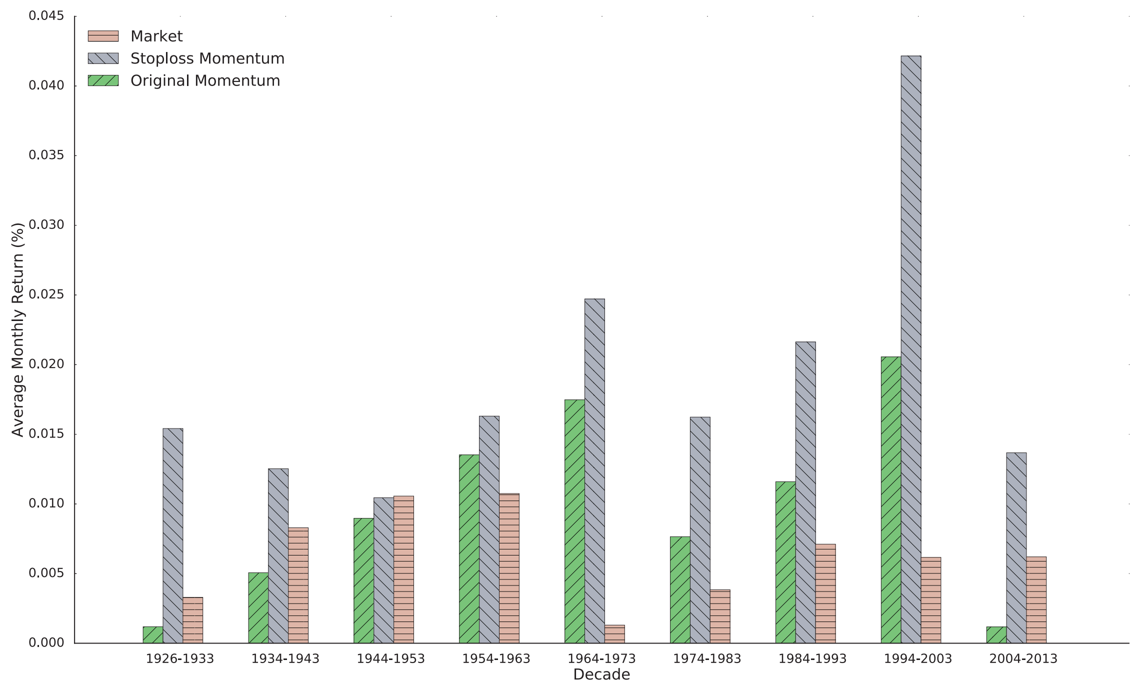

Figure 4: Stop-loss Momentum Performance in Subperiods.
This figure plots the average monthly returns of the stop-loss momentum, the original momentum, and the market, over each of the nine ten-year periods in the sample. To assign the ten-year periods, we start from the end of the sample (2013). Therefore, the first ten-year period from 1926 to 1933.

Table I
Stop-Loss Momentum

We compare the performance of the stop-loss momentum portfolios (Losers, Winners, and Winers-Minus-Losers (WML)) with that of the corresponding original momentum portfolios. The original momentum portfolios are formed using the last six-month cumulative returns from $t-7$ to $t-2$ as described in Section II. The stop-loss momentum portfolios are constructed as described in Section III. The stop-loss level is set to be 15% (Panel B), 10% (Panel C), or 20% (Panel D) above (below) the last month-end close price for the losers (winners) portfolios. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), Skewness, minimum and maximum returns, and percentage increase in M2 measure, which is measured using the corresponding original momentum portfolio. 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, 2013.

Variable	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)$(%)
	Panel A: Original Momentum						
Market	0.65***	5.43	0.119	0.19	-29.13	38.85	
	(3.87)						
Losers	0.24	8.81	0.028	1.17	-39.50	66.10	
	(0.89)						
Winners	1.24***	7.75	0.160	-0.29	-33.06	44.86	
	(5.17)						
WML	0.99***	6.01	0.165	-1.18	-49.79	45.11	
	(5.36)						
	Panel B: Stop Loss at 15%						
Losers	-0.40*	6.85	-0.059	-0.77	-39.50	29.20	
	(-1.90)						
Winners	1.53***	6.81	0.225	0.16	-22.17	43.94	
	(7.29)						
WML	1.93***	4.85	0.399	1.28	-17.43	46.52	141.38
	(12.93)						
	Panel C: Stop Loss at 10%						
Losers	-0.58***	6.22	-0.094	-1.02	-39.13	26.17	
	(-3.05)						
Winners	1.74***	6.22	0.280	0.47	-17.77	42.17	
	(9.05)						
WML	2.32***	4.61	0.504	1.54	-15.37	44.87	204.64
	(16.32)						
	Panel D: Stop Loss at 20%						
Losers	-0.24	7.24	-0.034	-0.57	-39.50	27.98	
	(-1.09)						
Winners	1.38***	7.17	0.192	-0.06	-24.75	44.66	
	(6.22)						
WML	1.62***	4.99	0.325	1.04	-16.79	47.13	96.50
	(10.53)						

Table II
Turnover Rates and Break-Even Transaction Costs

The table reports in Panel A the turnover rates of the original and the stop-loss momentum strategies, and in Panel B the break-even transaction costs required to make investors indifferent between the original momentum and the stop-loss momentum. We examine three cases: *Zero Mean Difference*, break-even costs that make the average returns of the two strategies the same; *Zero Sharpe Difference*, break-even costs that make the Sharpe ratios of the two strategies the same; and *5% Mean Difference*, break-even costs that make the difference in average returns of the two strategies insignificant at 5%. The sample period is from January, 1926 to December, 2013.

Panel A: Turnover

Momentum	Original Momentum		Stop-Loss Momentum		Additional Turnovers	
	Average(%)	Median(%)	Average(%)	Median(%)	Average(%)	Median(%)
Losers	45.05	44.41	58.57	52.94	13.53	8.23
Winners	39.11	38.42	49.08	43.44	9.98	4.87

Panel B: Break-Even Costs

Momentum	Zero Mean Difference		Zero Sharpe Difference		5% Mean Difference	
	Average(%)	Median(%)	Average(%)	Median(%)	Average(%)	Median(%)
Losers	4.76	7.83	5.61	9.22	3.25	5.35
Winners	2.97	6.08	4.47	9.15	1.90	3.90
WML	4.00	7.18	4.82	8.65	3.18	5.71

Table III
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 level is set at 15% above or below the last month-end close 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, 2013.

	CAPM		**Fama-French**			
Rank	$\alpha(\%)$	β_{mkt}	$\alpha(\%)$	β_{mkt}	β_{smb}	β_{hml}
	Panel A: Original Momentum					
Losers	-0.69***	1.44***	-0.82***	1.28***	0.72***	0.18**
	(-5.65)	(35.4)	(-8.65)	(36.6)	(7.03)	(2.05)
Winners	0.45***	1.22***	0.44***	1.09***	0.79***	-0.26***
	(3.67)	(21.5)	(4.24)	(29.2)	(6.31)	(-2.88)
Winners-Losers	1.14***	-0.23***	1.27***	-0.18***	0.07	-0.44***
	(6.86)	(-2.71)	(7.11)	(-2.77)	(0.36)	(-2.66)
	Panel B: Stop-Loss (15%) Momentum					
Losers	-1.10***	1.08***	-1.14***	0.99***	0.55***	-0.08
	(-9.05)	(15.4)	(-10.4)	(20.2)	(5.14)	(-0.84)
Winners	0.87***	1.02***	0.88***	0.93***	0.71***	-0.26***
	(6.80)	(14.6)	(7.63)	(21.6)	(6.91)	(-2.90)
Winners-Losers	1.97***	-0.06	2.01***	-0.06	0.16	-0.18
	(11.5)	(-1.13)	(10.9)	(-1.25)	(0.95)	(-1.37)

Table IV
Crash Months

This table compares the performance of the stop-loss momentum and original momentum during the crash periods. Panels A and B compare the performance during the crash months of the original momentum – the WML portfolio experiences losses exceeding 20%, while Panels C and D compare the performance for the ten worst months of the stop-loss momentum. We report the returns for the Losers, Winners and WML for both the original momentum and the stop-loss momentum, respectively. Returns are in percentage. The sample period is from January, 1926 to December, 2013.

Date	Losers(%)	Winners(%)	WML(%)	Losers(%)	Winners(%)	WML(%)
	Crash of Original Momentum					
	Panel A: Original Momentum			**Panel B: Stop-Loss (15%) Momentum**		
01/1931	24.57	3.68	-20.90	16.82	3.72	-13.10
07/1932	61.94	12.15	-49.79	17.04	7.42	-9.62
08/1932	60.43	39.98	-20.45	19.81	15.64	-4.17
04/1933	66.20	26.77	-39.43	18.19	21.02	2.83
09/1939	46.23	11.78	-34.46	29.21	11.78	-17.43
09/1970	24.15	4.08	-20.07	13.72	4.08	-9.64
01/1975	32.07	7.57	-24.50	15.56	7.80	-7.76
03/2000	7.34	-14.72	-22.06	4.41	-5.96	-10.37
04/2000	-1.22	-27.91	-26.69	-2.29	-15.04	-12.75
01/2001	29.02	3.78	-25.24	11.63	0.39	-11.25
11/2002	26.37	1.79	-24.57	12.56	1.56	-11.00
04/2009	39.22	3.98	-35.24	15.03	4.27	-10.76
	Crash of Stop-Loss Momentum					
	Panel C: Original Momentum			**Panel D: Stop-Loss (15%) Momentum**		
01/1931	24.57	3.68	-20.90	16.82	3.72	-13.10
11/1932	-4.50	-13.97	-9.47	-2.96	-14.25	-11.29
12/1932	-2.88	-4.42	-1.54	3.05	-8.45	-11.50
02/1933	-7.18	-24.32	-17.14	-2.24	-16.09	-13.85
07/1933	-7.50	-18.25	-10.76	-3.34	-18.11	-14.77
09/1939	46.23	11.78	-34.46	29.21	11.78	-17.43
04/2000	-1.22	-27.91	-26.69	-2.29	-15.04	-12.75
01/2001	29.02	3.78	-25.24	11.63	0.39	-11.25
11/2002	26.37	1.79	-24.57	12.56	1.56	-11.00
04/2009	39.22	3.98	-35.24	15.03	4.27	-10.76

Table V
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 the original momentum portfolio and corresponding stop-loss momentum portfolio. We compare the performance of the stop-loss momentum portfolio with that of the corresponding original momentum portfolio in each volatility quintile. The stop-loss level is set to be 15%. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*) and Skewness, minimum return, maximum return, and percentage increase in M2 measure, which is measured using the corresponding original momentum portfolio. 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, 2013.

Volatility Rank	WML						
	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)$(%)
Panel A: Original Momentum							
Least Volatile	0.46***	3.85	0.120	-0.33	-28.77	22.91	
	(3.88)						
2	0.74***	4.45	0.167	-0.19	-29.84	40.18	
	(5.41)						
3	0.86***	5.33	0.161	-1.36	-38.09	20.33	
	(5.21)						
4	0.96***	6.27	0.153	-1.05	-48.41	33.99	
	(4.95)						
Most Volatile	1.66***	7.70	0.216	-0.59	-49.66	54.23	
	(7.00)						
Panel B: Stop Loss Momentum at 15%							
Least Volatile	0.57***	3.53	0.160	0.01	-23.47	26.29	33.86
	(5.19)						
2	1.22***	4.15	0.293	0.59	-22.79	39.21	75.35
	(9.48)						
3	1.66***	4.62	0.359	0.23	-23.35	27.51	123.02
	(11.63)						
4	2.02***	5.40	0.374	0.68	-23.23	35.47	144.75
	(12.12)						
Most Volatile	2.78***	6.91	0.402	0.46	-34.53	57.17	86.11
	(13.03)						

Table VI
Performance of Stop-Loss for Illiquidity Sorted Momentum Portfolios

We first sort stocks into five quintiles according to their illiquidity, and then within each quintile we construct the original momentum portfolio and corresponding stop-loss momentum portfolio. We compare the performance of the stop-loss momentum portfolio with that of the corresponding original momentum portfolio in each illiquidity quintile. The stop-loss level is set to be 15%. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*) and Skewness, minimum return, maximum return, and percentage increase in M2 measure, which is measured using the corresponding original momentum portfolio. 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, 2013.

Illiquidity Rank	WML						
	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)$(%)
Panel A: Original Momentum							
Most Liquid	0.53**	7.42	0.071	-1.21	-55.09	48.52	
	(2.31)						
2	0.87***	7.62	0.115	-1.29	-61.43	46.62	
	(3.72)						
3	1.10***	7.48	0.147	-1.19	-72.35	60.60	
	(4.75)						
4	1.39***	6.31	0.221	-0.85	-43.30	43.21	
	(7.14)						
Least Liquid	0.97***	6.02	0.161	0.41	-38.94	68.50	
	(5.23)						
Panel B: Stop Loss Momentum at 15%							
Most Liquid	1.62***	6.15	0.263	0.84	-19.75	48.10	268.91
	(8.53)						
2	2.16***	6.02	0.360	1.01	-21.83	48.97	213.26
	(11.64)						
3	2.35***	5.98	0.392	1.87	-17.71	63.44	167.64
	(12.71)						
4	2.41***	5.50	0.437	1.19	-26.41	48.98	98.28
	(14.16)						
Least Liquid	1.41***	4.98	0.283	-0.43	-24.88	26.91	75.30
	(9.16)						

Table VII
Performance of Stop-Loss for Size Sorted Momentum Portfolios

We first sort stocks into five quintiles according to their size, and then within each quintile we construct the original momentum portfolio and corresponding stop-loss momentum portfolio. We compare the performance of the stop-loss momentum portfolio with that of the corresponding original momentum portfolio in each size quintile. The stop-loss level is set to be 15%. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*) and Skewness, minimum return, maximum return, and percentage increase in M2 measure, which is measured using the corresponding original momentum portfolio. 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, 2013.

Size Rank	WML						
	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)(\%)$
Panel A: Original Momentum							
Smallest	1.18***	6.78	0.174	-0.53	-57.62	52.60	
	(5.64)						
2	1.24***	6.63	0.188	-0.35	-47.75	52.40	
	(6.07)						
3	0.99***	7.10	0.139	-1.09	-55.92	53.95	
	(4.49)						
4	0.71***	7.31	0.097	-2.01	-74.18	47.00	
	(3.14)						
Largest	0.51***	6.68	0.077	-1.41	-60.89	48.66	
	(2.48)						
Panel B: Stop Loss Momentum at 15%							
Smallest	2.32***	5.62	0.413	0.85	-23.30	48.52	136.95
	(13.36)						
2	2.21***	5.77	0.383	1.15	-19.43	52.94	104.23
	(12.41)						
3	2.01***	5.85	0.343	1.04	-26.12	52.73	147.35
	(11.12)						
4	1.60***	5.70	0.281	1.07	-21.27	48.28	190.17
	(9.10)						
Largest	1.03***	5.54	0.186	0.90	-26.37	48.95	142.92
	(6.03)						

Table VIII
Performance of Stop-Loss Momentum in Recessions

We compare the performance of the stop-loss momentum portfolios (Losers, Winners, and WML) with that of the corresponding original momentum portfolios over the business cycles. Panel A reports the performance during expansions, whereas Panel B reports the performance during recessions. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), Skewness, and percentage increase in M2 measure. 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, 2013.

	Original Momentum				**Stop-Loss (15%) Momentum**				
Variable	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	$\Delta(M2)(\%)$
	Panel A: Expansion								
Losers	0.57**	7.26	0.079	1.36	-0.01	5.83	-0.002	-0.59	
	(2.27)				(-0.07)				
Winners	1.70***	7.20	0.236	-0.13	1.96***	6.50	0.302	0.41	
	(6.82)				(8.73)				
WML	1.13***	5.37	0.210	-0.39	1.98***	4.56	0.433	1.91	106.41
	(6.07)				(12.52)				
	Panel B: Recession								
Losers	-1.04	13.16	-0.079	1.04	-1.91***	9.73	-0.197	-0.53	
	(-1.15)				(-2.88)				
Winners	-0.56	9.39	-0.060	-0.32	-0.14	7.71	-0.019	-0.22	
	(-0.88)				(-0.27)				
WML	0.47	8.03	0.059	-1.89	1.77***	5.83	0.304	0.08	413.28
	(0.87)				(4.44)				

Table IX
Value-Weighted Stop-Loss Momentum

We compare the performance of the stop-loss momentum portfolios (Losers, Winners, and WML) with that of the corresponding original momentum portfolios. The portfolios are value-weighted by the last month-end market size. The stop-loss level is set to be 15% (Panel B), 10% (Panel C), or 20% (Panel D). The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), Skewness, Kurtosis, minimum and maximum returns, and percentage increase in M2 measure. 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, 2013.

Variable	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)$(%)
			Panel A: Original Momentum				
Losers	0.28	8.30	0.034	1.31	-39.18	77.94	
	(1.10)						
Winners	1.03***	7.21	0.142	-0.51	-33.60	37.70	
	(4.61)						
WML	0.74***	6.97	0.107	-1.69	-64.97	44.41	
	(3.46)						
			Panel B: Stop Loss at 15%				
Losers	-0.18	6.66	-0.027	-0.84	-39.18	23.24	
	(-0.88)						
Winners	1.24***	6.56	0.190	0.01	-23.45	37.60	
	(6.14)						
WML	1.42***	5.67	0.251	0.68	-22.10	44.82	135.21
	(8.13)						
			Panel C: Stop Loss at 10%				
Losers	-0.39**	6.14	-0.063	-1.08	-38.78	24.40	
	(-2.03)						
Winners	1.44***	6.06	0.238	0.27	-23.78	37.35	
	(7.72)						
WML	1.83***	5.36	0.342	1.01	-20.79	44.26	219.90
	(11.06)						
			Panel D: Stop Loss at 20%				
Losers	-0.03	7.01	-0.004	-0.56	-39.18	26.50	
	(-0.12)						
Winners	1.12***	6.86	0.163	-0.21	-24.34	37.66	
	(5.28)						
WML	1.14***	5.91	0.194	0.30	-27.52	44.78	81.38
	(6.27)						

Table X
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 WML portfolio experiences losses exceeding 20%. We report the returns for the Losers, Winners and WML 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(%)	WML(%)	Losers(%)	Winners(%)	WML(%)
	Panel A: Original Momentum			**Panel B: Stop-Loss (15%) Momentum**		
07/1932	62.87	5.48	-57.39	15.44	2.96	-12.48
08/1932	56.04	17.36	-38.68	18.14	6.55	-11.58
11/1932	-2.30	-25.80	-23.51	-4.19	-23.43	-19.24
04/1933	78.04	13.06	-64.97	17.55	16.55	-0.99
06/1938	37.75	13.32	-24.43	15.50	13.32	-2.18
09/1939	29.48	4.34	-25.14	23.25	4.34	-18.92
09/1970	21.96	1.35	-20.61	13.19	1.35	-11.84
01/1975	23.64	1.21	-22.43	14.27	1.41	-12.86
03/2000	14.09	-13.17	-27.26	9.37	-5.29	-14.66
05/2000	7.40	-16.97	-24.37	5.62	-14.06	-19.69
01/2001	29.45	-6.46	-35.91	13.67	-8.43	-22.10
11/2002	22.77	-0.72	-23.50	14.99	-0.82	-15.81
04/2009	35.49	-1.03	-36.51	15.17	-0.68	-15.85

Table XI
Stop-Loss Momentum Based on Past Twelve-Month Returns

We compare the performance of the stop-loss momentum portfolios (Losers, Winners, and Winers-Minus-Losers (WML)) with that of the corresponding original momentum portfolios. The original momentum portfolios are formed using the last 12-month cumulative returns from $t-13$ to $t-2$. The stop-loss level is set to be 15% (Panel B), 10% (Panel C), or 20% (Panel D). The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), Skewness, minimum and maximum returns, and percentage increase in M2 measure. 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, 2013.

Variable	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)$(%)
	Panel A: Original Momentum						
Losers	0.18	8.71	0.020	1.45	-38.79	84.84	
	(0.65)						
Winners	1.30***	8.05	0.161	-0.17	-33.96	50.50	
	(5.20)						
WML	1.12***	6.21	0.181	-1.20	-55.10	41.76	
	(5.83)						
	Panel B: Stop Loss at 15%						
Losers	-0.47**	6.74	-0.069	-0.73	-38.30	30.81	
	(-2.24)						
Winners	1.62***	7.08	0.228	0.28	-23.32	42.41	
	(7.38)						
WML	2.09***	5.06	0.412	1.25	-13.48	44.87	128.17
	(13.31)						
	Panel C: Stop Loss at 10%						
Losers	-0.63***	6.14	-0.103	-0.99	-37.91	27.55	
	(-3.33)						
Winners	1.84***	6.49	0.284	0.53	-19.03	39.84	
	(9.18)						
WML	2.48***	4.82	0.514	1.49	-12.78	43.45	184.39
	(16.59)						
	Panel D: Stop Loss at 20%						
Losers	-0.30	7.15	-0.042	-0.55	-38.30	31.38	
	(-1.36)						
Winners	1.46***	7.45	0.196	0.06	-25.23	43.06	
	(6.33)						
WML	1.76***	5.25	0.336	0.94	-15.19	44.89	85.87
	(10.84)						

Table XII
Alternative Strategies

This table reports the performance of the stop-loss momentum portfolios (Losers, Winners, and Winers-Minus-Losers (WML)) formed with alternative strategies. In Panel A, the stop-loss strategy only trades when the limit price is reached during the day . In Panel B and C, we use different thresholds. In Panel D, the stop-loss level is set to be three times of the daily volatility estimated in the previous month. The summary statistics reported are average excess returns (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), Skewness, minimum and maximum returns, and percentage increase in M2 measure. 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, 2013.

Variable	Avg Ret(%)	Std Dev(%)	Sharpe	Skewness	Min(%)	Max(%)	$\Delta(M2)(\%)$
	Panel A: Alternative Execution						
Losers	-0.50**	6.82	-0.074	-0.72	-39.50	37.55	
	(-2.40)						
Winners	1.60***	6.73	0.238	0.24	-21.13	43.97	
	(7.70)						
WML	2.10***	4.81	0.437	1.32	-25.78	46.78	164.45
	(14.17)						
	Panel B: Smaller Threshold						
Losers	-0.22	6.84	-0.033	-0.73	-39.50	28.55	
	(-1.06)						
Winners	1.41***	6.84	0.207	0.12	-23.66	43.70	
	(6.69)						
WML	1.64***	4.89	0.335	1.09	-16.79	46.02	102.63
	(10.85)						
	Panel C: Larger Threshold						
Losers	-0.49**	6.88	-0.071	-0.81	-39.50	27.60	
	(-2.29)						
Winners	1.60***	6.80	0.236	0.19	-20.74	44.05	
	(7.65)						
WML	2.09***	4.84	0.432	1.39	-15.83	46.78	160.99
	(13.98)						
	Panel D: Dynamic Stop-loss Level						
Losers	-0.35***	4.20	-0.084	-0.59	-23.38	17.62	
	(-2.72)						
Winners	1.46***	4.24	0.343	1.00	-19.68	34.87	
	(11.12)						
WML	1.81***	3.38	0.535	1.29	-17.69	30.89	223.18
	(17.31)						