Commodity Premia and Risk Management*

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Abstract

We examine the role of risk management in the context of commodity factor premia. Stopping losses in individual commodities effectively improves the average returns of long-short commodity premia through persistent reduction in the frequency and severity of drawdowns. The magnitude of improvement is related to the quality of the signal, commodity return volatility and autocorrelations, as well as transactions costs. The efficacy of a stop-loss strategy can be enhanced by dynamically calibrating loss thresholds in accordance with realized volatility, and it performs best in high conviction weighting schemes. Overall, we highlight the pivotal role of risk management beyond volatility targeting and risk-parity in harnessing commodity risk premia.

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Keywords: commodity futures; risk management; alternative risk premia; stop-loss

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1. Introduction

This paper explores the role of risk management in commodity risk premia. Recent studies devote significant attention to risk-managed (i.e., volatility targeting) factor premia, and found that managed premia tend to outperform their unmanaged counterparts on a risk-adjusted basis (Moreira and Muir, 2017; Harvey et al. 2018). In this article, we approach risk management from a different angle. We investigate the effect of risk management on commodity factor premia by deploying stop-loss strategies in individual commodity markets.

While there are some studies that tackle the issue of stop-loss, few consider stop-loss in a factor context.[1] The theoretical work by Kaminski and Lo (2014) and Lo and Remorov (2017) posit that when asset-price dynamics exhibit greater complexity than a random walk process, there exists a potential to enhance the buy-and-hold performance. Hence, it is unsurprising that Han et al. (2016) discovered the improvement of average return and total risk in the U.S. equity momentum strategy through the implementation of stop-loss, owing to the positive autocorrelation exhibited by past returns.

Intriguingly, stop-loss mechanisms have not garnered much attention within the commodity futures literature. The distinctive attributes of commodities, such as higher volatility and lower transaction costs (compared to stocks and bonds), coupled with the structural changes over the past decades (e.g., shale oil, financialization, Covid-19 and Ukraine war), present an intriguing and distinct setting for examining the impact of risk management. Our findings point to the crucial role of risk management beyond position sizing and risk weighting in harnessing commodity risk premia.

[1] For example, Kaminski and Lo (2014) point out that if the underlying asset price follows a random work, stop-loss will always underperform buy-and-hold (BH). Subsequently, Lo and Remorov (2017) highlight that serial correlation and volatility are key conditions for stop-loss to beat BH. Trading U.S. stocks, they find that tight stop-loss strategies tend to underperform due to excessive trading. Similarly, Dai et al. (2020) find that trailing stop-loss is effective at reducing VaR and Expected Shortfall, but generates lower returns than BH.

In the decade leading up to Covid-19, commodity risk premia (e.g., momentum, carry, basis-momentum, relative-basis, skewness, and to a lesser extend hedging pressure) experienced catastrophic drawdowns from 29% to 58% (Fan et al., 2023). The lackluster performance of both conventional and alternative commodity risk premia strategies has resulted in a substantial decline in investor interests and fund flows into CTAs and commodity hedge funds. Despite the inflationary boost experienced by commodity markets, a lingering sense of skepticism persists among institutional investors regarding the validity of commodity risk premia (Bloomberg, 2020).

Adding a risk management layer to commodity factor implementation, we find that commodity premia is alive and well even during the most unfavorable macro environments. From 1983 to 2022, commodity factors on average, with a fixed-stop (trailing-stop) generate a net Sharpe ratio of 0.92 (1.28), while experiencing a maximum drawdown of less than -20% and a positive return skewness (with the exception of the skewness factor). With stops, drawdowns are less severe and less frequent across all factors. These benefits accumulate overtime and are amplified through compounding, leading to substantially different average returns and terminal wealth compared to unmanaged factors.

Meanwhile, volatility-managed strategies often shine on their property of mitigating the crash risk of their unmanaged counterparts, while risk-weighting also improves the Sharpe ratio of the unmanaged factor strategy at the expense of higher drawdowns. Our findings reveal that employing simple fixed stop-loss strategies yields performance gains comparable to volatility targeting or risk-parity strategies. Furthermore, the implementation of a trailing stop-loss outperforms managed factors that do not incorporate a stop-loss mechanism by a significant margin. On average, implementing a standard momentum strategy with a trailing stop yields a Sharpe ratio that surpasses risk-parity (volatility targeting) by 70% (80%). Moreover, this approach mitigates the maximum drawdown by 30% compared to volatility targeting, all the while preserving a positive skewness profile. We also find that adding a stop-loss layer to rank- and risk-weighted momentum can significantly boost their risk-adjusted performances.

Finally, we explore the driving forces behind the success of stop loss. Stop loss is only effective in a factor context if it can effectively reduce drawdowns on the factor level. While Bianchi et al. (2021) find that stop-loss does not lead to improved factor performance, we stress the importance of managing risks on an individual asset level for factor strategies. The rationale is straight-forward. As opposed to stopping out of the entire factor portfolio when a loss threshold is triggered (see Bianchi et al., 2021), stopping out of individual commodities while keeping the other positions intact allows the non-stopped positions to continue generating potential returns for the factor strategy.[2] Intuitively, it is logical to assume that on average comovement among factor portfolio constituents are less than one. Thus, stop-loss has the potential to improve the risk-adjusted performance of factor strategies. Indeed, the effectiveness of stop loss in a factor context is in part determined by the quality of the investment signal, asset return volatility and serial correlations, as well as transactions costs.

2. Data

Our sample consists of 29 commodity futures traded across North America, Europe, and Singapore exchanges. Daily settlement price, volume, and open interest are obtained from Refinitiv Datastream, while weekly trader position data are retrieved from the Commodity Futures Trading Commission (CFTC) commitments of traders (CoT) report. The sample covers the period from April 1982 to September 2022. To compile the trading time-series returns, we assume that investors initiate a position in the contract with the highest open interest along a futures curve, and only roll over to the next maturity when its open interest becomes the highest for three consecutive trading days. To compute maturity-related signals (e.g., roll-yield), we

[2] This approach also echoes with the popular trading belief to "cut your losses short and let your winners run".

also compile the conventionally rolled 1st, 2nd, 3rd nearest variables, i.e., a roll-over occurs whenever the front contract enters the last trading month. Daily excess return is defined as $r_t = \frac{F_t}{F_{t-1}} - 1$, where F_t denotes the settlement price for a given contract at day *t*.

Table 1 reports the summary statistics of all commodities included in the sample. We report average daily returns (mean), standard deviations (SD), as well as the largest daily loss (Min.) and daily gain (Max.) along with their corresponding contract tickers and date of occurrence. Palladium (rubber) generates the highest (lowest) daily mean return of 0.048% (-0.021%). Consistent with empirical observations, natural gas (cattle) recorded the highest (lowest) daily volatility at 2.5% (0.9%). Across our sample of commodities, the average of daily mean returns and volatilities are 0.01% and 1.6%, respectively.

While price limits (otherwise known as circuit breakers) are in place to curb extreme price volatilities, commodity prices can move far beyond the initial limits set by the exchange. Interestingly, while max gain and loss tend to be a function of volatility, we observe that large losses or gains can occur in any commodities. These outsized price swings already speak to the importance of risk management. It is also worth noting that most of the extreme daily returns are observed post financialization (post-2001). Moreover, we report the median daily open interest (OI) and trading volume (VOL) in both lots and millions of dollars ($). Clearly, trader interests and market liquidity vary significantly across commodities. On average for example, oats, lumber, rubber and milk only traded less than eight million dollars' worth of contracts per day, whereas copper, soybean and gasoline can trade more than 1.2 billion dollars' worth of contracts per day. Consequently, institutional investors face nonnegligible capacity constraints when implementing diversified investment programs including commodity factor exposures.

3. Results

3.1. Fixed-stop

Our fixed stop-loss strategy is implemented as follows. At the end of each month, long-short positions are entered accordingly based on the signals and weights. During the subsequent investment month, losses (if incurred) are monitored daily relative to the entry balance, at individual commodity level.

$$Fixed\ loss = \frac{B_{t-M,i}}{B_{0-M,i}} - 1, \qquad if\ B_{t-M,i} < B_{0-M,i} \tag{1}$$

Where $B_{t-M,i}$ is the end balance on commodity *i* at day *t* in month *M*, $B_{0-M,i}$ is the beginning balance on commodity *i* in month *M*. A position will be liquidated when a pre-defined loss threshold Θ is triggered.

$$\Theta \in \{-5\%, -10\%, -20\%\}; \tag{2}$$

Table 2 reports performance of fixed-stop strategies on key commodity factors including momentum (MOM), carry (CARRY), relative-basis (RB), basis-momentum (BM), skewness (SKEW) and hedging pressure (HP).[3] For the momentum factor, we observe significant performance improvement with a simple stop-loss implemented on individual commodities. On average across thresholds and time, the Sharpe ratio sees nearly one-fold increase from 0.52 to 1.00. We also observe a modest improvement in Omega ratio suggesting that stopping losses at individual commodity level does improve the odds of generating a positive return on the factor level. Meanwhile, the maximum drawdown (Max.DD) is substantially reduced from -28.3% to -17.5%. Besides, stopping losses appear to markedly improve the return skewness profile. Turning to carry, we observe a similar pattern with the

[3] For details on factor construction, refer to Appendix A and Bianchi et al. (2023). We form factor portfolios using the entire cross-section, with a breakpoint of two and rebalance the factor portfolio monthly back to equal weights. At each rebalance, we keep the long-short factor portfolios dollar-neutral with 100% collateralization.

Sharpe ratio increasing from 0.61 to 1.12, and drawdown decreasing from -15.7% to -10.7%. However, the improvement in skewness is not as pronounced as momentum.

We then proceed to examine the effect of stop-loss on more recently introduced factors. Although they are not as profitable as conventional factors, relative-basis and basis-momentum factors continue to see significant improvements in risk-adjusted performance with stop-loss. Finally with skewness and hedging pressure, we observe a further deterioration of performance, compared to MOM and CARRY, with hedging pressure reporting an average return of merely 1.5%, barely significant at the 10% level. However, with the help of stop-loss, the Sharpe ratio improves from 0.24 to 0.68 and a 6% reduction in MaxDD. Similarly, the skewness factor reports a Sharpe ratio of 0.81 with stop-loss compared to 0.36 without. However, we do not observe much improvement in the skewness profile of its returns, suggesting that while stopping losses has the potential to improve the risk-adjusted performance and reduce the probability of crash, it does not automatically skew the return distributions towards the right. In other words, stop-loss cannot make a non-informative signal/trade more informative, it cannot replace the signal itself. Therefore, its efficacy also depends on the quality of the investment signal.

Overall, the findings in Table 2 suggest that a simple stop-loss can effectively improve the performance of commodity factor strategies. Moreover, our findings appear to favor a tighter loss threshold, as it (Θ=-5%) consistently reports the strongest performance across factors. However, given the choice of Θ is ex-post, and that stop-loss effectiveness may be regime-dependent, we focus on the average performance across narrow and wide thresholds.[4]

3.2. Trailing-stop

[4] Nevertheless, we continue to report results across thresholds as it allows us to better understand the mechanism driving the performance improvements. In particular, since wider loss thresholds report qualitatively similar results to unmanaged factors, it implies that commodities generally do not experience losses greater than 20% within a month. Therefore, narrower loss threshold can more effectively help stop losses on the factor level.

Having established that fixed stop-loss is successful at reducing losses of factor strategies, we now examine if factor performance can be further improved through a trailing-stop. The key difference between trailing- and fixed-stop is how losses are measured. In a fixed stop, a loss is relative to the month-beginning balance, while a trailing loss is relative to the within-month high. i.e.,

$$Trailing\ loss = \frac{B_{t-M,i}}{B_{H-M,i}} - 1, \qquad if\ B_{t-M,i} < B_{H-M,i} \tag{3}$$

Where $B_{H-M,i}$ is the within-month high balance for commodity *i* in month *M*. It is worth noting the two stop-loss mechanisms coincide with each other when a position never delivered a positive cumulative return within the month, i.e., the month-beginning balance is the within-month high ($B_{H-M,i} = B_{0-M,i}$). The advantage of trailing-stop is that it allows one to take profits on an individual asset quicker and earlier than a fixed-stop, when the asset's monthly cumulative performance is a bell-shaped curve. Therefore, trailing stop has the potential to further improve the average returns of factor strategies while keeping the other benefits intact. To be comparable with section 3.1, we apply the same set of loss threshold Θ in Eq (3).

Table 3 reports the performance of trailing-stop strategies on the same factors. For ease of comparison, we report the unmanaged factor performances alongside these results. Across all factors (with the exception of HP), we observe that even at the widest loss threshold ($\Theta = 20\%$), the Sharp ratios are consistently higher compared to the unmanaged counterparts. Indeed, this finding suggests that trailing stop can improve the risk-adjusted returns of factor strategies while keeping the benefit of crash-risk protection. Similarly, a narrow loss threshold ($\Theta = 5\%$) was already proven effective under a fixed-stop framework; once allowed for profit-taking through trailing-stop, we observe even stronger risk-adjusted performance with a remarkable MaxDD ranging from as little as -4.7% in basis-momentum to merely -11.5% in skewness, as well as Sharpe ratios greater than 2.0.

Nevertheless, for same reasons as previously mentioned, we focus on average trailing-stop performance (Avg.) across all thresholds. Across factors, we observe monotonic improvements in Sharpe ratio over fixed-stop by 42%, and a reduction in MaxDD by 15%. Consistent with the results in Table 2, while trailing-stop can meaningfully increase the average returns of the skewness strategy, it is unable to reduce the crash risk by more than the fixed-stop can, suggesting that a trailing-stop strategy is not "bulletproof". Overall, the findings presented in Table 3 suggest that trailing-stop can further improve the performance of factor strategies compared to fixed-stop. We present a more streamlined comparison which summarizes the performance improvements across strategies in the following section.

3.3. Transaction costs

Having established that trailing-stop is superior to fixed-stop in a factor context, the immediate question arises regarding the increased trading intensity and the corresponding transaction cost impact on factor returns. To gain more confidence in our proposed stop-loss approach, we apply a rather aggressive transaction cost estimate with the following assumptions:

(i) Portfolio turnover remains 200% at each rebalance, i.e., all positions are liquidated at end of each holding month, and proceeds are re-allocated in accordance with new information, e.g., long/short signals and new weights.[5]

(ii) Transaction costs (TC) consist of a commission fee of $1.5 as suggested by Gao et al. (2018), and a price impact component equivalent to 1 tick size.

[5] The estimated portfolio turnover across seven traditional risk premia averages at 1.36 during a similar sample period in Bianchi et al. (2023). This suggests our transaction costs are likely overestimated by at least 40%, hence increase our confidence in the net return statistics.

$$TC_t^i = \frac{C + 1 \times Tick_i \times M_i}{F_t^i \times M_i} \tag{4}$$

Where C denotes the commission fee, $Tick_i$ is the minimum price fluctuation for commodity i, M_i is the contract multiplier, and F_t^i is the contract price at the time of transaction.

(iii) Transaction costs are expressed in percentages and deducted from the gross returns on the days when transactions occur, to derive the net returns.

$$Net_t^i = Gross_t^i - TC_t^i \tag{5}$$

Table 4 reports the net performance of factors after accounting for transactions costs. Panel A reports unmanaged factors, Panel B reports volatility-managed factors, and Panel C reports the net performance of factors with trailing-stop averaged across thresholds. First, we find that factor performances deteriorated further after accounting for trading costs. Notably, relative-basis, skewness and hedging pressure factors no longer report statistically significant average returns. Consequently, we observe considerable declines in net Sharpe ratios across factors, with the highest ratio reported by carry. This finding lends support to the skepticism surrounding the validity and long-term sustainability of alternative risk premia (ARP), particularly commodity risk premia.

A simple mediating solution is to apply volatility management on the portfolio level (Moreira and Muir, 2017). Keeping the portfolio volatility constant through time, many studies have reported improved risk-adjusted performance of factors. Thus, we consider volatility management as an alternative to stop loss.[6] From Panel B, we find that volatility management

[6] The volatility-managed factor portfolios follow the method proposed by Moreira and Muir (2017). Specifically, $F_{t+1}^{managed} = \frac{c}{\sigma_t^2(F)} F_{t+1}$, where F is the unmanaged factor portfolio, $F^{managed}$ denotes the volatility-managed portfolio, $\sigma_t^2(F)$.is the previous-period realized volatility of the unmanaged factor portfolio, and c is the scaling constant that ensures both managed and unmanaged factor portfolios have the same volatility.

does not provide universal performance improvement net of transactions cost, as relative-basis, skewness and hedging pressure factor continue to report insignificant average returns, while volatility-managed carry and basis-momentum factors deliver quantitatively identical results to their unmanaged counterparts. Consistent with Kang and Kwon (2020), and Xu and Wang (2021), we find momentum to be the only factor that gains meaningful improvements over the unmanaged factor. Turning to Panel C, we observe that net of transactions costs, factor strategies implemented with trailing-stop continue to deliver statistically and economically significant average returns, with net Sharpe ratios ranging from 1.04 (skewness) to 1.43 (carry), and maximum drawdown ranging from -9.1% (carry) to -20% (skewness). Meanwhile, all but the skewness factor reports positive return skewness.

For ease of comparison, we present a heatmap style plot in Table 5 to summarize the factor performance gains using trailing-stop over its unmanaged (Panel A) and volatility-managed counterparts (in Panel B). To mitigate the influence of outliers, we compute the median improvements across factors in the last column of Table 5. Panel A illustrates that trailing-stop improves the factor returns, net of transaction costs, by an average of threefold, with the strongest results in hedging pressure. We observe a somewhat negligeable decline of total and downside volatilities, as well as value-at-risk (VaR). On average, the Sharpe (Sortino) ratio saw a 3.6x (3.8x) boost over unmanaged factors. Meanwhile, we observe an average reduction in MaxDD by 47%, as well as a 2.5x increase in return skewness. Moving to Panel B, the results remain largely consistent. Even if we focus only on momentum (as volatility management is only effective on momentum), trailing-stop still improves the net Sharpe and Sortino ratios of volatility-managed momentum by more than 100%, all while reporting a 45% better MaxDD and a 3.4x higher return skewness. These benefits can be better visualized in Figure 1. Overall, the combined evidence presented in Tables 4 and 5 suggest that stopping losses at individual asset level is a far superior solution to managing the risk of factor strategies than volatility management on the portfolio level.

Figure 1 illustrates the cumulative factor performance without risk management in Panel A (gross returns) and with trailing-stop in Panel B (net returns). The effect of risk management on factor performance is clearly visible as the wealth indices in Panel B appear much smoother compared to Panel A. With stops, drawdowns are less severe and less frequent. These benefits accumulate over time and are amplified through compounding, leading to substantially different terminal wealth from Panel A to Panel B. For example, with trailing-stop, the worst performing factor–hedging pressure still beats the best performing factor–carry without risk management based on terminal wealth.

3.4. What drives the success of stop-loss?

Given the superior performance of trailing-stop, one must ask the question why stop-loss is successful at improving the performance of commodity risk factors? We first rule out the possibility that the performance improvements in factors reaped by trailing-stop is regime-dependent, and it was only effective prior to financialization when factor performance was the strongest. In the decade leading up to Covid-19, momentum, carry, basis-momentum, relative-basis, and skewness experienced catastrophic drawdowns from 29% to 58% (Fan et al., 2023). Therefore, if trailing-stop is regime-dependent, we should observe significant reductions in Sharpe ratios in the last decade.

Figure 2 illustrates the Sharpe ratio of all factors in pre-financialization (pre-2001) and post-GFC (post-2009) periods. Panel A reports unmanaged factors and Panel B reports risk managed factors through trailing stop with a loss threshold $\Theta = -10\%$. Indeed, we observe significant performance deteriorations in the recent subperiod across the board (except for SKEW and HP) in Panel A, Interestingly, however, skewness and hedging pressure factors appear to perform better post-GFC. When stop-loss is implemented (Panel B), we observe a universal increase in Sharpe ratios in both sub-periods compared to Panel A. Particularly, we find that with trailing-stop, momentum almost reports the same Sharpe ratio post-GFC as pre-2001 without stops. Overall, the findings presented in Figure 2 reveal that stop-loss not only improves the factor performance pre-financialization but continues to be effective post-GFC in light of structural changes such as shale oil, definancialization, Covid-19 and Ukraine war.

Since the benefit of stop-loss for commodity factors is not regime-dependent, we investigate alternative explanations. Given that momentum is the most debated factor in the literature along with the fact that it is among the only factor that improves with volatility management, we focus on momentum for the remaining analyses. This is also useful in reducing the dimensionality of our results, given the large number of factors in previous tables.

Intuitively, stop-loss is only useful if it stops losses. Take for example the long leg of a momentum portfolio with fixed-stop. On the one hand, stopping out of a commodity too late does not help reduce losses if the price does not deteriorate any further. On the other hand, realizing the loss too early may not help if the price reverses quickly. The same logic applies to the trailing-stop. If prices move up, the stop level increases accordingly. The stop trigger is successful only if the price drop continues. In other words, the success of stop-loss relies on one key feature, namely positive autocorrelation in returns. Besides, volatility can also play a role in the effectiveness of stop-loss, because volatility is the “playground” for stop loss. Mechanically, the more volatile the commodity price is, the higher the potential for stop-loss to take effect and stop loses. Therefore, if volatility and autocorrelation are key drivers to the success of stop-loss strategies, we should observe stronger effects in commodities with higher volatilities and autocorrelations.

Table 6 reports the performance of the momentum strategy in sub-samples. Panel A examines the role of volatility, whereas Panel B explores autocorrelation. We sort all commodities into high versus low groups based on the full period daily standard deviation and

AR(1) coefficient, respectively. We then deploy momentum strategies in each sub-sample with and without a trailing-stop. Since the median standard deviation and autocorrelation are determined ex-post, we focus on comparing average returns, standard deviations and Sharpe ratios only, ignoring other performance statistics or implementation concerns.

From Panel A, we find that volatility indeed plays a role in explaining the performance of trailing-stop. Momentum strategy with trailing-stop implemented in the high volatility group generates 94% higher Sharpe ratio (1.41) compared to the low volatility group (0.73). The outperformance is statistically significant at 1% using stationary bootstrap as per Politis and Romano (1994). Furthermore, when examining the role of autocorrelations in Panel B, we find similar results where momentum with trailing-stop performs better in the high group, suggesting that autocorrelation is indeed a contributing factor to the success of the stop-loss.

To better visualize the impact of stop-loss, Figure 3 plots the cumulative performance of the unmanaged, volatility-managed, fixed- and trailing-stop managed momentum strategies. Since the momentum strategy suffered maximum drawdown post-2001, we focus on the sub-period from 2002 onwards and highlight the two largest drawdowns in grey. For the unmanaged strategy, the first major drawdown occurred around 2009 and did not recover until 2014 (approx. 5 years). The maximum drawdown occurred from 2015 and did not recover until early 2022, despite the commodity rallies seen since covid-19. During the period when the unmanaged momentum experiences a maximum drawdown of -28.3%, momentum with a fixed stop only lost -10.7%, whereas trailing-stop in fact gained 1.7% even after accounting for transactions costs. Meanwhile, managing the volatility of the strategy also helps reduce the MaxDD to -23.6%. For both drawdown events, it can be clearly seen that trading-stop effectively smoothed the tail risk of commodity momentum strategy. While maintaining the risk management properties of the fixed-stop, trailing-stop allows one to simultaneously improve factor returns. By continuously capping losses, the effect of risk management is amplified through time by the power of compounding.

4. Extensions

Having established that the quality of the signal, asset return volatility and serial correlations, as well as transactions costs are the primary driver of stop-loss effectiveness for factor returns, we now consider alternative stop-loss specifications.

4.1. Re-entry and dynamic stop thresholds

Up to this point in the paper, once a position is stopped out, we do not reestablish the position until the next rebalancing (i.e., the beginning of the following month). We now introduce the possibility to re-enter into the position if the commodity recoups the loss θ by $(1+\theta)\cdot(1+1.5\%)$ within the month. Drawing from the findings presented in Panel B of Table 6, re-entry will only add value if reversals occur within a month. Meanwhile, we have thus far only considered pre-determined loss thresholds for both fixed- and trailing-stop loss strategies. This may be sub-optimal because volatility levels can vary across commodities and time. To capture these variations, we let Θ vary with the volatility of each commodity in the momentum portfolio. To track the time-varying volatility, we follow Moskowitz et al. (2012) and employ the exponentially weighted volatility with a center of mass of 60 days.

Table 7 reports the effect of re-entry and dynamic threshold. For ease of comparison, we report the performance of momentum strategy with trailing stop loss (Θ = -10%) as a benchmark. We observe a moderate decline in Sharpe ratio from 1.15 to 1.07, and a negligible increase in MaxDD when re-entry is introduced. Instead, a dynamic loss threshold further improves the risk-adjusted performance of the momentum strategy to a Sharpe ratio of 1.32. While the MaxDD is not impacted, dynamic loss threshold does make the return skewness negative. Consistent with pre-defined loss threshold, re-entry does not appear to add any value to dynamic threshold in a factor context. Overall, the findings presented in Table 7 suggest that trailing-stop with dynamic thresholds has the potential to deliver improved factor performance over pre-determined thresholds at the expense of skewness. Therefore, portfolio managers face a trade-off between average return and skewness.

4.2. Opportunistic weights

Up to this point, we have kept the asset weights equal within each factor portfolio for simplicity and ease of interpretation. We now introduce additional complexities pertaining to portfolio construction. Practitioners favor three most common themes, namely strategic tilts, volatility management, and risk-parity. Strategic tilts involve overweighting (underweighting) commodities with higher-ranked (lower-ranked) signals in the cross-section.[7] This is preferred by some traders because it presents a higher level of conviction on the investment thesis. Secondly, we have already demonstrated that trailing stop strongly outperforms volatility-managed momentum. We now combine the best of both worlds by attempting to stop losses of a volatility-managed momentum portfolio. Lastly, risk-parity is one of the most widely used technique by multi-asset managers as return volatilities can vary drastically from one asset class to another.[8] Instead of splitting the dollar investments equally across portfolio constituents, risk parity targets equal risk allocation among portfolio constituents.

While the objective is clear, both rank- and risk-weighted portfolios are inevitably more concentrated than equal weighted portfolios. In our context, expressing a stronger conviction on the signal or risk requires more extreme weights in individual commodities within the momentum portfolio. This raises an intriguing question regarding the effect of stop-loss. In

[7] Following Asness et al. (2013), rank weight method defines the weight for commodity *i* at time *t* is defined as: $w_t^i = c_t\left(Rank(Signal_t^i) - \frac{\sum_i^N Rank(Singal_t^i)}{N}\right)$, where c_t is a scaling factor that ensures portfolio weights sum up to 1.

[8] Following Moskowitz et al. (2012), risk-parity is achieved by scaling individual asset's holding-period returns by a factor of $\frac{40\%}{\sigma}$, where σ is the annualized exponentially weighted volatility based on historical returns with a center of mass of 60 days. We set the maximum scaling factor to 5x to avoid extreme leverage.

theory, if stop loss is truly effective in a factor context, we expect stronger performance gains with extreme asset weights. Because if adverse commodity price movements happen on commodities with relatively extreme weights, the losses (that could be avoided) would have been larger compared to an equal-weighted portfolio. As discussed previously, more loss avoidance ultimately leads to better average and cumulative performance over time.

Table 8 reports the results of rank-weighted, volatility-managed, and risk-weighted momentum strategies with pre-defined or dynamic loss thresholds in trailing-stop framework, alongside their unmanaged counterparts (i.e., no-stop) using their respective weighting scheme. Indeed, we find that trailing-stop with pre-defined loss threshold improves the rank-weighted momentum (1.33x increase in Sharpe) more than it does on the equal-weighted momentum (1.23x increase in Sharpe). While the average return is substantially higher, rank weight generates a larger maximum drawdown even with trailing-stop. Turning to volatility-managed momentum, combining volatility-management with trailing-stop loss is found to generate significantly higher Sharpe ratio (1.28) compared to volatility management (0.71) or trailing-stop (1.15) alone.

Finally, we observe remarkable performance improvements in risk-weighted momentum portfolio. While risk-parity generates identical Sharpe ratio compared to volatility-management without stop loss, it reports a much higher maximum drawdown of -37.6%. This is explained in part by the level of leverage taken to achieve risk-parity, resulting in higher return volatility and tail risk. Despite the increased risk profile when adding trailing-stop to risk-parity, we observe a whopping 1.9x increase in Sharpe ratio over the no-stop risk-parity counterpart (from 0.73 to 2.12), while reducing the MaxDD by 65% to merely -13.1%. Once again, this finding suggests that stop loss is especially effective at stopping losses in the presence of extreme asset weights. Consistent with Table 7, we continue to observe stronger performance when applying a dynamic loss threshold across all weighting schemes.

5. Conclusion

This paper examined the effect of fixed and trailing stop-loss on commodity factor strategies. We found that while unmanaged factors delivered disappointing performance net of transactions costs, commodity factor premia are alive and well when implemented with simple stop-loss strategies on the asset level. With a fixed-stop (trailing-stop), commodity factors on average generate a Sharpe ratio of 0.92 (1.28), with less than 20% maximum drawdown, and a positive return skewness profile (except for the skewness factor). Using momentum as an example, the success of stop-loss in a factor context is not regime-dependent, but its effectiveness is primarily driven by the quality of the signal, commodity return volatility and serial correlations, as well as transactions costs. Accordingly, we demonstrated that the benefit of stop-loss can be amplified through dynamically calibrating loss thresholds with realized volatility. Finally, we highlighted that stop-loss performs best in factors constructed with high conviction weighting schemes. Overall, we emphasize the crucial role of risk management in commodity factor implementation.

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Appendix A. Factor signal construction

Factor	**Commodity-specific signals**	**Definition at the time of portfolio formation *t***	**References**
Momentum (MOM)	$MOM_t = \prod_{s=0}^{11}(1 + r_{t-s}) - 1$	r_t denotes the time *t* monthly excess return of the front contract.	Erb and Harvey (2006); Miffre and Rallis (2007); Bakshi et al. (2019)
Carry (Carry)	$RY_t = F_t^1/F_t^2 - 1$	F_t^1 and F_t^2 denote the prices of the nearest and 2nd nearest contract at time *t*, respectively.	Erb and Harvey (2006); Gorton and Rouwenhorst (2006); Szymanowska et al. (2014); Yang (2013); Bakshi et al. (2019)
Relative basis (RB)	$RB_t = \frac{ln(F_t^1/F_t^2)}{T_t^2 - T_t^1} - \frac{ln(F_t^2/F_t^3)}{T_t^3 - T_t^2}$	F_t^m denotes the time *t* price of the *m*th nearest contract, T_t^m represents the time to maturity of the *m*th nearest contract expressed in number of days at time *t*.	Gu et al. (2023)
Basis-momentum (BMOM)	$BM_t = \prod_{s=0}^{11}(1 + r_{t-s}^1) - \prod_{s=0}^{11}(1 + r_{t-s}^2)$	r_t^1 (r_t^2) represents the time *t* monthly excess return of the front (second-nearest) contract.	Boons and Prado (2019)
Skewness (SKEW)	$SKEW_t = \left\{\left[\frac{1}{D_1}\sum_{d=0}^{D_1-1}(r_{t-d} - \mu_t)^3\right] \Big/ \sigma_t^3\right\}$	r_d denotes the daily excess return of the front contract at time d, μ_t and σ_t denote mean and standard deviation of daily excess returns as measured at time *t* using daily data over the past year and D_1 is the number of days in the past one year.	Fernandez-Perez et al. (2018)
Hedging Pressure (HP)	$HP_t = \frac{1}{52}\sum_{w=0}^{51}\frac{S_{t-w} - L_{t-w}}{S_{t-w} + L_{t-w}}$	S_t and L_t correspond to the week *t* short and long positions of a given commodity as held by commercial traders in the CFTC report, respectively.	Basu and Miffre (2013); Kang et al. (2020)

Table 1 Summary statistics

This table reports summary statistics of individual commodity futures based on the most active maturity measured by open interest. Mean and SD are the daily average and standard deviation of excess returns, respectively. Min. and Max. are minimum and maximum daily returns with their corresponding contracts and dates of occurrence. The table also reports daily median liquidity in terms of number of contracts (lots) and dollar value in millions (m). The sample covers the period from April 1982 to September 2022.

Commodity Name	Return (%) Mean	Return (%) S.D.	Return (%) Min.	Contract	Date	Return (%) Max.	Contract	Date	OI (lots) Median	VOL (lots) Median	$OI (m) Median	$VOL (m) Median
Crude Oil	0.044	2.0	-28.9	CLN0^2	21/04/2020	22.2	CLM0^2	19/03/2020	72,618	24,054	1,963	749
Gasoline	0.034	2.2	-22.1	RBM0^2	16/03/2020	18.0	RBM0^2	2/04/2020	47,137	20,187	4,138	1,725
Heating Oil	0.031	1.9	-19.6	HOZ1^9	17/01/1991	10.6	HOZ9^1	16/09/2019	25,164	5,172	796	167
Corn	-0.002	1.5	-7.6	CK3^1	1/04/2013	9.0	CZ9^0	15/09/2009	227,447	44,308	2,927	584
Oats	0.010	1.8	-11.3	OK5^0	31/03/2005	11.1	OK5^0	30/03/2005	5,708	571	53	6
Rough Rice	-0.012	1.4	-6.7	RRH2^0	11/12/2001	7.9	RRN0^2	3/06/2020	6,279	469	148	11
Wheat	-0.011	1.7	-9.5	WK2^2	10/03/2022	9.2	WZ8^0	29/10/2008	77,476	17,521	1,254	306
Cotton	0.003	1.5	-6.9	CTZ2^1	21/06/2012	7.2	CTH9^0	8/12/2008	43,048	6,746	1,292	216
Lumber	-0.001	1.9	-8.8	LBU1^2	13/07/2021	10.9	LBX1^2	3/09/2021	2,512	464	18	4
Feeder Cattle	0.007	0.9	-5.8	FCH4^0	29/12/2003	5.5	FCK0^2	24/03/2020	7,411	1,319	306	56
Live Cattle	0.007	0.9	-6.2	LCG4^0	30/12/2003	5.6	LCM0^2	7/04/2020	50,329	10,039	1,447	292
Lean Hogs	-0.015	1.5	-8.5	LHM0^2	3/04/2020	7.8	LHM0^2	23/04/2020	21,451	5,505	496	126
Copper	0.026	1.5	-11.0	HGZ4^0	13/10/2004	12.3	HGZ8^0	29/10/2008	48,939	9,102	2,006	361
Gold	0.003	1.1	-9.3	GCM3^1	15/04/2013	9.2	GCZ9^9	28/09/1999	90,882	27,613	3,348	1,239
Silver	0.015	1.7	-17.7	SIF2^1	23/09/2011	13.3	SIK9^0	19/03/2009	44,642	9,040	1,358	271
Soybean Meal	0.030	1.5	-7.5	SMZ7^0	16/07/2007	7.9	SMZ1^2	30/06/2021	49,891	13,157	933	254
Soybean Oil	0.009	1.5	-9.5	BOZ1^2	17/06/2021	8.4	BOK5^0	22/02/2005	61,685	13,432	760	187
Soybean	0.014	1.4	-7.1	SX9^0	7/07/2009	6.9	SX9^9	2/08/1999	94,925	38,213	3,084	1,244
Cocoa	-0.007	1.8	-9.5	CCZ2^0	18/10/2002	12.9	CCZ0^9	24/08/1990	38,607	5,584	529	86
Coffee	0.005	2.2	-13.2	KCU9^8	3/07/1989	26.2	KCU4^9	27/06/1994	35,438	7,303	1,144	292
Orange Juice	0.003	1.8	-12.8	OJH0^1	11/01/2010	16.3	OJF7^0	12/10/2006	9,839	873	172	16
Natural Gas	-0.003	2.5	-19.6	NGH19^1	15/11/2018	20.5	NGH19^1	14/11/2018	55,476	10,069	3,198	533
Propane	0.035	2.1	-15.1	B0SM0^2	9/03/2020	16.0	B0SX9^1	16/09/2019	8,199	265	197	8
Canola	0.015	1.1	-7.9	RSF9^0	6/10/2008	6.9	RSX8^0	9/04/2008	33,303	3,698	212	26
Rubber	-0.021	1.6	-35.0	STFZ8^0	2/10/2008	31.9	STFF9^0	16/10/2008	5,960	327	44	2
Palladium	0.048	2.0	-21.2	PAM0^2	13/03/2020	25.8	PAM0^2	25/03/2020	4,106	368	95	9
Platinum	0.015	1.5	-11.5	PLN0^2	16/03/2020	11.8	PLN0^2	24/03/2020	10,850	1,674	290	49
Milk	0.022	1.2	-7.6	DCSU7^0	24/07/2007	7.3	DCSU7^0	23/07/2007	4,102	216	129	7
Sugar	0.010	2.0	-16.7	SBV8^8	26/07/1988	15.3	SBV5^8	26/07/1985	93,107	15,258	1,025	168

Table 2 Fixed stop

This table reports the performance statistics of six factor portfolios with (denoted as Threshold) and without (denoted as No-stop) fixed stop-loss, as well as the average (denoted as Avg.) performance based on three thresholds, i.e., 5%, 10%, and 20%. The fixed loss is calculated per Eq (1). Annu. represents annualized statistic. Factor portfolios on momentum (MOM), carry (CARRY), relative basis (RB), basis momentum (BM), skewness (SKEW), and hedging pressure (HP) are monthly rebalanced and constructed using the sorting variables presented in Appendix A. Newey and West (1987) adjusted *t*-statistics are reported. Omega ratio is calculated using empirical distribution. The sample covers the period from April 1982 to September 2022.

	No-stop	Threshold			Avg.	No-stop	Threshold			Avg.
		5%	10%	20%			5%	10%	20%	
	MOM					CARRY				
Annu. Mean	3.1%	8.5%	5.2%	3.3%	5.7%	3.2%	8.7%	5.2%	3.6%	5.8%
t-stat	3.4	10.0	5.8	3.6	6.5	3.9	11.3	6.5	4.4	7.4
Annu. S.D.	6.1%	5.5%	5.9%	6.1%	5.8%	5.3%	5.0%	5.2%	5.3%	5.2%
Annu. Sharpe	0.52	1.55	0.89	0.55	1.00	0.61	1.72	0.99	0.67	1.12
Annu. D.S.D.	4.1%	3.6%	3.9%	4.0%	3.8%	3.4%	3.3%	3.4%	3.4%	3.4%
Annu. Sortino	0.77	2.36	1.35	0.83	1.51	0.94	2.66	1.53	1.04	1.74
Skewness	-0.13	0.04	-0.03	-0.10	-0.03	-0.12	0.02	-0.06	-0.13	-0.06
Excess Kurtosis	1.57	3.69	2.61	2.00	2.76	1.20	3.50	2.09	1.35	2.31
99% VaR (C.F.)	-1.1%	-1.1%	-1.1%	-1.1%	-1.1%	-0.9%	-1.0%	-0.9%	-0.9%	-0.9%
Max.DD	-28.3%	-9.9%	-16.3%	-26.3%	-17.5%	-15.7%	-7.0%	-11.9%	-13.2%	-10.7%
Omega	1.08	1.20	1.11	1.08	1.13	1.10	1.20	1.13	1.11	1.15
	RB					BM				
Annu. Mean	2.0%	7.2%	3.9%	2.3%	4.4%	2.6%	7.6%	4.7%	3.0%	5.1%
t-stat	2.6	9.4	5.0	3.0	5.8	3.3	9.9	5.9	3.9	6.5
Annu. S.D.	5.1%	5.0%	5.1%	5.1%	5.1%	5.2%	5.0%	5.2%	5.2%	5.2%
Annu. Sharpe	0.39	1.44	0.76	0.45	0.88	0.50	1.51	0.89	0.58	1.00
Annu. D.S.D.	3.2%	3.1%	3.2%	3.2%	3.2%	3.5%	3.3%	3.5%	3.5%	3.4%
Annu. Sortino	0.62	2.28	1.19	0.71	1.39	0.75	2.28	1.34	0.88	1.50
Skewness	0.07	0.19	0.13	0.04	0.12	-0.06	0.07	-0.01	-0.09	-0.01
Excess Kurtosis	1.52	4.27	3.47	2.30	3.35	3.29	6.06	4.80	3.50	4.79
99% VaR (C.F.)	-0.8%	-1.0%	-1.0%	-0.9%	-0.9%	-1.0%	-1.1%	-1.1%	-1.0%	-1.1%
Max.DD	-14.7%	-8.4%	-11.9%	-14.6%	-11.6%	-18.5%	-8.7%	-13.8%	-17.2%	-13.2%
Omega	1.03	1.14	1.07	1.04	1.08	1.06	1.18	1.11	1.06	1.12
	SKEW					HP				
Annu. Mean	2.1%	7.4%	3.9%	2.4%	4.6%	1.5%	7.2%	3.3%	1.7%	4.1%
t-stat	2.4	8.5	4.3	2.7	5.2	1.6	7.3	3.4	1.8	4.2
Annu. S.D.	5.9%	5.5%	5.8%	5.9%	5.7%	6.2%	5.9%	6.1%	6.2%	6.1%
Annu. Sharpe	0.36	1.35	0.67	0.41	0.81	0.24	1.21	0.55	0.28	0.68
Annu. D.S.D.	4.1%	3.9%	4.1%	4.1%	4.0%	4.4%	4.3%	4.4%	4.4%	4.4%
Annu. Sortino	0.51	1.92	0.95	0.58	1.15	0.34	1.66	0.76	0.40	0.94
Skewness	-0.40	-0.30	-0.41	-0.44	-0.38	-0.10	0.03	-0.06	-0.09	-0.04
Excess Kurtosis	12.44	19.26	15.15	13.15	15.85	19.56	24.79	21.35	20.04	22.06
99% VaR (C.F.)	-2.0%	-2.4%	-2.2%	-2.1%	-2.2%	-2.7%	-3.0%	-2.8%	-2.8%	-2.9%
Max.DD	-28.8%	-12.0%	-20.3%	-26.0%	-19.4%	-23.4%	-13.3%	-16.8%	-21.7%	-17.3%
Omega	1.06	1.17	1.08	1.06	1.11	1.05	1.17	1.08	1.06	1.10

Table 3 Trailing stop

This table reports the performance statistics of six factor portfolios with (denoted as Threshold) and without (denoted as No-stop) trailing stop-loss, as well as the average (denoted as Avg.) performance based on three thresholds, i.e., 5%, 10%, and 20%. The fixed loss is calculated per Eq (3). Annu. represents annualized statistic. Factor portfolios on momentum (MOM), carry (CARRY), relative basis (RB), basis momentum (BM), skewness (SKEW), and hedging pressure (HP) are monthly rebalanced and constructed using the sorting variables presented in Appendix A. Newey and West (1987) adjusted *t*-statistics are reported. Omega ratio is calculated using empirical distribution. The sample covers the period from April 1982 to September 2022.

	No-stop	Threshold			Avg.	No-stop	Threshold			Avg.
		5%	10%	20%			5%	10%	20%	
	MOM					CARRY				
Annu. Mean	3.1%	11.8%	6.5%	3.5%	7.3%	3.2%	11.7%	6.1%	3.7%	7.2%
t-stat	3.4	16.1	7.3	3.8	9.1	3.9	17.3	7.9	4.6	9.9
Annu. S.D.	6.1%	4.7%	5.6%	6.0%	5.4%	5.3%	4.4%	5.1%	5.3%	4.9%
Annu. Sharpe	0.52	2.54	1.15	0.58	1.42	0.61	2.69	1.21	0.70	1.53
Annu. D.S.D.	4.1%	2.9%	3.6%	4.0%	3.5%	3.4%	2.6%	3.2%	3.4%	3.1%
Annu. Sortino	0.77	4.13	1.79	0.88	2.27	0.94	4.54	1.89	1.08	2.51
Skewness	-0.13	0.25	0.04	-0.08	0.07	-0.12	0.33	0.00	-0.12	0.07
Excess Kurtosis	1.57	2.33	2.35	1.99	2.22	1.20	2.48	1.83	1.36	1.89
99% VaR (C.F.)	-1.1%	-0.7%	-1.0%	-1.1%	-0.9%	-0.9%	-0.7%	-0.9%	-0.9%	-0.8%
Max.DD	-28.3%	-5.3%	-11.9%	-24.4%	-13.9%	-15.7%	-4.9%	-8.8%	-12.7%	-8.8%
Omega	1.08	1.28	1.13	1.08	1.17	1.10	1.31	1.16	1.11	1.19
	RB					BM				
Annu. Mean	2.0%	10.3%	4.9%	2.4%	5.9%	2.6%	10.8%	5.8%	3.1%	6.6%
t-stat	2.6	15.4	6.4	3.1	8.3	3.3	15.8	7.4	4.0	9.1
Annu. S.D.	5.1%	4.3%	4.9%	5.1%	4.8%	5.2%	4.3%	5.0%	5.2%	4.8%
Annu. Sharpe	0.39	2.42	0.99	0.47	1.29	0.50	2.55	1.15	0.60	1.43
Annu. D.S.D.	3.2%	2.5%	3.1%	3.2%	2.9%	3.5%	2.5%	3.2%	3.4%	3.1%
Annu. Sortino	0.62	4.21	1.59	0.74	2.18	0.75	4.26	1.79	0.92	2.33
Skewness	0.07	0.48	0.22	0.05	0.25	-0.06	0.41	0.07	-0.06	0.14
Excess Kurtosis	1.52	2.90	3.49	2.33	2.91	3.29	3.78	3.61	3.39	3.59
99% VaR (C.F.)	-0.8%	-0.7%	-0.9%	-0.9%	-0.8%	-1.0%	-0.7%	-1.0%	-1.0%	-0.9%
Max.DD	-14.7%	-4.3%	-10.7%	-14.6%	-9.9%	-18.5%	-4.7%	-8.6%	-15.1%	-9.4%
Omega	1.03	1.23	1.10	1.05	1.13	1.06	1.26	1.13	1.06	1.15
	SKEW					HP				
Annu. Mean	2.1%	9.9%	4.8%	2.5%	5.8%	1.5%	10.3%	4.5%	1.5%	5.5%
t-stat	2.4	12.7	5.5	2.8	7.0	1.6	11.7	4.6	1.6	6.0
Annu. S.D.	5.9%	4.7%	5.6%	5.8%	5.4%	6.2%	5.3%	6.0%	6.2%	5.8%
Annu. Sharpe	0.36	2.09	0.87	0.43	1.13	0.24	1.95	0.75	0.25	0.98
Annu. D.S.D.	4.1%	3.3%	3.9%	4.1%	3.8%	4.4%	3.9%	4.3%	4.4%	4.2%
Annu. Sortino	0.51	3.00	1.25	0.61	1.62	0.34	2.64	1.05	0.34	1.34
Skewness	-0.40	-0.36	-0.33	-0.40	-0.37	-0.10	0.09	-0.09	-0.09	-0.03
Excess Kurtosis	12.44	29.49	16.27	13.15	19.64	19.56	38.06	23.43	19.58	27.02
99% VaR (C.F.)	-2.0%	-2.8%	-2.2%	-2.1%	-2.4%	-2.7%	-3.7%	-2.9%	-2.7%	-3.1%
Max.DD	-28.8%	-11.5%	-20.6%	-25.5%	-19.2%	-23.4%	-8.6%	-14.9%	-23.4%	-15.6%
Omega	1.06	1.24	1.11	1.06	1.14	1.05	1.27	1.11	1.05	1.14

Table 4 Net performance

This table presents the performance statistics net of transaction costs, for unmanaged (Panel A), volatility-managed (Panel B), and trailing stop-loss based (Panel C) factor portfolios. Annu. represents annualized statistic. The volatility-managed portfolios follow the procedures in Moreira and Muir (2017), while the trailing stop-loss strategies are the same as in Table 3. The six factor portfolios are momentum (MOM), carry (CARRY), relative basis (RB), basis momentum (BM), skewness (SKEW), and hedging pressure (HP). The factor portfolios are monthly rebalanced and constructed using the sorting variables presented in Appendix A. Transaction costs consist of a commission fee of $1.5 per Guo et al. (2018), and a price impact component equivalent to 1 tick size per Eq (4). Portfolio turnovers are assumed to be 200% at each rebalance. Newey and West (1987) adjusted *t*-statistics are reported. Omega ratio is calculated using empirical distribution. The sample covers the period from April 1982 to September 2022.

	MOM	CARRY	RB	BM	SKEW	HP
Panel A: Performance of factors						
Annu. Mean	2.2%	2.3%	1.1%	1.7%	1.2%	0.7%
t-stat	2.5	2.9	1.5	2.2	1.4	0.8
Annu. S.D.	6.1%	5.3%	5.1%	5.3%	5.9%	6.2%
Annu. Sharpe	0.37	0.43	0.21	0.32	0.20	0.11
Annu. D.S.D.	4.1%	3.5%	3.2%	3.5%	4.1%	4.5%
Annu. Sortino	0.55	0.67	0.33	0.48	0.29	0.15
Skewness	-0.13	-0.13	0.06	-0.07	-0.41	-0.15
Excess Kurtosis	1.56	1.19	1.52	3.29	12.50	19.56
99% VaR (C.F.)	-1.1%	-0.9%	-0.8%	-1.0%	-2.0%	-2.7%
Max.DD	-30.7%	-19.1%	-16.2%	-18.7%	-33.8%	-30.1%
Omega	1.06	1.08	1.02	1.03	1.04	1.04
Panel B: Performance of volatility-managed factors						
Annu. Mean	3.2%	2.6%	1.1%	1.8%	0.9%	0.2%
t-stat	3.4	3.1	1.5	2.3	1.1	0.4
Annu. S.D.	6.1%	5.3%	5.1%	5.3%	5.9%	6.2%
Annu. Sharpe	0.53	0.48	0.21	0.34	0.15	0.04
Annu. D.S.D.	3.9%	3.4%	3.2%	3.4%	4.1%	4.4%
Annu. Sortino	0.84	0.76	0.34	0.53	0.22	0.05
Skewness	0.01	-0.01	0.01	0.02	-0.36	-0.19
Excess Kurtosis	1.09	1.25	0.85	1.45	9.44	14.97
99% VaR (C.F.)	-1.0%	-0.9%	-0.8%	-0.9%	-1.8%	-2.3%
Max.DD	-26.2%	-18.9%	-19.1%	-19.6%	-41.0%	-37.4%
Omega	1.06	1.08	1.02	1.04	1.04	1.04
Panel C: Average performance with trailing-stop						
Annu. Mean	6.8%	6.7%	5.4%	6.1%	5.3%	6.1%
t-stat	8.5	9.3	7.7	8.5	6.5	8.5
Annu. S.D.	5.4%	4.9%	4.8%	4.8%	5.4%	4.8%
Annu. Sharpe	1.34	1.43	1.19	1.34	1.04	1.34
Annu. D.S.D.	3.5%	3.1%	2.9%	3.1%	3.8%	3.1%
Annu. Sortino	2.13	2.35	2.01	2.16	1.50	2.16
Skewness	0.07	0.07	0.24	0.13	-0.38	0.13
Excess Kurtosis	2.22	1.87	2.89	3.57	19.68	3.57
99% VaR (C.F.)	-0.9%	-0.8%	-0.8%	-0.9%	-2.4%	-0.9%
Max.DD	-14.4%	-9.1%	-10.3%	-9.6%	-20.0%	-9.6%
Omega	1.15	1.18	1.11	1.14	1.12	1.14

Table 5 Performance improvement heatmap

This table reports the average improvements of trailing stop-loss strategies relative to its no-stop and volatility-managed counterparts, based on net returns estimated in Table 4 Panel C. Annu. represents annualized statistic. Δ represents percentage change over the comparator. The volatility-managed portfolios follow the procedures in Moreira and Muir (2017), while the trailing stop-loss strategies are the same as in Table 3. The six factor portfolios are momentum (MOM), carry (CARRY), relative basis (RB), basis momentum (BM), skewness (SKEW), and hedging pressure (HP). The factor portfolios are monthly rebalanced and constructed using the sorting variables presented in Appendix A. The sample covers the period from April 1982 to September 2022.

	MOM	CARRY	RB	BM	SKEW	HP	Median
Panel A: Improvement over unmanaged factors							
ΔAnnu. Mean	2.1x	1.9x	4.0x	2.6x	3.4x	6.8x	3.0x
ΔAnnu. S.D.	-11%	-8%	-6%	-8%	-9%	-7%	-8%
ΔAnnu. Sharpe	2.7x	2.3x	4.6x	3.2x	4.1x	7.8x	3.6x
ΔAnnu. D.S.D.	-14%	-11%	-9%	-12%	-9%	-5%	-10%
ΔAnnu. Sortino	2.9x	2.5x	5.0x	3.5x	4.1x	7.6x	3.8x
ΔSkewness	2.5x	2.5x	3.2x	3.8x	0.1x	0.7x	2.5x
Δ99% VaR (C.F.)	-12%	-9%	-2%	-13%	16%	15%	-6%
ΔMax.DD	-53%	-52%	-36%	-48%	-41%	-46%	-47%
ΔOmega	8%	9%	9%	10%	8%	9%	9%
Panel B: Improvement over volatility-managed factors							
ΔAnnu. Mean	1.1x	1.6x	4.0x	2.4x	4.9x	21.8x	3.2x
ΔAnnu. S.D.	-11%	-8%	-6%	-8%	-9%	-7%	-8%
ΔAnnu. Sharpe	1.5x	2.0x	4.6x	2.9x	5.9x	24.6x	3.8x
ΔAnnu. D.S.D.	-10%	-9%	-9%	-9%	-7%	-4%	-9%
ΔAnnu. Sortino	1.5x	2.1x	4.9x	3.1x	5.8x	23.6x	4.0x
ΔSkewness	3.4x	-12.6x	28.0x	5.7x	0.0x	-0.5x	1.7x
Δ99% VaR (C.F.)	-4%	-7%	2%	4%	34%	35%	3%
ΔMax.DD	-45%	-52%	-46%	-51%	-51%	-57%	-51%
ΔOmega	8%	9%	9%	10%	8%	9%	9%

Table 6 Volatility and autocorrelation

This table presents the (average) performance statistics of momentum strategy with no-stop (trailing stop), in two sets of subsamples. Panel A splits the full sample by daily volatility, whereas Panel B divides the sample based on autocorrelation coefficient of each commodity. Annu. represents annualized statistic. Newey and West (1987) adjusted *t*-statistics are reported. The difference in Sharpe ratio test is conducted using stationary bootstrap (Politis and Romano, 1994). The sample covers the period from April 1982 to September 2022.

	HIGH		LOW	
	Unmanaged	Trailing-stop	Unmanaged	Trailing-stop
Panel A: Volatility				
Annu. Mean	5.0%	10.4%	1.7%	4.2%
t-stat	3.7	9.0	1.9	4.9
Annu. S.D.	9.1%	7.9%	6.6%	6.1%
Annu. Sharpe	0.54	1.41	0.26	0.73
Ho: $\text{Sharpe}_{\text{trailing}}$ > $\text{Sharpe}_{\text{unmanaged}}$	0.00		0.00	
Ho: $\text{Sharpe}_{\text{trailing HIGH}}$ > $\text{Sharpe}_{\text{trailing LOW}}$	0.00			
Panel B: Autocorrelation				
Annu. Mean	3.4%	7.0%	1.8%	6.7%
t-stat	3.1	7.2	1.6	6.4
Annu. S.D.	7.0%	6.3%	8.9%	7.8%
Annu. Sharpe	0.49	1.17	0.20	0.95
Ho: $\text{Sharpe}_{\text{trailing}}$ > $\text{Sharpe}_{\text{unmanaged}}$	0.00		0.00	
Ho: $\text{Sharpe}_{\text{trailing HIGH}}$ > $\text{Sharpe}_{\text{trailing LOW}}$	0.00			

Table 7 Re-entry and dynamic threshold

This table exhibits the performance statistics of momentum strategy based on (1) trailing-stop with a loss threshold of 10%, (2) trailing-stop with a loss threshold of 10% and a subsequent re-entry threshold of 1.5%, (3) trailing-stop with a dynamic loss threshold proxied by exponentially weighted volatility (EWV), and (4) trailing-stop with a dynamic loss threshold proxied by exponentially weighted volatility, and a subsequent re-entry threshold of 1.5%. The trailing-stop follows the same as in Table 3, while EWV is estimated with a center of mass of 60 days. A re-entry threshold of 1.5% means the proceeds from liquidating a stop-loss triggered commodity would be re-allocated back if the commodity recovers to a level that is 1.5% above the exit level in the same month. Annu. represents annualized statistic. Newey and West (1987) adjusted *t*-statistics are reported. Omega ratio is calculated using empirical distribution. The sample covers the period from April 1982 to September 2022.

	(1) Pre-defined threshold 10%	(2) Pre-defined threshold +Re-entry	(3) Dynamic threshold σ	(4) Dynamic threshold +Re-entry
Annu. Mean	6.5%	6.2%	7.5%	7.5%
t-stat	7.3	6.8	8.5	8.4
Annu. S.D.	5.6%	5.8%	5.7%	5.8%
Annu. Sharpe	1.15	1.07	1.32	1.30
Annu. D.S.D.	3.6%	3.7%	3.8%	3.8%
Annu. Sortino	1.79	1.66	1.99	1.99
Skewness	0.04	0.00	-0.08	-0.07
Excess Kurtosis	2.35	2.28	2.79	2.23
99% VaR (C.F.)	-1.0%	-1.0%	-1.1%	-1.0%
Max.DD	-11.9%	-12.1%	-10.6%	-11.9%
Omega	1.13	1.13	1.16	1.15

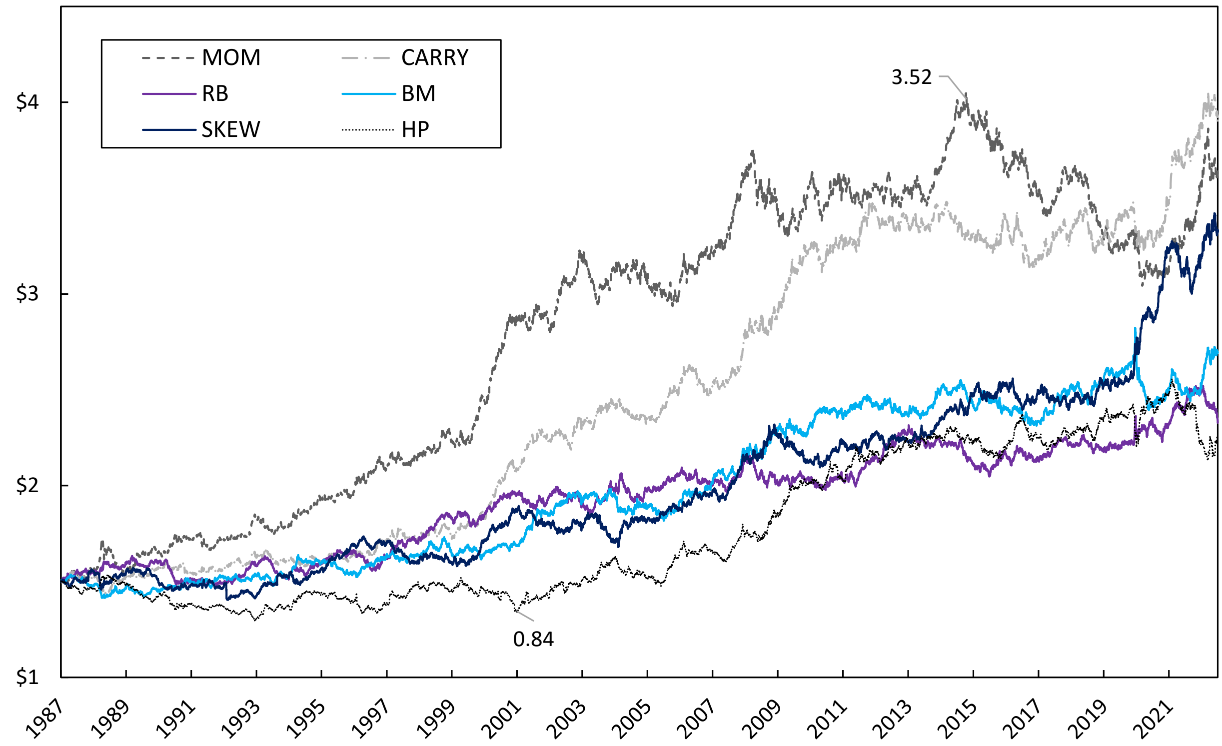
Table 8 Opportunistic weights

This table presents the performance statistics of opportunistically weighted momentum strategy with no-stop, trailing-stop (10% loss threshold), and trailing-stop (dynamic loss threshold). The opportunistic weights are rank-weight, volatility-managed, and risk-weight. Volatility-managed strategy portfolio follows the method in Moreira and Muir (2017), while rank-weight and risk-weight are consistent with Asness et al. (2013) and Moskowitz et al (2012), respectively. Annu. represents annualized statistic. Newey and West (1987) adjusted *t*-statistics are reported. Omega ratio is calculated using empirical distribution. The sample covers the period from April 1982 to September 2022.

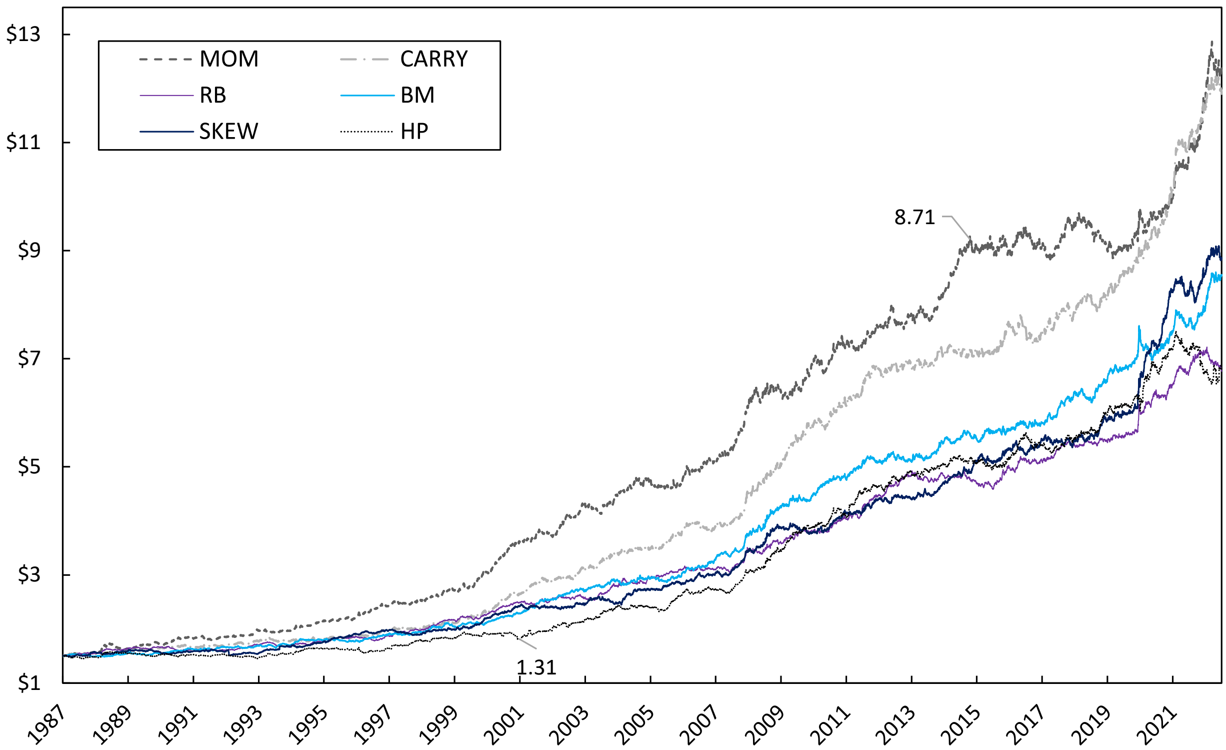
	Rank-weight			Volatility-managed			Risk-weight		
	No-stop	Trailing-stop	Dynamic threshold	No-stop	Trailing-stop	Dynamic threshold	No-stop	Trailing-stop	Dynamic threshold
Annu. Mean	3.9%	8.1%	8.4%	4.3%	7.2%	8.6%	7.2%	18.2%	20.6%
t-stat	3.3	7.3	7.6	4.5	8.0	9.5	4.8	13.4	17.2
Annu. S.D.	7.9%	7.1%	7.2%	6.1%	5.6%	5.7%	9.8%	8.6%	7.4%
Annu. Sharpe	0.49	1.14	1.17	0.71	1.28	1.51	0.73	2.12	2.80
Annu. D.S.D.	5.3%	4.5%	4.8%	3.8%	3.5%	3.5%	6.5%	5.3%	4.5%
Annu. Sortino	0.73	1.79	1.76	1.12	2.08	2.43	1.11	3.47	4.60
Skewness	-0.15	0.02	-0.09	0.04	0.10	0.07	-0.12	0.12	0.29
Excess Kurtosis	1.65	1.66	2.13	1.05	1.06	1.18	1.66	1.44	2.84
99% VaR (C.F.)	-1.4%	-1.2%	-1.3%	-1.0%	-0.9%	-0.9%	-1.7%	-1.3%	-1.2%
Max.DD	-31.6%	-14.2%	-12.8%	-23.6%	-12.3%	-9.4%	-37.6%	-13.1%	-9.0%
Omega	1.09	1.15	1.15	1.08	1.13	1.16	1.11	1.24	1.32
Sharpe improvement		1.3x	1.4x		0.8x	1.1x		1.9x	2.8x

Figure 1 Cumulative performance

A. Unmanaged factors



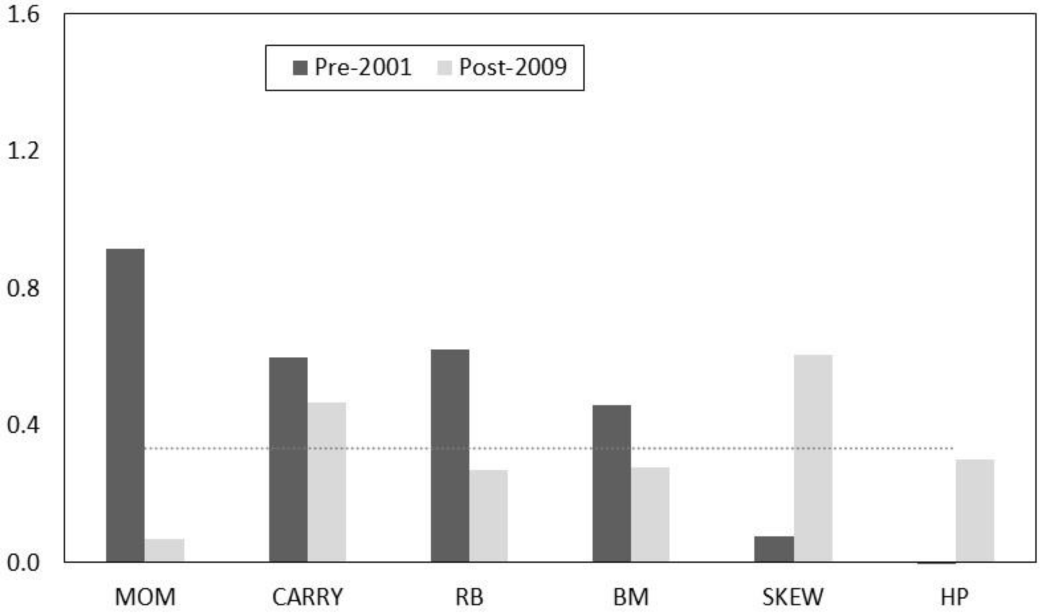
B. Factors with trailing-stop net of transactions costs



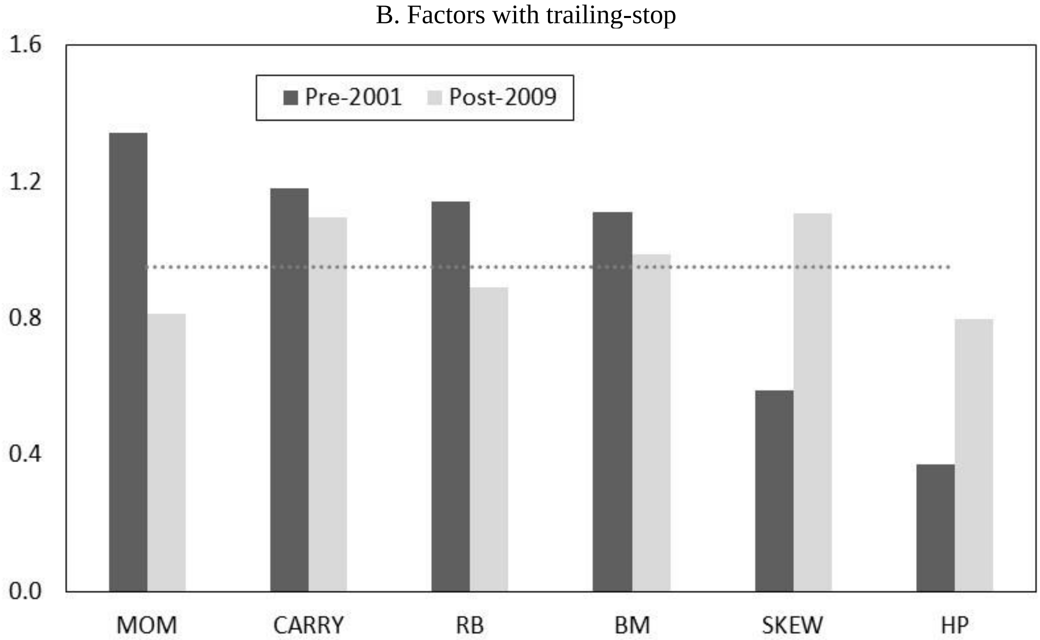
This figure illustrates the gross cumulative performance for unmanaged factor portfolios in Panel A, and the net cumulative performance for average trailing-stop factor portfolios in Panel B, using the strategy returns reported in Tables 2 and 4, respectively.

Figure 2 Sub-period Sharpe ratios

A. Unmanaged factors

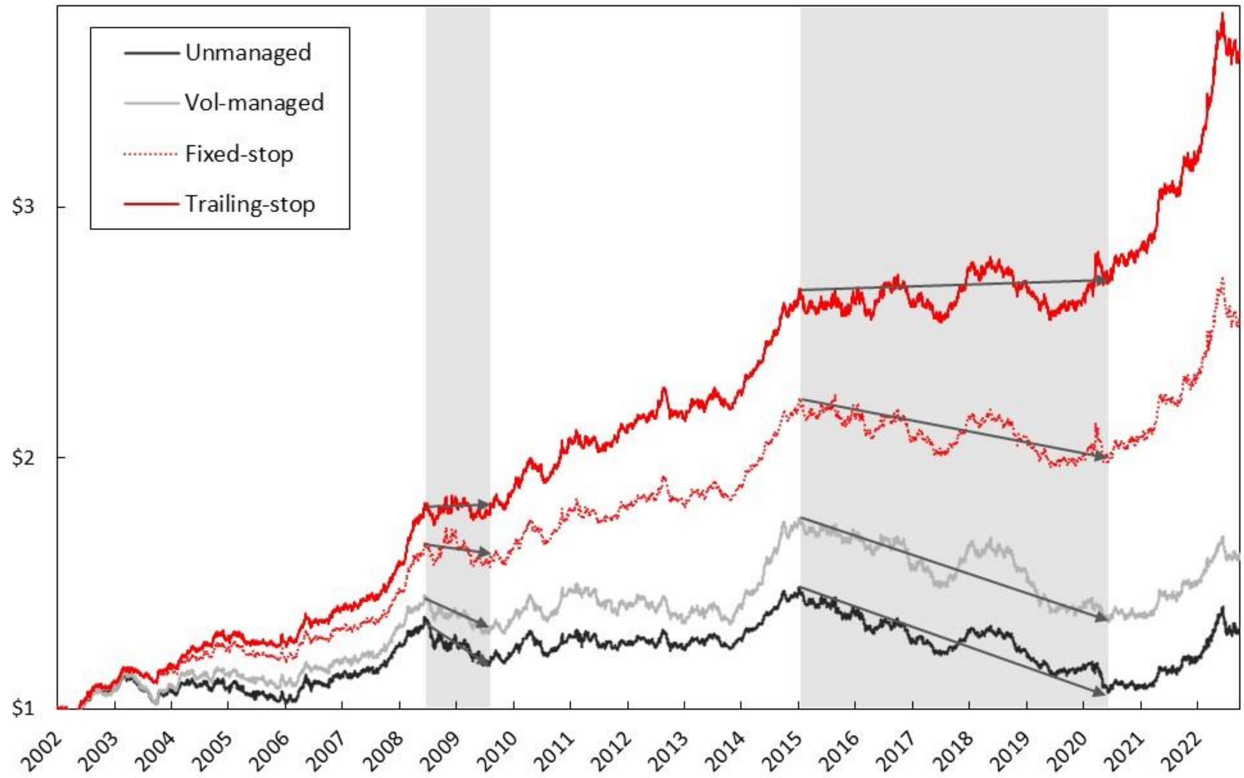


B. Factors with trailing-stop



This figure illustrates the subperiod Sharp ratios of factor portfolios with no-stop in Panel A and trailing-stop (loss threshold=10%) in Panel B, using the returns reported in Table 2 and Table 3.

Figure 3 Momentum, volatility management and stop loss



This figure plots the cumulative performance of momentum strategy with no-stop, volatility-managed, fixed-stop, and trailing-stop. The two largest drawdown periods are shaded in grey.