“Dynamic stop-loss rules as universal performance enhancers”

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DYNAMIC STOP-LOSS RULES AS UNIVERSAL PERFORMANCE ENHANCERS

Abstract

This paper provides ample empirical evidence, using US equity and bond indices, why daily stop-loss rules can be considered as viable performance enhancers. While a longer-term stop-loss rule can help investors to avoid market crashes by being out of the market, investors may obviously lose on the up-market days too. Furthermore, a shorter-term stop-loss rule may not miss the good market days by allowing investors to stay for a longer time in the market at the obvious expense of increased risk and higher drawdowns. This paper illustrates how daily stop-loss rules can significantly outperform the buy and hold equity and bond benchmarks, their equally weighted portfolio and the trend following strategy, simple moving average, which is driven from those asset classes – for both long and short positions. The results are robust to a variety of variations on the initial theme and it's shown that performance enhancements can come from a variety of other sources related to a static stop-loss rule.

Keywords stop-loss, exchange traded fund rotation, risk management, simple moving average, bonds & equities

JEL Classification C50, G10, G11, G15

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INTRODUCTION

Stop-loss rules are a risk management tool, which can help practitioners to control their risk by covering their positions and rotating to safety assets such as cash, short-term treasury bills, etc. Using stop-loss rules has the significant advantage of decreasing a portfolio's volatility and drawdown; however, it may reduce total portfolio return, because investors are out of the market and may lose on up-markets bounces. As most equity markets increase in value over time, they do experience significant volatility and protracted periods of drawdown. Therefore, being out of the market can be risky too when missing positive (negative) days for investors with long (short) positions. For these periods where the volatility and drawdown dominate return in a market, investors may consider that he might obtain potential performance enhancements by the use of the stop-loss trading rules on the portfolio or strategy of an investor. This paper is of theoretical and empirical relevance. First, in terms of its theoretical relevance, it explores specific stop-loss rules, both static and dynamic, which are easily replicable and easy to implement as well. Second, in terms of its practical relevance, it shows that finance practitioners do not have to wait being out of the market for protracted periods of time – and this is important as is discussed below, missing some of the good days can destroy the return profile of an investment strategy.

In considering any stop-loss rule, investors must acknowledge that two variables drive its level: (a) the strategy rebalancing frequency and (b) the investor's risk aversion. Investors with high risk aversion will chose tight stop-loss levels and will find themselves in safety assets for longer periods of time. When the rebalancing frequency is high, the stop-loss level should again be tight, because allowing for wider stop-loss levels might not be as effective. When, on the other hand, the rebalancing frequency is relatively low, the stop-loss level should be wider, because setting a tight stop-loss will bring the investor to safety assets for longer periods and might miss market up-swings. As investors are striving to explore the optimal relationship between rebalancing frequency and the ideal stop-loss level, they can now pose the basic questions that explored in depth in this paper: (a) How fast should one rebuild their positions after the stop-loss rule has been triggered? (b) Is there an optimal rebalancing frequency for determining the ideal stop-loss level? (c) What are the effects of various stop-loss rules and how do they relate to risk aversion and rebalancing frequency? These questions were explored in depth in the paper, starting with the next section where it links previous literature with our approach, and continuing with the rest of our arguments in later sections.

The rest of the paper is structured as follows: section 1 presents a related literature review; section 2 describes our main methodology both for the investment strategies and the ways of setting the stop-loss levels; section 3 presents and discusses our initial performance results and also explores the implications of the overnight returns and the way investment strategies are affected when they are or they are not exposed to overnight returns; section 4 presents additional robustness results on how to avoid increased volatility at the opening of the market and suggest some additional methods for enhancing. Last section concludes and offers some extensions of the current research.

1. LITERATURE REVIEW

Although stop-loss rules are not a popular item in academic research, Yufeng et al. (2014) showed how using a stop-loss rule with the standard momentum strategy (Jegadeesh & Titman, 1993) can avoid momentum crashes. They also showed how there isn't an even trade-off between the volatility and drawdown to annualized return. Using a simple stop-loss rule, with different levels of exiting the momentum strategy, can increase the annualized return and decrease the volatility and drawdown at the same time. Similar to a stop-loss rule which dictates market timing, there are related strategies that consider the concept of timing through seasonal effects; see, for example, Sias (2007) and the references therein. As with the stop-loss rules, seasonal trading implies being in and out of the market (using any strategy, in the aforementioned paper, the strategy is momentum) in particular periods of the year and, when out of the market, re-investing.

The literature has many articles which claim stop-loss strategies are inefficient when compared to the buy and hold portfolio (e.g. Dybvig, 1988). This paper also found evidence for this inefficiency and in doing so it helped us to determine the optimal rebalance interval. It can be assumed that the buy and hold portfolio is efficient, hence a stop-loss strategy with the nearest interval to the buy and hold strategy will be the most efficient – that is exactly the reason why this paper decided to eventually use a daily stop-loss. Our strategy is fully dynamic, which means rebuilding positions (return to the buy and hold approach) every time when a stop-loss is triggered. Therefore, the days when the portfolio is invested in cash (out of the market) are minimized.

Gollier (1997) also made claims for inefficiency in investing 100% equity or cash (binary strategies), because there is always preferred a portion of a risky asset in our portfolio when it has positive expected return (Arrow, 1970). Although our strategy can be invested in 100% cash part of the time, it still found it significant and efficient, since it's not a regular stop-loss strategy where the strategy can remain several days and up to month/s out of the market. This paper's approach aims at avoiding these embedded disadvantages of other stop-loss strategies and minimize the time out of the market to the intra-day trading hours only. In addition, the paper will show that minimizing the losses during the day and rebuilding the position on the same day will improve the total return and the relevant performance statistics.

Kaminski and Lo (2008) also showed that when a portfolio return follows a random walk, during momentum periods, a stop-loss strategy may add value, however, a simple use of the stop-loss will always reduce return. Clare, Seaton, and Thomas (2012) implemented a simple stop-loss rule on S&P 500 index between 1988–2011 and found that it underperformed the index. To determine whether to move to riskless asset, they used a moving average methodology both for exiting and entering the index.

Our paper doesn't argue with such simple stop-loss strategies such as moving average or once-only for a low frequency interval which can cause scenarios where the portfolio is out of the market for long periods (such as weeks and months). Statistically, over a long-time horizon, markets generate positive returns (between 7-10%, annualized). Therefore, any attempt to time the market by a low frequency stop-loss strategy may eventually cause lower returns, because there are chances to be out of the market while the market rises. In our analysis, it is illustrated how a dynamic stop-loss rule which maximizes the time in the market can avoid these risks and outperform the indices. In addition, the paper will show that moving average strategies are not recommended to use on high volatility indices as a stop-loss rule, because they create a "false alarm" situation and unnecessary trades. When this rule is implemented on an equity index (SPY), it outperformed the index, however, when it implemented on a bond index with faster fluctuations (TLT), it significantly underperformed the index. Hence, using a moving average as a stop-loss trading rule is not really recommended.

2. METHODS

This paper use daily ETF data from Bloomberg. The ETF represent diversified asset classes of equities and bonds. For the equity asset class, it uses SPY (SPDR S&P 500 ETF TRUST) and for the bond asset class, it uses TLT (ISHARES 20+ YEAR TREASURY BONDS).

To set the stage for the discussion that follows, consider the conventional (cross-sectional) momentum strategy: ranking of stocks from the top performers (winners) to the bottom ones (losers) from a given universe and divide it to deciles. The winners should outperform the losers, so a basic long-short momentum strategy will be to buy the winners and sell the losers (WML, winners minus losers). However, there could be some periods where the opposite happens and the losers outperform the winners (e.g. 2009 when the momentum crashed over the S&P 500). This situation will of course cause a serious problem to this WML portfolio. For reducing that risk, the literature is full of different approaches how to find better ways to distinguish between the winners and the losers. For example, residual momentum (Blitz et al., 2011) succeeds to minimize the conventional momentum downside by implementing the momentum only on the residual return which is given by the three-factor model of Fama and French (1993), thus producing lower risk. That is, instead of considering the (cumulative) returns of the i-th asset, they consider the regression residual, i.e. the residual from the following regression:

$$\varepsilon_{ti} = R_t^i - \left(\alpha_i + \beta_{1i} RMF_t + \beta_{2i} SMB_t + \beta_{3i} HML_t\right), \quad (1)$$

where R_t^i is the expected stock return, $\left(RMF_t,\ SMB_t,\ HML_t\right)$ are the standard three-factor models – Market risk, Size and Value, simultaneously. β is the factors' coefficient while, α is the intercept. Another example, like the one above, for reducing risk based on factors is to use a z-score approach for blending between momentum and value (Asness et al., 2013), which succeeds in smoothing out momentum crashes. Finally, as noted in the literature review, one can use a stop-loss trading rule (Yufeng et al., 2014) to achieve the same goal. The primary objective of this paper is to exploit the advantages of using stop-loss rules to reduce portfolio volatility and drawdown rather than exploring new factors with the same goals. Why would one expect, a priori, that using a stop-loss rule might have advantages over other, more traditional, approaches? The WML or a similar investment strategy exhibits variability only at the time of rebalancing, while in the interim periods, it does nothing; ranking assets by any factor may not be sufficient to maintain portfolio risk because of extreme market moves that destroy the strategy's average performance, albeit, the use of stop-loss rules is not without fail: depending on the kind of investment strategy to which the stop-loss rules are applied, one might find itself making consistent timing mistakes, thus not only eroding average returns, but also unnecessarily increasing portfolio volatility. Thus, our efforts are directed to understanding and implementing stop-loss rules that can offer their advantages in a consistent way.

When applying our stop-loss methodology, the aim is to outperform the (a) benchmarks SPY and TLT, (b) the equally weight portfolio of the two of them and (c) the simple moving average (SMA) strategy, which are implemented on each asset, all by using only stop-loss trading rules. Initially, the paper considers how to determine the optimal frequency to reset the stop-loss on our data. As mentioned earlier, the lower the frequency of rebalancing, the wider the stop-loss level investor can afford to use. The SPY is used as our pivot asset to help us determine this frequency by extracting its daily return from February 1, 1993 to January 31, 2015: during this period, approximately 39% of its average annualized return is driven by only 10 trading days! This observation nicely describes what would happen to annualized return when a buy and hold investor uses the wrong stop-loss rule and accidently loses on those best 10 trading days. In this case, the investor will achieve an average annualized return of only 5.57% instead of the buy and hold average annualized return, which is 9.14%. A similar observation applies when investor is considered as one who hedges his strategy by going short on the SPY. How can investors avoid occasions like the above without jeopardizing their portfolio return when market goes to the wrong direction?

Our stop-loss approach will consider the above example to broadly recommend that investors minimize their "out-of-the-market" periods, thus putting the stop-loss problem into a conventional "optimization" setting. Therefore, our stop-loss rule goal will be to remain in the market as long as it can, but, at the same time, attempt to reduce the portfolio risk, benchmarking on the buy and hold strategy – these recommendations are explained below.

Let us start off by calculating the net of slippage and commissions, overnight return of any asset that investor holds with respect to the closing price of the previous day, i.e.:

$$R_t^x = \frac{P_t^x}{P_{t-1}^c} - 1 - (g + c),\ x \in O, H, L, \quad (2)$$

$$c = g = 1 \text{ basis points round trip}, \quad (3)$$

where x is the open, high and low price on day t. For a long portfolio, let us calculate the overnight open return R_t^O and the overnight low return R_t^L, while for a short portfolio, let us calculate the overnight open return R_t^O and the overnight high return R_t^H. Here g is considered as the slippage (assumed fixed), c considered as trading commission (assumed fixed) and our stop-loss level is denoted by S (assumed positive) thus giving the following stop-loss rules and corresponding strategy return R_t first for a long-portfolio:

$$R_t^O \geq -S \geq R_t^L \Rightarrow R_t = -S - (g + c), \quad (4)$$

$$R_t^O < -S \Rightarrow R_t = R_t^O - (g + c). \quad (5)$$

The stop-loss rule for the long portfolio is straightforward: if the negative stop-loss is between and equal to the open return and daily low return, then the stop-loss order is triggered and the daily return is equal to the stop-loss (with negative sign) minus slippage (this paper assumes continuously trading with our tickers) and commissions. However, if the open return is lower than the stop-loss, then the stop-loss order is triggered immediately and the daily return will be the open return minus slippage and commission.

Similarly, for a short portfolio:

$$R_t^O \leq S \leq R_t^H \Rightarrow R_t = S + g + c, \quad (6)$$

$$R_t^O > S \Rightarrow R_t = R_t^O + g + c. \quad (7)$$

The most obvious problem when using a stop-loss rule is that once it is triggered and the investor is out of the market, it will lose any profitable opportunities if the market bounces back. This kind of problem is similar in nature with backward looking indicators like the moving average: for example, a moving average strategy outperformed SPY in 2008, because it has signaled to stay out of the market for a prolonged period in that year, but the SPY outperformed the moving average in 2009, because it took a while until the indicator signaled a switch to re-enter the market. Note, however, that with the use of a daily stop-loss, while there is exposure to this phenomenon, it is expressed with a much lower magnitude. Why is that? Because instead of being exposed to missing days, weeks or even months, while the market bounces, there is exposure to a daily rebalancing if and when investor exits the market when the stop-loss rule is triggered. With the proposed stop-loss rules in this paper, on a daily basis, investors are always investing when the market opens and depending on how the trading day goes, investors might stay or exit the market. This approach will provide benefits during both trending markets and volatile markets: in the first case, it will allow the investor to stay in the market while the trend deploys and in the second case, it will allow him to take advantage of market swings (of course with the accompanied level of risk, but note that this risk will be mitigated by the stop-loss rule).

Finally, for robustness purposes and for further experiments to improve the stop-loss performance, the stop-loss benchmark was changed with respect to the open price (on daily basis) only when the stop-loss level supposed to be triggered at the open price. Then, the formula will be as follows:

$$R_t^x = \frac{P_t^x}{P_t^O} - 1 - (g + c),\ x > o, \tag{8}$$

$$\text{short position: } R_t^x > S \Rightarrow R_t = S + g + c, \tag{9}$$

$$\text{long position: } R_t^x < -S \Rightarrow R_t = -(S + g + c). \tag{10}$$

2.1. A note on slippage and commissions

Both SPY and TLT have highly liquid daily turnover (USD 10 billion and USD 1 billion on average, respectively). This liquidity is crucial for our stop-loss strategy, because lack of liquidity can cause material slippage or even price impact. Therefore, our strategy cannot be recommended to be implemented on illiquid securities. Furthermore, expert practitioners can use the corresponding futures to the SPY and TLT – ESA Index[1] and USA Comdty[2], respectively, for minimizing the slippage even more. Those futures have significantly higher liquidity (approximately 10-20 times higher than the ETFs), however, investor should remember that his trade is subjected to the contract size.

Commissions have also high influence on our strategy because of the higher frequency than other conventional stop-loss approaches. When the stop-loss is triggered, the strategy rebuilds its position, which implies that investor has more trades than a lower frequency stop-loss rule. Contrary to slippage which is very difficult to control, with commissions, there is a wide range of levels (depending on the brokerage house). Acceptable stock commissions vary between 0.3-1 cent per share – the higher the trading frequency, the lower the commission.

In our research, we assume 0.5 bps for slippage and 0.5 cent per share commission – per single trade. Due to the average SPY and TLT prices during the sample period, the commission can also be convertible to 0.5 bps. Hence, in each trade, the strategy loses in total 1 bps, and a full trade (round trip – exit by stop-loss and enter again the MOC) costs 2 bps in total. Using other financial instruments, such as futures, can further reduce these costs. However, our results are significant up to 4 bps round trip costs (slippage and commissions) – beyond that, our strategy loses its performance significance.

3. RESULTS

To examine whether the use of the stop-loss rules this paper suggests has practical value, it will follow a three-pronged approach, as noted above: (a) first, for each individual ETF, it considers the buy and hold strategy with different stop-loss levels[3] and 1 bps slippage and commission in total (per trade); (b) second, it considers the equally weight portfolio of the two ETFs and applies again the stop-loss rules from (a) and finally, (c) it applies a 12 month simple moving average strategy (SMA), with a monthly rebalance, on both ETFs and considers again the stop-loss rules.

The paper purposefully considers the moving average strategy here: this is to illustrate the usefulness of the stop-loss rules for an indicator that can

1 S&P 500 E-mini Active Contract (Bloomberg)

2 US Treasury Long Bond Active Contract (Bloomberg)

3 In our paper, we present results of 1% stop-loss level, but discuss the different levels too.

put you in the wrong side of the market during market transitions. To illustrate this (Tables 4-5), let us consider the period that starts with the subprime crisis in late 2007 and ends in 2010. During the crisis in 2007–2008, the maximum drawdown of the SMA and the SPY was –16.09% and –55.19%, respectively. Then, in 2009–2010, the SMA and the SPY cumulative return was 28.09% and 45.3%, respectively. That is, it took the SMA more than 16% in losses to exit the market during the crisis and then approximately a total of 30% to rotate back to the market. This problem becomes even more pronounced when the underlying asset is highly volatile.

3.1. Implementing the daily stop-loss rule on the buy and hold of SPY and TLT

Between January 1, 2004 and October 13, 2015 (the "sample period"), the strategy calculates the open, high and low daily returns of the SPY and TLT. Following our earlier rules for a long portfolio, the strategy implements the daily stop-loss rule. When the rule is triggered, the strategy first not only exits the market, but also re-opens our positions at the closing price using "Market on Close" order. Every day, the strategy calibrates its positions. Table 1 (panel A) and Figures 1-4 and Table 2 (panel A) and Figures 5-8, found in the Appendix, contain the summaries and visuals for the discussion that follows. During the sample period, the average annualized return for SPY was 7.25%, while its standard deviation and drawdown were 19.44% and 55.19%, respectively. In addition, the maximum daily drawdown was 9.84%, while the best daily return was 14.52%. To illustrate the intuition behind our daily stop-loss trading rule, it considers what happens when it opens and maintains two opposite positions on SPY.

Examining the bullish (long) position which bought the SPY, occasionally sold it based on the stop-loss rule and then re-opened, it achieved a 9.97% average annualized return, while the volatility and drawdown were 16.42% and 45.17%, respectively. The Sharpe ratio, Calmar ratio and skewness for this strategy were 0.61, 0.22 and 1.92, respectively, which are significantly higher than the corresponding measures of the buy and hold – 0.37, 0.13 and 0.21, respectively. Furthermore, the addition of the stop-loss rule not only didn't miss the best daily returns, but also improved the maximum daily drawdown, which is now only 6.23%. The stop-loss rule was activated only 21% of the time, and thus 79% of the time the strategy was just tracking the buy and hold benchmark. Let us denote by t_j the relative time in the market for a given period j and by TTD_j the total trading days for the same period. Therefore, $1-t_j$ is the relative time while we're out of the market and the equivalent number of trading days for the same period equal to $OTD_j = TTD_j\left(1-t_j\right)$. The lower is, t_j the lower should be the volatility of the strategy, because there are more observations with identical value return (zero, in our case). In addition, the drawdown should be lower too, because the strategy is less exposed to market fluctuations. Our results for the long portfolio show that the intuition for the stop-loss based strategy is probably accurate, as it obtains both a higher return and a lower drawdown and volatility. What increases the strength of the results is the fact that the most negative daily observations in SPY were mostly distributed in the 21% of trading days when the long strategy was out of the market because of the triggering of the stop-loss rule. Similar results hold when considering a strategy that sells SPY, e.g. for hedging. This strategy had a 5.74% average annualized return while the volatility, drawdown and skewness were 16.39%, 47.08% and –1.68% respectively. The strategy didn't miss the maximum daily drawdown at 9.52%, and at the same time, avoided the best daily return at 14.52% by exiting while at only 7.13%. In this case, the strategy was 29% of the time out of the market.

The same analysis as above was repeated using the TLT bond ETF. Being broadly negative-correlated with SPY, it is an appropriate example to examine the efficacy of our suggested method. During the sample period, and for the buy and hold strategy, the TLT average annualized return was 7.21%, while the volatility and drawdown were 14.09% and 26.58%, respectively. The long portfolio with the daily stop-loss rule achieved a 12.42% average annualized return, while the standard deviation and drawdown were 13.08% and 21.3%, respectively. The Sharpe ratio, Calmar ratio and skewness for this strategy were 0.95, 0.58 and 0.59, respectively, significantly higher than the buy and hold strategy, which were 0.51, 0.27 and 0.05, re-

Table 1. SPY summary statistics with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	Mean	SD	Max DD	SR	CR	Skewness	Kurtosis
Panel A. 1% stop-loss from last daily close							
SPY-Winner	9.97	16.42	–45.17	0.61	0.22	1.92	25.59
SPY-Loser	5.74	16.39	–47.08	0.35	0.12	–1.68	13.13
SPY-WML	3.46	12.23	–17.92	0.28	0.19	1.09	25.8
SPY	7.25	19.44	–55.19	0.37	0.13	0.21	19.15
Panel B. 1% stop-loss from open price							
SPY-Winner	11.54	16.95	–37.46	0.68	0.31	1.61	22.67
SPY-Loser	5.21	17.15	–57.45	0.3	0.09	–1.32	12.97
SPY-WML	5.61	10.49	–10.39	0.53	0.54	0.86	32.08
SPY	7.25	19.44	–55.19	0.37	0.13	0.21	19.15

Notes: The table presents the performance report on the strategies vis-à-vis the buy and hold benchmark. The statistics below are: Mean, the annualized geometric average of the returns; SD, the annualized volatility of the returns; Max DD, the maximum drawdown; SR, the Sharpe ratio; CR, the Calmar ratio; Skewness, the sample skewness; Kurtosis, the sample kurtosis. The strategies are: SPY-Winner is the strategy which sell the SPY when stop-loss is being triggered, and buy it again on the same day at the closing price; SPY-Looser is the strategy which buy the SPY when stop-loss is being triggered, and sell it again on the same day at the closing price; SPY-WML is the strategy which buy 100% SPY-winner and sell 100% SPY-losers 100% (200% (0%) gross (net) exposure); SPY is the buy and hold benchmark. In panel A, the stop-loss threshold is 1% with respect to the last close on daily basis. In panel B, the stop-loss threshold is 1% with respect to the last close, however, if the stop-loss should be triggered at the opening, the stop benchmark price is changed to the open price.

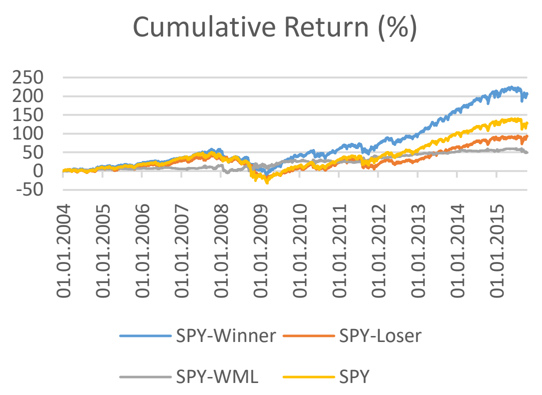

Figure 1

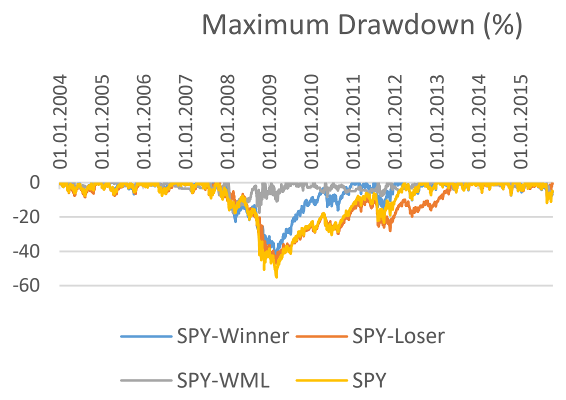

Figure 2

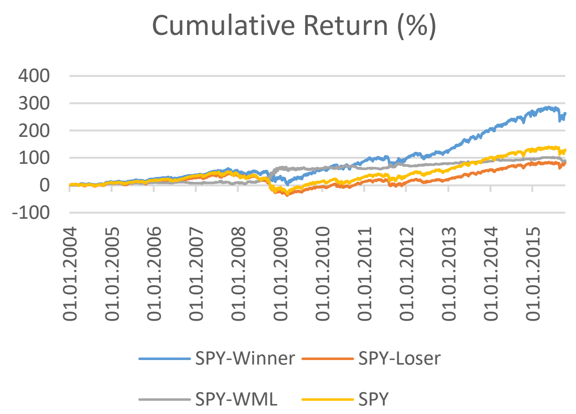

Figure 3

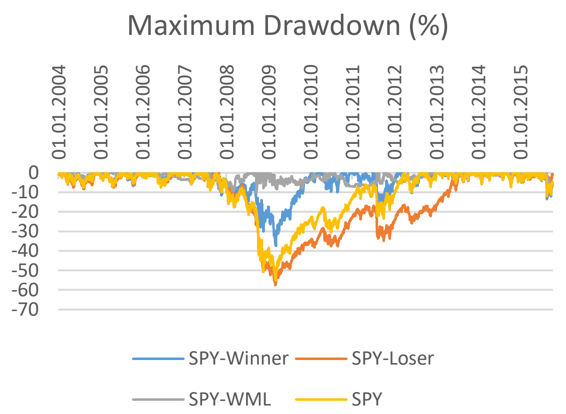

Figure 4

Notes: The figures present the cumulative return and the maximum drawdown plots of the following strategies: SPY-Winner is the strategy which sell the SPY when stop-loss is being triggered, and buy it again on the same day at the closing price; SPY-Looser is the strategy which buy the SPY when stop-loss is being triggered, and sell it again on the same day at the closing price; SPY-WML is the strategy which buy 100% SPY-winner and sell 100% SPY-losers 100% (200% (0%) gross (net) exposure); SPY is the buy and hold benchmark. Figures 1 and 2 (equivalent to panel A in Table 1) presents the plots where the stop-loss threshold is 1% with respect to the last close on daily basis. Figures 3 and 4 (equivalent to panel B in Table 1) presents the plots where the stop-loss threshold is 1% with respect to the last close, however, if the stop-loss should be triggered at the opening, the stop benchmark price is changed to the open price.

Figures 1-4. Cumulative return and maximum drawdown January 1, 2004 – October 13, 2015

Table 2. TLT summary statistics with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	Mean	SD	Max DD	SR	CR	Skewness	Kurtosis
Panel A. 1% stop-loss from last daily close							
TLT-Winner	12.42	13.08	–21.3	0.95	0.58	0.59	4.41
TLT-Loser	2.51	13	–35.88	0.19	0.07	–0.54	4.03
TLT-WML	9.47	6.02	–10.05	1.57	0.94	0.58	16.7
TLT	7.21	14.09	–26.58	0.51	0.27	0.05	4.88
Panel B. 1% stop-loss from open price							
TLT-Winner	10.48	13.42	–21.25	0.78	0.49	0.39	4.6
TLT-Loser	2.64	13.25	–33.18	0.2	0.08	–0.33	4.46
TLT-WML	7.51	5.05	–6.8	1.49	1.11	0.84	21.3
TLT	7.21	14.09	–26.58	0.51	0.27	0.05	4.88

Notes: The table presents the performance report on the strategies vis-à-vis the buy and hold benchmark. The statistics below are: Mean, the annualized geometric average of the returns; SD, the annualized volatility of the returns; Max DD, the maximum drawdown; SR, the Sharpe ratio; CR, the Calmar ratio; Skewness, the sample skewness; Kurtosis, the sample kurtosis. The strategies are: TLT-Winner is the strategy which sell the TLT when stop-loss is being triggered, and buy it again on the same day at the closing price; TLT-Looser is the strategy which buy the SPY when stop-loss is being triggered, and sell it again on the same day at the closing price; TLT-WML is the strategy which buy 100% TLT-winner and sell 100% TLT-losers 100% (200% (0%) gross (net) exposure); TLT is the buy and hold benchmark. In panel A the stop-loss threshold is 1% with respect to the last close on daily basis. In panel B, the stop-loss threshold is 1% with respect to the last close, however, if the stop-loss should be triggered at the opening, the stop benchmark price is changed to the open price.

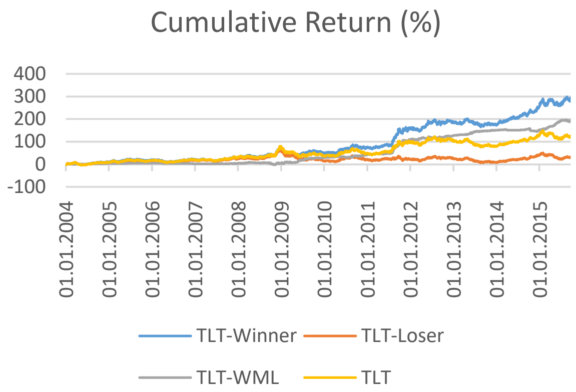

Figure 5

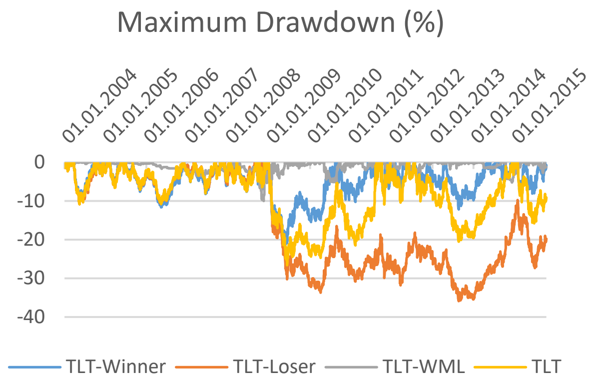

Figure 6

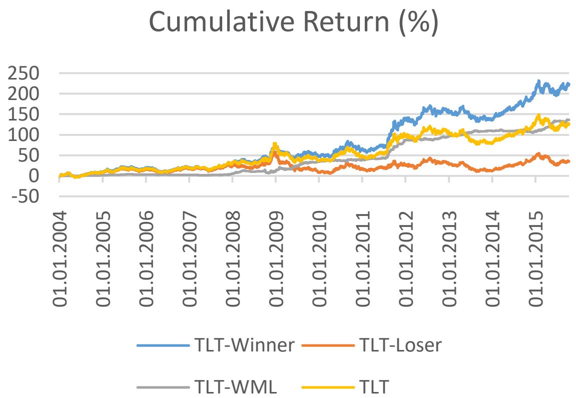

Figure 7

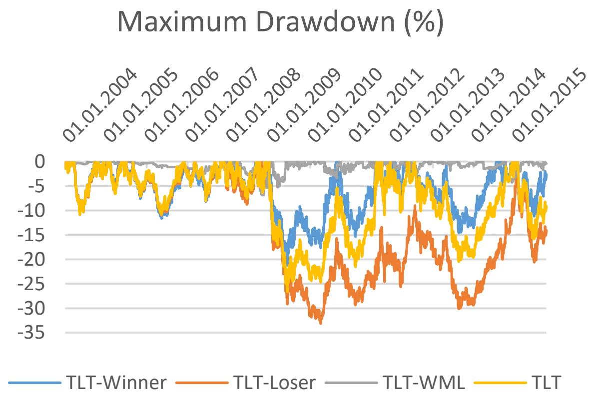

Figure 8

Notes: The figures present the cumulative return and the maximum drawdown plots of the following strategies: TLT-Winner is the strategy which sell the TLT when stop-loss is being triggered, and buy it again on the same day at the closing price; TLT-Looser is the strategy which buy the TLT when stop-loss is being triggered, and sell it again on the same day at the closing price; TLT-WML is the strategy which buy 100% TLT-winner and sell 100% TLT-losers 100% (200% (0%) gross (net) exposure); TLT is the buy and hold benchmark. Figures 5 and 6 (equivalent to panel A in Table 2) presents the plots where the stop-loss threshold is 1% with respect to the last close on daily basis. Figures 7 and 8 (equivalent to panel B in Table 2) presents the plots where the stop-loss threshold is 1% with respect to the last close, however, if the stop-loss should be triggered at the opening, the stop benchmark price is changed to the open price.

Figures 5-8. Cumulative return and maximum drawdown January 1, 2004 – October 13, 2015 spectively. As before, the application of the stop-loss rule didn't miss the best daily return of 5.17%, but it did avoid the maximum daily drawdown of 5.04%, and instead had a loss of only 3.48%. The stop-loss rule was active 26% of the trading. For the short portfolio, the average annualized return is 2.51%, while the volatility, drawdown and skewness were 13%, 35.88% and –0.54%, respectively. As in the long portfolio, again here, the strategy didn't miss the maximum drawdown day of TLT, but it avoided the best day of 5.17%, and had only a 3.54% loss instead. This time, the strategy was out of the market for 31% of the time.

The empirical results of this section clearly suggest that using the proposed stop-loss rules indeed acts as performance enhancer, vis-à-vis the buy and hold benchmark and for both kinds of assets, the equity and bond ETFs. While the data this paper uses are particular ones, they are broad and liquid enough to provide the necessary credibility on the method for wider usage. Furthermore, as it is illustrated next, the method this paper proposes works on different combinations of strategies as well.

3.2. Implement the daily stop-loss rule on the equally weighted SPY-TLT portfolio and the SMA trading rule

The second layer of the daily stop loss trading rule implementation is constructing an equally weighted portfolio between the assets which was used in the first layer, previously discussed. New benchmark was created, the SPY-TLT portfolio, in anticipation that as the stop-loss trading rule outperforms each ETF separately in buy and hold, there is probably little doubt that it will outperform the portfolio of both as well. Our discussion here is structured as before (Table 3, Figures 9-10).

During the period January 1, 2004 – October 13, 2015, the SPY-TLT portfolio achieved a 7.88% annualized return, while the volatility and drawdown were 9.07% and 24.67%, respectively. However, the long position of this portfolio using the daily stop-loss achieved 11.80% annualized return with volatility and maximum drawdown of 8.51% and 18.60%, respectively. In addition, it had significant higher skewness than the equally weighted portfolio of 0.80 versus 0.12 and the risk ratios were better too: Sharpe ratio and Calmar ratio of 1.39 and 0.63, while the equally weighted benchmark had 0.87 and 0.32, respectively.

Next discussion are the implications of the use of the stop-loss trading rules on the WML portfolio, a reasonable proposition to consider, given that this section uses two assets. The WML performance, based on the risk metrics, is significantly better than the corresponding benchmark – the Sharpe ratio and Calmar ratios are now 0.91 and 0.66, respectively. In addition, the maximum drawdown is the lowest among both the long position and the portfolio benchmark and it's only 10.10%. Obviously, the WML implementation can also be used in the first layer of our discussion on the independent ETFs, but for diversification purposes, it is recommended to use it on the equally weighted portfolio (although the TLT-WML outperforms the equally weighted portfolio). Another advantage of the WML portfolio is its relative time out of the market: both the WML portfolio and the hedging strategy are the main reason for the low drawdown. Practitioners may also go long for the winners and sell the benchmark instead of the losers, on the one hand, or sell the loser and buy the benchmark, on the other hand.

Turning to the last (for this paper) use of the daily stop-loss trading rules for trying to enhance a trend following strategy such as the simple moving average (SMA), which is defined as follows:

$$\text{if}\begin{cases} \dfrac{P_t^i}{P_{T,mean}^i} > 1 & \text{Buy risky asset} \\ \text{Othewise} & \text{Buy riskless asset} \end{cases}, \qquad (11)$$

where P_t^i is the last price of security i on day t, and $P_{T,mean}^i$ denoted to the average price of security i in a period of length T, up to and including day t. The period length of computing the mean, T, is usually taken as the last 1, 3, 6, 10 and 12 months. A higher T implies, as expected, lower frequency of rotation in and out of the market and a lower turnover for the strategy. This paper implementation uses the 12 months as our period T (a usual recommendation of the literature) and combine it with our daily stop-loss rules. The results are summarized in Table 5 and Figures 13-14.

Table 3. Summary statistics of SPY-TLT equal weight portfolio with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	Mean	SD	Max DD	SR	CR	Skewness	Kurtosis
	1% stop-loss from the last daily close						
SPY-TLT-Winner	11.80	8.51	–18.60	1.39	0.63	0.80	14.92
SPY-TLT-Loser	4.66	8.31	–19.43	0.56	0.22	–0.89	7.96
SPY-TLT-WML	6.67	7.34	–10.10	0.91	0.66	1.01	21.41
EW-SPY-TLT	7.88	9.07	–24.67	0.87	0.32	0.12	10.79

Note: The table presents the performance report on the strategies vis-à-vis the buy and hold benchmark. The statistics below are: Mean, the annualized geometric average of the returns; SD, the annualized volatility of the returns; Max DD, the maximum drawdown; SR, the Sharpe ratio; CR, the Calmar ratio; Skewness, the sample skewness; Kurtosis, the sample kurtosis. The strategies are: SPY-TLT Winner is the strategy which sell the SPY-TLT equally weight portfolio when stop-loss is being triggered, and buy it again on the same day at the closing price; SPY-TLT Looser is the strategy which buy the SPY-TLT equally weight portfolio when stop-loss is being triggered, and sell it again on the same day at the closing price; SPY-TLT WML is the strategy which buy 100% SPY-TLT winner and sell 100% SPY-TLT losers 100% (200% (0%) gross (net) exposure); SPY-TLT is the equally weight portfolio buy and hold benchmark. The stop-loss threshold is 1% with respect to the last close on daily basis.

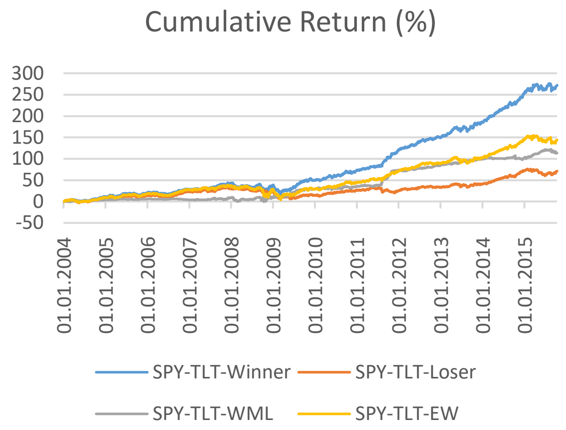

Figure 9

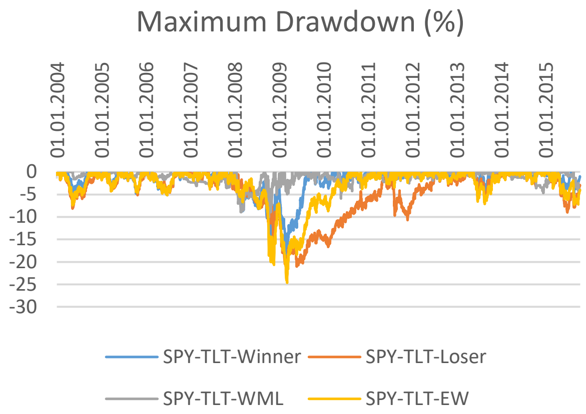

Figure 10

Notes: The figures present the cumulative return and the maximum drawdown plots of the following strategies: SPY-TLT Winner is the strategy which sell the SPY-TLT equally weight portfolio when stop-loss is being triggered, and buy it again on the same day at the closing price; SPY-TLT Looser is the strategy which buy the SPY-TLT equally weight portfolio when stop-loss is being triggered, and sell it again on the same day at the closing price; SPY-TLT WML is the strategy which buy 100% SPY-TLT winner and sell 100% SPY-TLT losers 100% (200% (0%) gross (net) exposure); SPY-TLT is the equally weight portfolio buy and hold benchmark. Figures 9 and 10 present the plots where the stop-loss threshold is 1% with respect to the last close on daily basis.

Figures 9-10. Cumulative return and maximum drawdown January 1, 2004 – October 13, 2015

A casual glance at the tables suggests that here also are numerous performance enhancements. Consider the Sharpe ratio of the SPY-SMA (Table 4 and Figures 11-12) with a 1% daily stop-loss, which rises from 0.68 to 0.88, while the drawdown decreased from 16.09% to 13.96% and the sample skewness becomes positive (–0.47 to 0.28). Note that it's improving on an already improved version of the benchmark of buy and hold: during the sample period, the SPY-SMA strategy is better that SPY itself. The sustainable trend over a long period and the more than a year transition after the 2008 crisis allows the SMA to perform quite well, but even now the stop-loss rules can help in improving the strategy. However, one should consider that if a large fluctuation happens within the period of a few months, say close to a year or so, then the benefit from the use of the stop-loss rule would be even greater.

The TLT-SMA (Table 6 and Figures 13-14) performance over the TLT helps in illustrating what just noted above. Let's examine, therefore, the annual performance of the period 2008–2011: during 2008, the crisis year, the TLT gained significant momentum increasing in return by approximately 34%. Both the TLT-SMA and TLT-SMA with the daily stop-loss rule had performance which was very similar to the TLT buy and hold benchmark. However, in 2009, when the market was recover-

Table 4. Summary statistics of SPY-SMA with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	Mean	SD	Max DD	SR	CR	Skewness	Kurtosis
	1% stop-loss from last daily close						
SPY-SMA	8.01	11.81	–16.09	0.68	0.5	–0.47	7.08
SPY-SMA-SL	9.56	10.85	–13.96	0.88	0.68	0.28	5.98
SPY	7.25	19.44	–55.19	0.37	0.13	0.21	19.15

Notes: The table presents the performance report on the strategies vis-à-vis the buy and hold benchmark. The statistics below are: Mean, the annualized geometric average of the returns; SD, the annualized volatility of the returns; Max DD, the maximum drawdown; SR, the Sharpe ratio; CR, the Calmar ratio; Skewness, the sample skewness; Kurtosis, the sample kurtosis. The strategies are: SPY-SMA is the strategy which buy the SPY based on the 12-month simple moving average, SPY-SMA-SL is the strategy which buy the SPY after implementing both 12-month simple moving average and stop-loss trading rule in a sequence. SPY is the buy and hold benchmark. The stop-loss threshold is 1% with respect to the last close on daily basis.

Table 5. Yearly return of SPY-SMA with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004
SPY-SMA	–2.14	8.87	32.31	15.99	–5.74	7.11	19.59	–3.35	3.12	15.44	1.87	7.06
SPY-SMA-SL	–1.54	11.58	37.68	14.27	–1.60	5.30	18.42	–2.09	11.63	13.44	0.94	10.32
SPY	–1.15	13.46	32.31	15.99	1.89	15.06	26.35	–36.79	5.15	15.85	4.83	10.7

Note: The table presents the annualized return (%) of the following strategies: SPY-SMA, SPY-SMA-SL and the buy and hold benchmark (SPY).

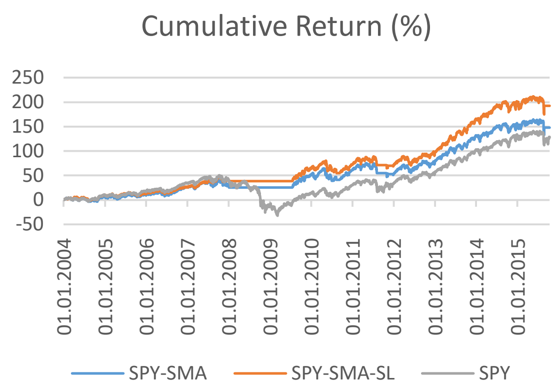

Figure 11

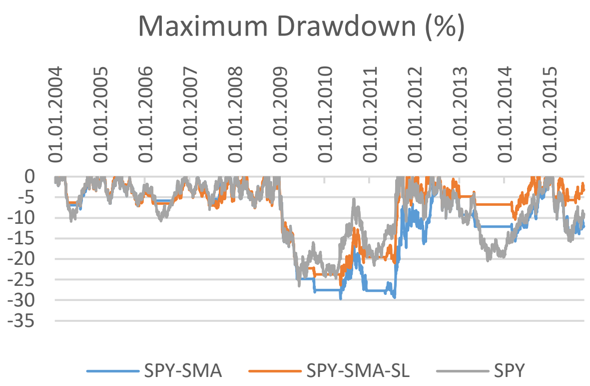

Figure 12

Note: The figures present the cumulative return and the maximum drawdown plots of the following strategies: SPY-SMA, is the strategy which buy the SPY based on the 12-month simple moving average, SPY-SMA-SL, is the strategy which buy the SPY after implementing both 12-month simple moving average and stop-loss trading rule in a sequence. SPY, is the buy and hold benchmark. Figures 11 and 12 presents the plots where the stop-loss threshold is 1% with respect to the last close on daily basis.

Figures 11-12. SPY-SMA cumulative return and maximum drawdown January 1, 2004 – October 13, 2015

ing, the TLT dropped sharply by –21.8%, but for the SMA, it took more than –26% before rotating to cash. Meanwhile, the TLT-SMA strategy with the daily stop-loss rule dropped by –22.11%. In 2010, the fluctuation continued and the TLT rose again approximately by 9.01%, but the TLT-SMA was too slow due to the high volatility and lost 0.27%, while the daily stop-loss rule enhanced TLT-SMA which gained 5.50%.

In 2011, the results were again similar and decomposing the return of that year will show that approximately 58% of the total return for the TLT-SMA with daily stop-loss rule attributed to the plain TLT-SMA, while the rest 42% attributed to the implementation of the daily stop-loss rule. So, and to connect with the ending of our discussion about SPY-SMA, why in 2008 the TLT-SMA succeeded to reach the same annualized return as the TLT but in 2011 it didn't? It should be now clear that in 2007, the momentum in TLT was significant without sharp fluctuations and hence the TLT-SMA strategy was fully invested in the TLT. The effects of the length of transition time can be seen when such events as the crisis happens and the linkage that there is with past momentum at the time of the event. Our argument here, made on the empirical results which had so far, is that

Table 6. Summary statistics of TLT-SMA with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	Mean	SD	Max DD	SR	CR	Skewness	Kurtosis
	1% stop-loss from the last daily close						
TLT-SMA	4.47	12.11	–29.77	0.37	0.15	0.19	7.46
TLT-SMA-SL	7.94	11.58	–23	0.69	0.35	0.87	6.49
TLT	7.21	14.09	–26.58	0.51	0.27	0.05	4.88

Notes: The table presents the performance report on the strategies vis-à-vis the buy and hold benchmark. The statistics below are: Mean, the annualized geometric average of the returns; SD, the annualized volatility of the returns; Max DD, the maximum drawdown; SR, the Sharpe ratio; CR, the Calmar ratio; Skewness, the sample skewness; Kurtosis, the sample kurtosis. The strategies are: TLT-SMA is the strategy which buy the TLT based on the 12-month simple moving average, TLT-SMA-SL is the strategy which buy the SPY after implementing both 12-month simple moving average and stop-loss trading rule in a sequence. TLT is the buy and hold benchmark. The stop-loss threshold is 1% with respect to the last close on daily basis.

Table 7. Yearly return of TLT-SMA with daily stop loss January 1, 2004 – October 13, 2015

Strategy type	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004
TLT-SMA	–3.39	15.03	–5.34	2.63	26.89	–0.27	–26.00	33.94	5.50	0.47	8.26	7.70
TLT-SMA-SL	6.31	17.14	–3.8	9.93	41.73	5.50	–22.11	31.04	3.92	0.47	8.85	9.15
TLT	–0.12	27.3	–13.38	2.63	34	9.01	–21.8	33.95	10.31	0.71	8.6	8.7

Note: The table presents the annualized return (%) of the following strategies: TLT-SMA, TLT-SMA-SL and the buy and hold benchmark (TLT).

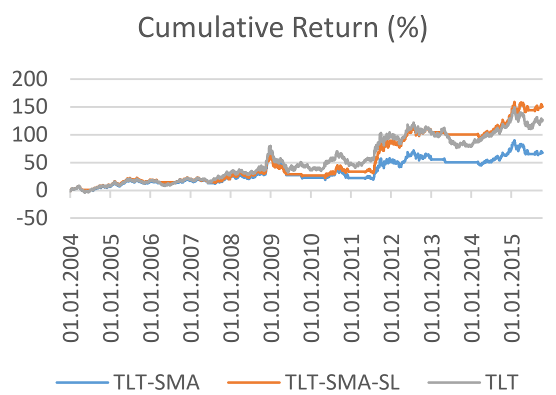

Figure 13

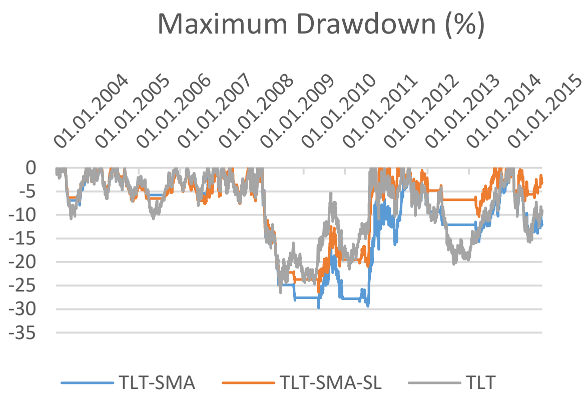

Figure 14

Notes: The figures present the cumulative return and the maximum drawdown plots of the following strategies: TLT-SMA is the strategy which buy the TLT based on the 12-month simple moving average, TLT-SMA-SL is the strategy which buy the SPY after implementing both 12-month simple moving average and stop-loss trading rule in a sequence. TLT is the buy and hold benchmark. Figures 13 and 14 presents the plots where the stop-loss threshold is 1% with respect to the last close on daily basis.

Figures 13-14. TLT-SMA cumulative return and maximum drawdown January 1, 2004 – October 13, 2015

the implementation of the daily stop-loss rule not only provides performance enhancements during "good" or trending periods, but also, more importantly, helps avoiding disastrous results during periods of sharp and protracted market corrections.

Summarizing our results so far, it was shown via examples from our analysis that the daily stop-loss rule as implemented can improve a variety of positions and strategies, both long and short for either the SPY or TLT, which are highly negative correlated assets, and also for their equally weighted portfolio and the WML portfolio and the SMA-based strategy. It appears that being able to come back to the market "fast enough" during periods of higher volatility drives this performance enhancement. This issue will be explored in more detail in what follows.

4. ROBUSTNESS: IMPROVING STRATEGY PERFORMANCE VIA DYNAMIC ADJUSTMENTS

This section suggests two additional different approaches to improve strategy performance. The first is based on the use of the daily spot price when comparing it to the stop-loss threshold and the second is based on the adjustment of the stop-loss threshold itself.

In the first approach, the stop-loss threshold level is compared to the daily open return which is calculated with respect to the last close. It means that every time when the open return is lower (higher) than the stop-loss level, the long (short) position is executed by this open return. The literature (see, for example, Lockwood & Linn, 1990) shows that the volatility during the opening is much higher than the rest of the day, and the main reason for that is the overnight phenomenon. This fact causes a lot of stop-loss execution during the sample period in the opening. Changing the stop-loss level with respect to the open price and not to the last close might succeed to reduce by eliminating all the executions at the opening. This new adjustment will only be used when the open daily return exceeds the stop-loss threshold; otherwise investor remains with the original stop-loss threshold with respect to the last close. The reason for not changing the spot price consistently to the opening price is to avoid the high volatility at the opening, but only when that volatility is against our position. There is no reason to change the spot price from the last close to the opening one when the high volatility is in our positions side, or when the volatility is very low and has no influence when the market is open on our positions[4]. Therefore, the intra-day return and the stop-loss execution rule after changing the benchmark will be with respect to the opening price.

Now the stop-loss can be executed only after the opening and it can be illustrated by using a long position example: in the original stop-loss rule with respect to the last close price, when the opening is very volatile and against our desired direction, the stop-loss should be triggered. Our positions are then being closed immediately without any opportunity to exploit volatility reduction after the opening of the market. If eventually the market bounces back, the strategy won't be part of it because it's already out of the market. By changing the benchmark price only in situation like this, investor gets another chance to be in the market and maybe exploit this volatility reduction. However, he can increase our losses when the volatility remains, and markets continue with the "wrong" direction against our chosen position.

When testing this approach on the SPY and TLT, the results were conflicting. With the SPY (Table 1, Figures 1-4, panel B), changing the price benchmark improved the winners annualized return by more than 1.5%, while the losers had lower return by approximately 0.5%. Therefore, the WML portfolio gained more than 2% more annualized with the new stop-loss method. The Sharpe ratio and Calmar ratio of the WML portfolio have raised from 0.28 to 0.53 and from 0.10 to 0.54, respectively. These results show that changing the initial price benchmark can possibly reduce noisy executions. However, TLT results were not corresponding (Table 2, Figures 5-8, panel B). Here the WML portfolio had lower return (7.51% against 9.47%), but the volatility was also lower (5.05% against 6.02%). Therefore, the Sharpe ratio of both methods was quite similar (1.49 vs 1.57). As explained before, the reason this paper suggests an adjustment to the benchmark price is to avoid volatility at the opening. During the sample period, the TLT volatility, is much lower than the SPY (14% and 19%, respectively), and, as expected, the higher the historical volatility, the higher the improvement by changing the benchmark price. 0.5% stop-loss level for the TLT (instead of 1%), and then make the adjustment – the results would correspond to SPY too[5].

In all our previous discussion, the assumption was that the stop-loss rule is using a fixed threshold.

4 We also applied our analysis by using the stop-loss rule with respect to the opening price. The results were underperforming the original daily stop-loss (with respect to the previous close). The reason for this is simple: using the opening price as a benchmark can convert the stop-loss rule to a take profit method. This way we miss days where the market opens high (low) for long (short) positions, make a short correction, triggers the stop-loss (which is now reacting like take-profit) and eventually bounces again. The main logic of the stop-loss is to cut losses but ride on profits, but if we use it as a take profit device implies that we will miss on performance.

5 For research purposes, we tested the TLT also with a 0.5% daily stop-loss with different price as benchmark: previous close and open price. The latter outperform the first as the SPY did it with 1% daily-stop loss.

An obvious potential improvement, at least in theory, is to suggest a way to make the stop-loss rule threshold time-varying. This is the second improvement proposed in this section. For making the threshold time-varying, it can consider the use of historical volatility as a guide: every rebalance date calculates the historical volatility of each asset for a given historical period. Then, depending on investor risk aversion, it can determine the stop-loss level for each asset. But how exactly? It is important to notice that a combination of high volatility with low stop-loss threshold level will create too many executions, while low volatility with a high stop-loss threshold level probably won't trigger the stop-loss. Multiplying the historical volatility with the k (where $0.5 < k < 1.5$), standard deviation can be one way to set the stop-loss level. In addition, it can be multiplied by a fixed number, which represents investor risk aversion. This paper leaves this issue for future research.

CONCLUSION

Many practitioners use stop-loss for hedging their downside risk. However, reducing the risk involved may also reduce the return, mostly because they then stay too much time in riskless asset and out of the market. Therefore, the time being spent with the riskless asset is crucial, and the biggest question is what that period should be. Following the literature, it is common to rebuild the position simultaneously with the portfolio rebalance date: the lower the rebalance frequency, the higher the risk to miss the best (worst) days for long (short) positions.

It is shown in this paper how significant can be the impact of missing the best 10 days over the SPY – between January 1, 2004 – October 13, 2015, it reduced the B&H return from 9.14% to 5.57% (more than 39%). For avoiding long term stop-loss methods, this paper suggested a novel way to implement the stop-loss trading rule by using it on a daily basis: when the stop-loss is triggered return to the market in the same day at the closing price and adjust again the daily stop-loss with respect to this new price. Rebuilding a position every day (instead of every week/month – depending on the rebalance frequency) will significantly reduce the risk of missing good days.

The paper illustrated that using the daily-stop loss strategy not only reduces the risk factors, volatility and maximum drawdown, but also improves the annualized return. For the SPY, the stop-loss strategy return and Sharpe ratio were 9.97% and 0.61, respectively, while the SPY itself stayed behind with only 7.25% and 0.37 annualized return and Sharpe ratio. Consistent results were found for the TLT, were the stop-loss strategy increased the buy and hold return from 7.21% to 12.42% and the Sharpe ratio from 0.51 to 0.95. Substantially creating a portfolio from the SPY and TLT, were the stop-loss outperformed it as well (which is as expected, since it outperformed each one separately). Finally, it was shown also how this rule can improve trend following strategies like the 12-month simple moving average. For the SPY, the stop-loss strategy annualized return increased from 8.01% to 9.56%, while the Sharpe ratio increased from 0.37 to 0.68. With the TLT, the stop-loss strategy achieved annualized return and Sharpe ratio of 7.94% and 0.69, respectively, while the SMA strategy itself achieved only 7.94% and 0.37. The results on the application of the stop-loss rules suggest that they are robust enough and easy enough for real life applications.

This is part of ongoing research on the efficacy of rebuilding positions using both static and dynamic approaches. One of the main open issues for future research is to expand the examination of the stop-loss rules in a wider area of quantitative strategies and to examine whether a stop-loss threshold can be made dynamic, ideally linked with several underlying factors representing market or economic conditions. The authors are currently pursuing these lines of research.

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