Time Series Reversal in Trend-Following Strategies[⋆,⋆⋆]

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Abstract

This paper empirically studies the reversal pattern following the formation of trend-following signals in the time series context. This reversal pattern is statistically significant and usually occurs between 12 and 24 months after the formation of trend-following signals. Employing a universe of 55 liquid futures, we find that instruments with sell signals in the trend-following portfolio ("losers") contribute to this type of reversal, even if their profits are not realised. The instruments with buy signals in the trend-following portfolio ("winners") contribute much less. A double-sorted investment strategy based on both return continuation and reversal yields to portfolio gains which are significantly higher than that of the corresponding trend-following strategy.

Keywords: Reversal, Trend-following Strategies, Market Timing, Time Series Momentum, Return Signal Momentum

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1. Introduction

The time series continuation of financial asset returns[1] has been widely studied in the academic literature, through investigating serial correlation (Fama and French, 1988; Lo and MacKinlay, 1988; Lewellen, 2002; DeMiguel et al., 2014) and time series momentum (TSM) (Moskowitz et al., 2012; Menkhoff et al., 2012; Georgopoulou and Wang, 2016). One practical application of time series continuation is the trend strategy which in recent years has become increasingly popular among hedge funds. However, what has not yet been examined exhaustively is the reversal effect which emerges after the continuation pattern.[2]

This paper empirically investigates the reversal property of various financial assets and analyses its relationship with continuation focusing exclusively on the time series dimension. Return continuation and reversals are usually closely related and discussed together in the literature. Historically, most studies have focused on cross-sectional momentum and reversals which have been documented internationally and in various financial assets.[3] According to a number of well-known behavioural theories by Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) among others, the rationale behind momentum and reversals is related to short-term under-reaction and delayed over-reaction. In the time series context, Moskowitz et al. (2012) also attribute the TSM effect to these behavioural features. Some recent studies attempt to explain the momentum and reversal effect using rational expectation models, for example, information percolation (Andrei and Cujean, 2017), heterogeneous beliefs (Ottaviani and Sørensen, 2015) and time-varying factor loading (Kelly

[1] Return continuation is seen in the finance literature as an analogue of momentum; see, among others, Rouwenhorst (1998) and Fama (1998). Sometimes these two words are used interchangeably. However, return continuation is applicable across a wider range of dynamics.

[2] Though some studies in the literature mention it, for example, Moskowitz et al. (2012) uncovered a long-term reversal beyond one year of TSM signals.

[3] Cross-sectional momentum and reversals have been extensively studied in various financial markets, see, e.g., the US stock market (De Bondt and Thaler, 1985; Lo and MacKinlay, 1990), international stock markets (Fama and French, 1998; Rouwenhorst, 1998), country indices (Bhojraj and Swaminathan, 2006), various asset classes (Asness et al., 2013), and commodities (Miffre and Rallis, 2007; Gorton et al., 2013).

et al., 2021). The above-mentioned literature suggests the existence of a certain linkage between time series continuation and reversal.

Recently, however, Conrad and Yavuz (2017) argue that cross-sectional momentum and reversals are not pervasively linked to each other. This finding contradicts the conventional view that, if momentum and reversals are linked, the securities which exhibit momentum should also exhibit reversals soon afterwards. This increases our interest in investigating time series continuation and time series reversal.

In our empirical study, we decompose different trend-following strategies based on a portfolio of 55 of the world's most liquid commodity and financial futures. We find that time series momentum and reversal do *not* occur in the same group of assets. Those assets that show strong momentum profit do not experience significant reversal. This means that we arrive at a conclusion similar to that of Conrad and Yavuz (2017) regarding the cross-sectional analysis. Interestingly, we observe that instruments with sell signals (past "losers") contribute to this type of reversal. By contrast, the instruments with buy signals (past "winners") contribute much less.

Our finding challenges the prominent behavioural theories in the areas of momentum and reversal, especially the unified theory of Hong and Stein (1999). According to the latter, momentum and reversal can be generated simultaneously by a model based on a single risky asset. Therefore, Hong and Stein (1999) provide the behavioural explanation for momentum and reversal more in the time series context rather than in the cross-sectional one. The empirical results in the present study, suggest that time series momentum is *not* linked to time series reversal, implying that the unified theory of Hong and Stein (1999) could be misleading.

But, our results are consistent with several studies proposing that momentum and reversal should be treated as separate effects. George and Hwang (2004, 2007) put forward two separate theories to explain the two phenomena in which momentum is caused by anchoring bias whereas reversal is linked to capital gain lock-in theory. Yao (2012) suggest that the reversal effect could be driven by the January seasonality in the stock market, whereas momentum is not. A number of empirical studies suggest that reversal does not necessarily follow momentum in stock markets; see, e.g., Lee and Swaminathan (2000), Cooper et al. (2004), and Conrad and Yavuz (2017). Li and Galvani (2018) also find a similar result in the corporate bond market.

One effective way to examine time series reversal in financial assets is to employ contrarian trend-following strategies. Trend-following trading signals depend on their own past returns without a cross-sectional comparison. The simple moving average is one of the most intuitive trend-following strategies based on technical analysis. Recently, researchers have attributed the profitability of trend-following strategies to time series continuation and introduced more advanced methods such as TSM, see Moskowitz et al. (2012), and return signal momentum (RSM), see Papailias et al. (2021). Therefore, we base our investigation on these two momentum approaches in the time series domain.

We first capture the timing of time series reversal and find that it occurs from 12 to 24 months after the portfolio formation. This finding differs from the traditional cross-sectional reversals which usually last longer, between 2 and 5 years after the portfolio formation date.[4] Moskowitz et al. (2012) document a strong short-term (1–12 month) TSM, but no statistically significant long-term (2–5 years) reversal.

Like Conrad and Yavuz (2017), we classify instruments in trend-following strategies into four groups: "realised winner", "realised loser", "contrarian winner", and "contrarian loser". The realised winner sub-portfolio consists of instruments with positive trend-following trading signals (winners) whose profits are realised in the subsequent investment horizon (1–12 months). The realised loser sub-portfolio consists of instruments with negative trading signals (losers) that later produce negative returns, meaning that the losers portfolio realises its profit. By contrast, the contrarian winners and contrarian losers include instruments with positive and negative signals that fail to gain profits. The construction of the above four sub-portfolios allows us to see which part of the trend-following returns contributes most to time

[4]Of course, we cannot rule out the possibility that this difference might occur due to various factors such as the sample period and the specific market. For example, cross-sectional reversals require a long-term ranking period of 2–5 years in stock markets (De Bondt and Thaler, 1985), but reduce to 1.5–3 years in commodity markets, as suggested by Bianchi et al. (2015). Bhojraj and Swaminathan (2006) find that the reversals of country indices occur from 2 to 3 years after the 1-year momentum effect.

series reversal.

Next, to properly investigate the relationship between time series continuation and reversal, we perform both sign analysis and performance evaluation to determine the future returns of the above-mentioned portfolio segmentations. In the sign analysis, we find that the loser sub-portfolios, no matter whether their profits are realised or not, i.e. both realised losers and contrarian losers, experience strong subsequent reversal. By contrast, the results from the winner subgroups lead to mixed answers: the realised winners exhibit strong reversal, while the contrarian winners do not.

The results of performance evaluation again suggest that the loser subgroups, especially the contrarian losers, contribute the most to the time series reversal. This conclusion is consistent with the results about cross-sectional reversal noted by Conrad and Yavuz (2017); they do not observe statistically significant returns for realised portfolios (realised winners minus realised losers) but do observe significant returns for contrarian portfolios (contrarian winners minus contrarian losers). We take a step further by showing that the positive returns generated by the realised winner and the realised loser offset each other when considered together. However, the reversal of a contrarian loser is much stronger than that of a contrarian winner, which leads to more statistically significant results for contrarian portfolios.

A double-sorted trading strategy is then constructed, holding the four previously mentioned decompositions of trend-following strategies. We call this a "trend-following reversal strategy", since it combines time series continuation and reversal. It differs from the widely documented cross-sectional reversal as it does not require any relative return comparisons. For each single asset, we first sort on the 12-month returns skipping the most recent 12 months (ranking period 1) and second sort on the recent 12-month returns (ranking period 2), and then invest in the following month. For instance, a realised winner strategy contains assets with positive returns in both ranking periods, 1 and 2. Figure 1 illustrates how these four double-sorted strategies are constructed. Our results suggest that holding the realised winner and the contrarian loser subgroups can yield annualised returns as high as 22% and 24%, respectively. These strategies are liquid and well diversified in the context of real market trading.

To understand the risk exposure of these strategies, we run factor regressions on the trend-following reversal returns against a series of standard financial market risk factors. The regression output reveals that the trend-following reversal returns are closely related to the market as well as the momentum factors. However, certain strategies, especially the contrarian loser, produce significant alphas which are not explained by the popular risk factors. Moreover, the contrarian loser represents an effective strategy for investors to avoid momentum risks, owing to its low correlation with trend-following factors.

In short, the contribution of this paper to the literature is threefold. First, we find that time series reversal usually occurs between 12 and 24 months after the formation of trend-following strategies, which is much shorter than the findings documented in the cross-sectional reversal literature. Second, we determine which of the trend-following components contributes most to the reversal profits; this finding contradicts the prominent behavioural theory of Hong and Stein (1999). Third, we document a trend-following reversal strategy earning significant abnormal returns based on both time series continuation and reversal.

The rest of the paper is organised as follows. In Section 2 we describe our data collection and transformation methods, and explain the intuitions of different trend-following trading signals. Section 3 presents the performance results of multiple trend-following strategies and uncovers the timing of time series reversal. In Section 4, we perform two analyses—sign analysis and sub-portfolio performance evaluation—to investigate the reversal property of each subgroup via a decomposition of trend-following strategies. Section 5 introduces the trend-following reversal strategy and explores its factor loadings. Finally, Section 6 summarises the conclusions.

2. Data and Trading Signals

2.1. Future Contracts and Other Data

We collected data for 55 of the world's most liquid exchange traded futures from January 1985 to March 2015. Such a dataset is similar to that used in TSM studies by Moskowitz et al. (2012), and also in other trend-following studies, e.g., Hutchinson and O'Brien (2015), Kim et al. (2016), and Baltas and Kosowski (2013). The pool consists of 24 commodity futures, nine foreign exchange futures, nine equity indexes of developed countries, and 13 government bonds of various maturities for six developed countries. The data were sourced from Bloomberg and DataStream; see Section A in the Online Appendix for more details.

The futures prices of the nearest contracts are concatenated to form long time series for reasons of tractability. For robustness, we also splice the futures prices based on the trading volume. To mimic a real-life trading situation, once the trading volume of the second nearest contract exceeds that of the nearest one, we do not allow the nearest contract to be chosen again even if its trading volume subsequently rise higher. The results show that the descriptive statistics for our spliced data do not vary greatly from those obtained using the nearest contract data.

As in Moskowitz et al. (2012) and Papailias et al. (2021), we compute the daily excess returns for each instrument and calculate its cumulative returns. This allows us to proxy for prices and compute our periodic returns. In this paper, we focus on monthly returns, which are calculated from the previously mentioned daily excess cumulative return series. This allows us to directly compare our results with the literature.

In Table 1, we summarise the descriptive statistics of the original series. The table presents the date of the first available data point for each series, and the annualised arithmetic mean, standard deviation, skewness, and kurtosis of the monthly excess returns of each individual instrument. The last available month for all series is March 2015. Most futures have positive long-term annualised means, while some of the currency futures show slightly negative values. We found that volatility varies across different asset classes. The volatilities of commodities and equities are much higher than those of currencies and bonds. To illustrate, Natural Gas futures have a volatility of 54.39%, whereas the 2-year maturity US bond (US2) offers the lowest volatility at 2.84%.

For the factor regression analysis which follows, we used Bloomberg to collect the monthly returns of four major financial asset class indices: the MSCI World Index

(MSCI), S&P GSCI, Barclays Aggregate Bond Index (BOND), and US Dollar Index (USDI). The percentage changes of Fama and French (1993) three factors (SMB, HML), Fama and French (2015) five factors (RMW, CMA) as well as the risk free rate were downloaded from Kenneth French's website.[5] Finally, the Value (VAL) and Momentum (MOM) Everywhere factors of Asness et al. (2013) are available from the AQR website.[6] Data for all the above are available from January 1985 to March 2015.

2.2. *Trading Signals of Trend-Following Strategies*

Two types of trend-following strategies are employed in this study, TSM and RSM.[7] Previous studies suggest that 12 months is the optimal look-back period (j) for trend-following strategies, and holding period (h) usually ranges from 1-12 months, see, among others, Moskowitz et al. (2012), Zhou and Zhu (2013) and Papailias et al. (2021). Hence, in this study we adopt a 12-month value of j for all the benchmark strategies.[8]

The TSM signals are generated in the same way as in Moskowitz et al. (2012), where a long position is indicated if the period return is positive, i.e., the annual return using $j = 12$; otherwise, the investor opens a short position on security s. The TSM returns are given as follows:

$$R_t^s | PR_{t-12,t-1}^s = \begin{cases} +r_t^s, & PR_{t-12,t-1}^s > 0 \\ -r_t^s, & PR_{t-12,t-1}^s < 0 \end{cases}, \tag{1}$$

where $PR_{t-12,t-1}^s$ is the period return of instrument s during time $t-12$ to $t-1$, as suggested by our look-back period $j = 12$.

The RSM signals are generated when the empirical probability of the positive

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[6] https://www.aqr.com/

[7] We also examine the properties of time series reversal based on a simple moving average (SMA) trading rule, which is one of the most fundamental trend-following strategies. The results of SMA are very similar to those of TSM and RSM, and are discussed in Section B of the Online Appendix.

[8] We also have additional results based on look-back periods other than 12 months which are available upon request.

returns in the past 12 months exceeds a certain threshold value. Following Papailias et al. (2021), we calculate the RSM returns using the following equation:

$$R_t^s | P_{t-12,t-1}^s, q = \begin{cases} +r_t^s, & P_{t-12,t-1}^s > q \\ -r_t^s, & P_{t-12,t-1}^s < q \end{cases}, \tag{2}$$

where $P_{t-12,t-1}^s$ denotes the probability of positive returns of the past 12-month period, and q is the threshold value. For simplicity, we select the most intuitive threshold value, $q = 0.5$, indicating that a long position is established when the empirical probability $P_{t-12,t-1}^s$ is greater than 0.5, whereas a short position is established when this probability is smaller than 0.5.

In line with Moskowitz et al. (2012), when investigating the profitability of the trend-following reversal strategies, we implement a volatility scaling approach to weight the portfolio. This approach calculates the portfolio weights, or the position sizes for individual instruments, in a time-varying way. Specifically, we control the position size of each instrument to be inversely proportional to its ex-ante realised volatility σ_t, which is calculated as follows:

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2, \tag{3}$$

where the parameter δ is defined when the centre of mass is equal to 60 days. The benefit of controlling for volatility is that it can lead to more profitable investment strategies, because it takes a crucial role in adjusting the position size of momentum strategies (Barroso and Santa-Clara, 2015; Kim et al., 2016; Papailias et al., 2021).

To form a portfolio of various instruments, we calculate the trend-following position signals in the same way as in Equations 1 and 2, and allow the portfolio weight for each instrument to be given as a function of its ex-ante realised volatility σ_t^2. We use a target value for the annual volatility of 40% as in Moskowitz et al. (2012). This aligns our results with the current literature and also mimics a real-world trading scenario with a capital margin of about 5–20%. Then, the TSM and RSM position returns for an asset s are given by:

$$R_t^s|PR_{t-12,t-1}^s = \begin{cases} +r_t^s \frac{40\%}{\sigma_{t-1}^s}, & PR_{t-12,t-1}^s \geqslant 0 \\ -r_t^s \frac{40\%}{\sigma_{t-1}^s}, & PR_{t-12,t-1}^s < 0 \end{cases}, \tag{4}$$

$$R_t^s|P_{t-12,t-1}^s, q = \begin{cases} +r_t^s \frac{40\%}{\sigma_{t-1}^s}, & P_{t-12,t-1}^s > q \\ -r_t^s \frac{40\%}{\sigma_{t-1}^s}, & P_{t-12,t-1}^s < q \end{cases}. \tag{5}$$

Finally, for a universe of S assets, the portfolio return is calculated as:

$$R_t^p = \frac{1}{S} \sum_{s=1}^{S} R_t^s|P_{t-12,t-1}^s, q, \tag{6}$$

where R_t^s is the risk-adjusted return of each trend-following strategy for each individual instrument, using the above volatility scaling method, and R_t^p is the mean of all the R_t^s.

3. Time Series Reversal

According to the results of the OLS pooled regressions in Moskowitz et al. (2012)[9], time series reversal pattern is statistically insignificant. However, they have only used single month return and return sign as the explanatory variables, which are not exactly equivalent to the blocks that form time series momentum signals. Time series momentum considers the past month returns as a whole, for instance, period return over the past 12 months. By contrast, Papailias et al. (2021) examined the predictive power of RSM strategies by using a lagged average of return signs P. P covers all the return signs in the look-back period and can directly form the RSM signal. Their results suggest that a significant reversal pattern exists following the short-term momentum effect.

In this section, we extend the above studies by adding more explanatory variables to investigate the predictive power of TSM and RSM signals. First, as in Moskowitz et al. (2012), we regress the volatility-scaled return r_t^s/σ_{t-1}^s on the lagged signal

[9]See Figure (1) in their paper.

month return $r^s_{t-h}/\sigma^s_{t-h-1}$ and lagged sign of return, $sign(r^s_{t-h})$. The equations are specified as follows:

$$r^s_t/\sigma^s_{t-1} = \alpha + \beta_h r^s_{t-h}/\sigma^s_{t-h-1} + \epsilon^s_t, \tag{7}$$

$$r^s_t/\sigma^s_{t-1} = \alpha + \beta_h sign(r^s_{t-h}) + \epsilon^s_t, \tag{8}$$

where r^s_t is the excess return of asset s in month t adjusted by its available ex ante volatility σ^s_{t-1}. $sign(r^s_{t-h})$ takes the value +1 if $r^s_{t-h} \geqslant 0$ or -1 if $r^s_{t-h} < 0$. h is the number of lags used in the regressions which ranges from 1 to 60. Finally, ϵ^s_t denotes the error term, which has zero mean and finite variance.

Second, we repeat the above regressions by employing two alternative regressors: (i) the 12-month period return $PR_{t-h-11,t-h}$, and (ii) the 12-month mean return sign $P_{t-h-11,t-h}$. These two variables are directly related to the formation of TSM and RSM signals. Finally, the TSM and RSM signals, namely $S^{TSM}_{t-h-11,t-h}$ and $S^{RSM}_{t-h-11,t-h}$, are used as the third set of regressors. TSM and RSM signals take the value of +1 when $PR_{t-h-11,t-h}$ and $P_{t-h-11,t-h}$ indicates a buy signal, and the value of -1 for a sell signal.

In order to avoid the return co-movement across different futures contracts and keep the regression results adjusted for time series dependence, we calculate the t-statistics based on the robust standard error method proposed by Thompson (2011). This approach addresses the problem that the residuals are correlated across both firms (in our case, different futures contracts) and time.[10] Therefore, it generates consistent asymptotic efficiency standard errors and perform relatively well in small sample situations.

Figure 2 shows the time series predictability of the previously mentioned three sets of explanatory variables on future returns. In Panel A, we can see that it is not

[10]Moskowitz et al. (2012) claimed that their OLS pooled regression using volatility scaled return is equivalent to a GLS approach. This means that they did use standard errors that cluster by both futures contract and time effect. However, they did not adjust for simultaneous correlation across both futures contract and time.

easy to capture a persistent reversal pattern following the first 12 months of return continuation. The results are consistent with Moskowitz et al. (2012). However, if we use an alternative set of regressors which covers all the information over the look-back period, the time series reversal is more observable. As shown in Panel B, the 12 months period return and mean return sign lead to a strong reversal after the short-term momentum effect. Between month 12 and 24, the t-statistics of beta coefficients are lower than -3 for most months, indicating statistical significance at the 1% level. Interestingly, time series reversal is "double-humped", with t-statistics also being significant during months 36–60. Although the average t-statistics for months 36–60 are only slightly lower than those during months 12–24, they do not produce an obvious contrarian profit.[11] Therefore, we conclude that this 36–60 month reversal is weak and decide not to cover it in the paper.

The results shown in Panel C of Figure 2 further validate the existence of time series reversal. Both TSM and RSM signals are positively correlated with the future returns in the short-run. In the medium-run, they experience a statistically significant reversal. The next two subsections inspect the timing and profitability of time series reversal.

3.1. Return Decays of Multiple Holding Periods Strategies

In an attempt to evaluate trend-following strategies with multiple holding periods (i.e., holding the underlying assets for more than 1 month), we find that these strategies never outperform the same strategy using a 1-month holding period. A similar result was also found in Moskowitz et al. (2012). The authors tested the alphas of different TSM strategies with various holding periods demonstrating that the 1-month holding period strategy specification outperforms all other specifications with holding periods of more than 1 month. The longer the holding period, the lower the alpha, indicating that trend-following profits are gradually offset by the subsequent reversals.[12]

[11] This is discussed in the next subsection and reflected in return decays shown in Figure 3.
[12] See Table 2 in Moskowitz et al. (2012).

To thoroughly investigate the phenomenon of return decays, we examine two trend-following trading strategies—TSM and RSM—based on a look-back period of $j = 12$. Figure 3 illustrates the decay in trend-following strategies as the holding period h increases. We report the annualised returns of the above strategies under different holding periods, for $h = \{1, 2, 3, 6, 9, 12, 18, 24, 30, 36, 48, 60\}$ months. From the figure, we can see that returns gradually decrease when moving from $h = 1$ to $h = 24$, indicating that the benefit of return continuation is largely offset by the subsequent time series reversal. The average returns remain stable after a holding period of more than 24 months, meaning that the reversal pattern stops after the end of the second year. The effect of the long-term reversal (36–60 month) uncovered in the previous section is weak, since it does not further reduce the mean returns. These results are consistent across the two strategies.

3.2. Timing of Time Series Reversal

If time series reversal ensues after the formation of trend-following signals, when does it begin and end? To answer this question, we implement TSM and RSM contrarian trend-following strategies using different time lags. This means that we take the opposite positions to those suggested by the trend-following strategy signals but using different lags from 2 to 36 months. Therefore, a total of 70 (35×2) lagged contrarian strategies are implemented using the trading signals with a holding period of $h = 1$.

Figure 4 shows a plot of the annualised mean returns of the aforementioned contrarian strategies, revealing the timing of the time series reversal. In the short term, contrarian strategies produce negative returns (2–10 months for TSM and 2–12 months for RSM). The negative short-term returns are followed by an intermediate reversal, which usually lasts for more than a year (12–26 months for TSM and 13–25 months for RSM). The portfolio returns become negative again after the intermediate-term reversal. None of these contrarian strategies produce statistically significant returns that outperform a naïve 1/N buy-and-hold strategy. Hence, simple contrarian trend-following strategies do not outperform the market.

Yao (2012) argues that January seasonality is one of the main reasons for contrarian returns. According to her study, the classic cross-sectional contrarian strategy results could be overturned in the US stock market when controlling for January seasonality. In that sense, we also examine the impact of January seasonality on time series reversal (TSM and RSM) reporting in Section C of the Online Appendix. We find that the profitability of time series reversal is not centralised in January, but is shown in the other 11 months as well. This can be explained by the fact that our universe includes different types of futures contracts whereas the January effect is more commonly found in equity markets.

Since these contrarian strategies are performed using the volatility scaling method, low volatile instruments, e.g., bond futures, may dominate the portfolio. As shown in Table 1, the volatilities of bond futures are mostly below 10%, which are much lower than the volatilities of the three remaining asset classes. Therefore, we also apply contrarian strategies the same as in Figure 4 using the sample portfolio but excluding all bond futures. We note that time series reversal still holds after controlling for bond futures. These results are presented in Section D of the Online Appendix.

In summary, time series reversal is a pervasive but not economically significant phenomenon across the two strategies and time horizons. Normally, it occurs between the end of the first year and the end of the second year, after the trend-following signal is generated. The results differ from those in the existing literature, where the long-term reversals, cross-sectional or time series, usually last for much longer.[13] Time series reversal vanishes after the end of the second year.

4. Linkage Between Time Series Momentum and Reversal

In this section, two approaches are adopted to investigate the linkage between time series momentum and reversal: the sub-portfolio sign analysis and the performance evaluation. These two analyses further track the decomposed trend-following

[13] For example, cross-sectional reversals require a long-term ranking period of 2–5 years in stock markets (De Bondt and Thaler, 1985) and 1.5–3 years in commodity markets (Bianchi et al., 2015). Bhojraj and Swaminathan (2006) find that the reversals of country indices occur from 2 to 3 years after the 1-year momentum effect. Moskowitz et al. (2012) document a statistically insignificant long-term (2–5 years) TSM reversal.

portfolio beyond the conventional holding period of 1–12 months. This helps us to understand the behaviour of the four sub-portfolios and illustrates which one contributes most to the time series reversal. The performance evaluation period is extended to a post-holding period of 13–60 months after the signal.[14]

The time horizon is divided into three parts: (i) the 12-month look-back period j prior to month 1 (see ranking period 1 in Figure 1); (ii) the holding period h ranging from month 1–12 (see ranking period 2 in Figure 1);[15], and (iii) the 13–60 month post holding period. As before, the same two trend-following strategies—TSM and RSM—are performed. A rolling method is employed to generate and renew the trading signals every month.

Analogous to Conrad and Yavuz (2017), we decompose the trend-following portfolio into four subgroups: realised winner, realised loser, contrarian winner, and contrarian loser. First, based on each instrument's signals formed in ranking period 1 ($j = 12$), we divide the entire portfolio into winners and losers. We then classify the winner and loser portfolios into the above-mentioned four subgroups by evaluating whether or not their profits are realised during ranking period 2 ($h = \{1, 2, 3, 6, 12\}$).[16]

More specifically, the realised winner represents a sub-portfolio with instruments that were past winners during period j and continue to generate positive returns during period h. The realised loser represents a sub-portfolio that consists of past losers during period j that continue to generate negative returns during period h. By contrast, the contrarian winner represents a sub-portfolio comprising past winners during period j, which then fail to generate positive returns during period h. The contrarian loser represents a sub-portfolio with past losers that go on to generate positive returns during period h. These four subgroups cover all the assets in the

[14]Post-holding period study of momentum strategies was also seen in Jegadeesh and Titman (2001), who tracked cross-sectional momentum performance up to 60 months after the formation of momentum signals.

[15]We leave $h = \{1, 2, 3, 6, 12\}$ as this is usual in calculating momentum profits, see, e.g., Moskowitz et al. (2012).

[16]Figure 1 illustrates how these four sub-portfolios are constructed.

trend-following portfolio, as either a positive (winner) or a negative (loser) signal is assigned to each instrument at each point in time.

4.1. Sub-portfolio Sign Analysis

Sign analysis allows us to see which sub-portfolios exhibit strong time series reversal. Here, we calculate the frequency of positive signs for sub-portfolio components during the post trend-following holding period (13–60 months). We divide the post holding period into four separate periods, each lasting for one year. These are 13–24 months, 25–36 months, 37–48 months, and 49–60 months after portfolio formation.

Based on the above-mentioned settings, (j, h) sub-portfolios are established for analysis. For instance, in a $(12, 12)$ scheme, the trend-following signal (winner/loser) at time t is based on the returns during months $t - 11$ to t for each individual instrument. Then, we determine whether the profits of these winners and losers are realised or not during the next $h = 12$ periods, i.e., $t + 1$ to $t + 12$. Finally, we calculate how many instruments in each subgroup generate positive returns over months $t + 13$ to $t + 60$ and report the rate of positive returns. The same process is followed for each month from January 1985 to March 2015.

Our primary focus is on the results during months 13–24 of the post holding period, when time series reversal occurs. Figure 5 shows these results as a plot of the aggregated probability of positive signs for all the instruments classified as one of the four sub-portfolios.[17] The loser subgroups, i.e., the realised losers and the contrarian losers, exhibit positive rates of around 65–66% and 63%, respectively, during this period. These success rates are much higher than the unconditional positive rate of 58.7%, which was calculated using all the 55 individual instruments from January 1985 to March 2015. We also employ a proportion test developed by Newcombe (1998a,b) to examine whether the success rates of these subgroups are statistically different from those for the unconditional rate. The results suggest that the rates of both the realised loser and contrarian loser sub-portfolios are significantly different

[17] We also show results of sign analysis for the rest of the post holding period (25–60 months) using different (j, h) settings. These results are reported in Section E of the Online Appendix.

at the 1% level. Moreover, the differences persist across different (j, h) schemes and strategies.

By contrast, the winners, i.e. the realised winners and the contrarian winners, show positive rates lower than the unconditional rate, at about 55–56% and 57%, respectively. The positive rates of the realised winner subgroups are significantly lower than the average at the 1% level, while those of the contrarian winner are not. To summarise, both of the loser sub-portfolios exhibit strong time series reversal. In the winner group, only the realised winners show statistically significant reversal.

Our findings indicate that the instruments which contribute to trend-following profits, or the instruments that fall into the realised winner and realised loser subgroups, do experience a strong reversal during the time series reversal period (13–24 months). The two remaining portfolios, i.e., the contrarian winners and contrarian losers, which do not generate trend-following profits, behave differently to each other. The contrarian losers still produce significant reversals, whereas the contrarian winners do not.

After the 13–24-month period, time series reversal ceases to occur. The superior positive rates of the realised loser and contrarian loser subgroups are discontinued during the subsequent holding periods of 25–36 months and 37–48 months. Finally, during the 49–60-month period, the rates increase slightly again, to around 62% and 61%, respectively. Similarly, the rates for the realised winners rebound to the unconditional rate during the 25–36-month and 37–48-month periods, after which they fall back to approximately 57–58% in the 49–60-month period. Finally, the positive rates of the contrarian winner are not statistically significant over the majority of the sample. Details of the above results are available in Section E of the Online Appendix.

4.2. Sub-Portfolio Performance

To further investigate how each sub-portfolio evolves during the 4-year post-holding period (13–60 months), we evaluate the strategy performance with the underlying instruments of the four subgroups for 12 months. Four sets of strategies, with holding periods of 13–24 months, 25–36 months, 37–48 months, and 49–60 months after the formation of TSM and RSM signals, are run to match the previous analysis. The realised winner, realised loser, contrarian winner, and contrarian loser groups are determined using the previously described (j, h) schemes.

Table 2 summarises the performance of TSM and RSM strategies in subgroups categorised using the $(12, 12)$ scheme from January 1985 to March 2015.[18] Trading signals for four different 12-month holding periods are generated, covering the 13–60 months after the formation of the original TSM and RSM signals. Following the methodology in Jegadeesh and Titman (1993), we compute the 12-month holding period returns by averaging the returns of overlapping portfolios. We use equally weighted method to construct each sub-portfolio. For each strategy, the annualised mean return, annualised volatility, Sharpe ratio, and maximum drawdown are reported.[19] Throughout the strategy evaluation part of this paper, we compute the t-statistics to check whether the returns are significant or not, using the Newey–West standard error of lag(4)(Newey and West, 1986).

As shown in Table 2, the contrarian loser portfolio generates the highest returns and Sharpe ratio across the four subgroups during the first year of the post trend-following holding period (13–24 months).[20] The Newey–West t-statistics suggest that all the trend-following contrarian loser sub-portfolios produce positive returns at a 1% level of significance. The realised losers also display strong reversals during both the 13–24-month and the 25–36-month periods. However, the reversal pattern is much stronger during the 25–36-month period, when all the returns of the three strategies are significant at the 1% level. Both of the loser groups, which one would expect to perform poorly (short signals) during the trend-following holding period, exhibit strong reversal during the 13–24- and 13–36-month periods. These results are consistent with the previous sign analysis.

[18]Similar tables using the $(12, 1)$, $(12, 3)$, and $(12, 6)$ schemes are available in Section F of the Online Appendix. The results are robust across different trend-following holding periods h.

[19]Details of the strategy evaluation criteria are listed in Section G of the Online Appendix.

[20]For robustness check, in Section H of the Online Appendix, we perform the same analysis by assigning the same weight (25%) for each asset class and find the consistent results. The contrarian loser show the strongest reversal effect which is statistically significant at the 1% level.

Next, we move on to the winner subgroups. The realised winner generally does not exhibit strong returns except in the TSM case, where it barely produces an annualised return of 4.4% (significant at the 10% level). The contrarian winner sub-portfolio, which does not produce any significant returns during the 13–24-month period, produces strong positive returns during the 25–36-month period. After the first and second year of the post trend-following holding period, neither time series continuation nor reversal exists.

Conrad and Yavuz (2017) conclude that the realised portfolio, namely realised winners minus realised losers, which contributes to the momentum profits, does not contribute to the 13–24-month reversal. According to our results, this is because the difference between realised winner and realised loser during this period is very small (0.002 for TSM and 0.001 for RSM). Therefore, their returns are offset when one is subtracted one from the other. Conrad and Yavuz (2017) also claim that the contrarian portfolio, namely contrarian winners minus contrarian losers in our case, generates significant returns. Our empirical finding suggests that in our sample this is solely because of the contrarian losers.

If we consider the realised portfolio (realised winner minus realised loser)and the contrarian portfolio (contrarian winner minus contrarian loser), we find that our results are consistent with those of Conrad and Yavuz (2017). The assets that show momentum effect do not display strong long-term reversal, whereas the assets that exhibit reversal do not experience short-term momentum. Therefore, we conclude that time series momentum and reversal are not linked. Our conclusion challenges the unified theory of Hong and Stein (1999) which used a single asset model to illustrate both momentum and reversal. It may indicate that momentum and reversal are two separate phenomena.

To sum up, during the first year of the post trend-following holding period (13–24 months), time series reversal is statistically significant when sub-portfolios are considered. These patterns cease to hold beyond the end of Month 24. The realised winners and the contrarian winners, which are supposed to produce high returns, i.e., with buy signals, no longer earn significant profits after the trend-following holding period. On the other hand, the realised losers and the contrarian losers generate high returns, indicating strong reversal. Among the four subgroups, the contrarian loser subgroup shows the strongest reversal during the 13–24-month period.

5. Trend-Following Reversal Strategies

In this section, we introduce a new type of strategy that combines time series continuation and reversal, called the trend-following reversal strategy. Then, the risk exposure of trend-following reversal strategy is studied by employing multi-factor models.

5.1. A Decomposition of Trend-Following Strategies

To construct such a strategy, we use the same decomposition as in Section 4, namely realised winner, realised loser, contrarian winner, and contrarian loser subgroups, using a (j, h) scheme, where $j = 12$ and $h = \{1, 3, 6, 12\}$. The investment decision is made in the following month to avoid look-ahead bias. Trading signals are generated every month, so that the position sizes are rebalanced every month. To mimic a real world situation, we use a time-varying volatility scaling method to adjust the portfolio weights, following the work of Moskowitz et al. (2012). In this method, the weight for each individual instrument is inversely proportional to its realised ex-ante volatility.

The trend-following reversal strategy is a type of double-sorted strategy in which the trend-following ranking (j) is the first sort and the realised/unrealised profit (h) is the second sort.[21] The trend-following reversal strategy maintains its tractability and requires no external information other than the price returns. It also makes more sense, as the first ranking period is the conventional trend-following look-back period, and the second ranking period is the trend-following holding period.

[21] There are numerous studies which employ and evaluate double-sorted momentum strategies. Lee and Swaminathan (2000), Sagi and Seasholes (2007), Fuertes et al. (2010), and Conrad and Yavuz (2017) combine momentum signals with other external variables such as term structure, firm-specific attributes, trading volume, and value/book-to-market ratios as the second criterion, while Bianchi et al. (2015) combine a long-term momentum ranking with a medium-term momentum ranking and find superior abnormal returns.

Table 3 summarises the performance of the 12 decomposed sub-portfolios under three trend-following categories using $(j, h) = \{(12, 1), (12, 3), (12, 6), (12, 12)\}$ double-sorting periods. As suggested by the Newey–West t-statistics, the realised winner and the contrarian loser sub-portfolios produce statistically significant returns at a 1% level in all cases, regardless of the trend-following strategies and the ranking scheme chosen. The annualised mean returns of the realised winners range from 14.4% to 26.6%, and the returns of the contrarian losers range from 9.8% to 24.4%. The contrarian winner subgroup shows significant profits only when the $(12, 1)$ and $(12, 6)$ schemes are used. Finally the contrarian winner group produces hardly any statistically significant returns. The profitability of the realised winner declines as h increases. Conversely, the contrarian loser performance improves as the value of h increases.

If investors go long in realised winners and contrarian winners and go short in realised losers and contrarian losers, their positions are equivalent to a trend-following strategy (TSM or RSM) holding for 13–24 months. However, trend-following reversal strategies suggest that investors only take a long position in the realised winner and contrarian loser sub-portfolios. This means that the past trend-following winners $(j = 12)$, which continue to generate profits $(h = 1 - 12)$, will maintain the upward trend, while the past losers, which earn positive returns later, will also increase in the future.

In an optimum case, we can combine two specific sub-portfolios, realised winner $(12, 1)$ and contrarian loser $(12, 12)$, into a larger portfolio. This yields an annualised portfolio return between 21.4% and 24.4%, while the volatility is reduced as more instruments are included in the portfolio. In this study, we align the (j, h) sub-portfolios for reasons of comparability. However, practitioners can choose any combinations of different (j, h) settings to achieve portfolio diversification or profit maximisation.

Figure 6 plots the cumulative returns of the realised winner and the contrarian loser under the TSM and RSM $(12, 12)$ frameworks. These two sub-portfolios perform better than the original TSM and RSM strategies as benchmarks.[22] A \$1 investment in TSM, TSM realised winner, and TSM contrarian loser strategies would be worth \$16.63, \$143.82, and \$209.07, respectively at the end of the sample period.[23] When the RSM frameworks is used, the realised winners and the contrarian losers also show substantially higher performance than the original RSM strategy.

We contend that our trend-following reversal strategies can be applied by practitioners. Based on our dataset, which consists of 55 instruments, each subgroup has sufficient assets allocated to it across time. Therefore, trend-following reversal strategies are liquid and tradable, as each sub-portfolio has at least five instruments in most cases. Figure 7 illustrates the proportions of individual instruments falling into the four sub-portfolios under a TSM trading strategy using a $(12, 12)$ scheme.[24] Generally, the four subgroups are allocated evenly across different instruments, except that the realised winner subgroup accounts for a slightly larger proportion and the realised losers account for a smaller proportion. This reflects the asset diversification of trend-following reversal strategies.

5.2. Risk Exposure Analysis

To understand the dynamics of the trend-following reversal strategies, we regress the returns of these sub-portfolios for each of the TSM and RSM strategies $(12, 12)$ on four classes of market risk factors. First, Table 4 shows the results of the Fama–French three-factor and five-factor models as in Fama and French (1993) and Fama and French (2015), respectively. Second, in Table 5 Panel A, we detail the global asset class factors consisting of the MSCI World Index, S&P GSCI, Barclays US

[22]The outperformance of the realised winner and the contrarian loser holds when we use a similar sample by excluding all the bond futures. These results are available in Section D of the Online Appendix.

[23]The transaction costs are not considered here as we use the nearest futures contracts which are required to roll each month. Therefore, the transaction costs will be indifferent across all the strategies including the buy-and-hold strategy. For example, if the average rolling cost for the portfolio is 10 basis points each month, then approximately 1.2% transaction cost is subtracted from the annual return of each strategy.

[24]Similar results, obtained under the RSM trading strategies and using different $(12, k)$ schemes, are also available on request.

Aggregate Bond Index, and US-Dollar Index. In Panel B, The Value and Momentum Everywhere (Asness et al., 2013) factor regressions are run to examine the risk exposure of the four decomposed strategies.

In general, we observe approximately 30–40% changes in most of these trend-following reversal strategies, owing to changes in the stock market as proxied by MSCI. One special case is that the contrarian loser strategies reduce this change to approximately 20% or even less. In both Fama–French three-factor and five-factor models, the remaining factors (SMB, HML RMW and CMA) explain very little of the changes in these sub-portfolio returns. Overall, the realised winners and the contrarian losers still generate statistically significant alphas which are not explained by the model.

Next, as shown in Table 5 Panel A, the global asset class factor models allow us to examine the sensitivity of these sub-portfolios to changes in the international major asset class indices. It is clear that the model explains the realised winner returns better than the others, with R^2 values being above 30%. With the exception of USDI, most coefficients of the factors are statistically significant at the 5% and 1% levels. It can be argued that this is due to the fact that bond futures play a prominent role in the time series reversal portfolios and, therefore, are over-explained by the bond index. The addition of more market factors results in a better goodness-of-fit but a lower alpha for the realised winner. This is because the realised portfolios are somewhat explained by the market factors whereas the contrarian portfolios -which go against the momentum- are not. Despite of its lower alpha, the contrarian loser still displays statistically significant alpha for TSM (t=1.73), but this is not the case for RSM.

Finally, in Table 5 Panel B, we regress the four sub-portfolio returns on the Value and Momentum Everywhere factors. Unsurprisingly, these sub-strategies are closely correlated to the movement of the market factor, and both the VAL and MOM factors. The realised winner and the contrarian loser show stronger abnormal returns compared to the other two subgroups, with alphas being statistically significant at the 1% level across all the three strategies.

To conclude, we see that trend-following reversal returns are closely related to the market factors, but has less exposure to the other factors. Some of the trend-following reversal returns is not explained by the known factors and generates significant alphas. This is particularly true for the contrarian loser strategy, as it has the lowest correlation with the market and also with trend-following factors. Owing to its relatively low co-movement with the existing factors, it might be particularly useful for investors who wish to avoid momentum risks[25] and still obtain persistent high returns.

6. Concluding Remarks

This paper studies the time horizon and magnitude of time series reversal as well as its relationship with time series continuation in an asset pool consisting of various global commodity and financial futures across a time horizon of 30 years. By performing multiple trend-following strategies, we observe a pervasive but not statistically significant reversal between 12 and 24 months after the trend-following signals are generated. The time series reversal period is much shorter than that of conventional cross-sectional reversal recorded in the literature.

We show that the time series reversal effect varies across different subgroups when we decompose the trend-following portfolio into four sub-portfolios, namely realised winners, realised losers, contrarian winners, and contrarian losers. Our results show that time series momentum and reversal are not linked. Our results are consistent with a small but growing body of literature suggesting that momentum and reversal are separate phenomena, see, e.g., Cooper et al. (2004), Conrad and Yavuz (2017), and Li and Galvani (2018). They contradict the conventional behavioral theories such as Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) which focus on explaining the linkage between momentum and reversal.

Our findings also suggest that the loser components of the trend-following strategies (whether realised or not) generate significant post trend-following reversal. The sub-portfolio with instruments which are past losers and later generate positive returns, the contrarian loser subgroup, contributes the most to time series reversal.

[25] See, e.g., Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

By contrast, the winner sub-portfolios do not show statistically significant reversal patterns. Moreover, the contrarian loser strategy also displays a lower volatility and lower maximum drawdown than the other three, indicating that it potentially forms the basis of an efficient trading strategy.

Based on these results, a new type of double-sorted trading strategy is introduced, called a trend-following reversal strategy. It removes the part of the traditional trend-following strategy that does not produce strong price return continuation/reversal in the time series. The realised winners and contrarian losers are the two most significant sub-portfolios within trend-following reversal strategies. Moreover, compared with the other three sub-portfolios, the contrarian losers show the lowest correlation with momentum factors. Future research could focus on the potential of this approach to reduce the risk of momentum strategies by partially mitigating the impact of momentum crashes.

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Table 1: Summary statistics.

This table reports the start date, mean, volatility/standard deviation, skewness and kurtosis for the 55 instruments from their earliest availability. The arithmetic monthly mean returns and standard deviation are both annualised. The detailed data sources are described in Section A of the Online Appendix. As seen in the table, the average monthly returns and volatilities vary quite dramatically across different asset classes.

Asset	Start Date	Annual Mean	Annual Volatility	Skewness	Kurtosis
Commodity futures					
Aluminum	1987-06-02	0.026	0.206	0.132	3.867
Brent	1988-06-24	0.100	0.322	0.454	6.156
Cocoa	1970-01-06	0.081	0.327	0.517	3.975
Coffee	1972-08-17	0.091	0.387	1.090	6.338
Copper	1986-04-02	0.082	0.254	0.110	6.607
Corn	1970-01-06	0.064	0.279	0.410	6.213
Cotton	1970-01-06	0.067	0.297	-0.402	7.419
Gas Oil	1989-07-04	0.104	0.331	0.327	4.867
Gold	1975-01-03	0.066	0.196	0.528	6.707
Heating Oil	1980-01-03	0.084	0.356	0.739	8.227
Lean Hogs	1986-04-02	0.073	0.343	0.191	4.519
Live Cattle	1970-01-06	0.057	0.197	0.037	4.078
Natural Gas	1990-04-04	0.165	0.544	0.494	4.044
Nickel	1987-01-06	0.135	0.418	2.531	20.747
Platinum	1984-01-27	0.039	0.229	0.024	7.909
RBOB	1986-08-22	0.130	0.401	0.707	6.006
Silver	1970-01-06	0.104	0.342	1.353	14.729
Soy Meal	1970-01-06	0.088	0.349	1.913	18.949
Soy Oil	1970-01-06	0.074	0.316	0.897	7.382
Soybeans	1970-01-06	0.071	0.291	0.776	9.254
Sugar	1970-01-06	0.123	0.459	1.659	9.671
Wheat	1970-01-06	0.069	0.291	0.592	5.091
WTI	1983-03-31	0.068	0.329	0.422	5.980
Zinc	1989-01-05	0.035	0.244	-0.053	4.887
Currency futures					
AUD	1971-01-06	-0.002	0.110	-0.725	7.182
CAD	1971-01-06	-0.003	0.065	-0.289	8.058
EUR	1971-01-06	-0.002	0.111	-0.183	3.821
JPY	1971-01-06	0.022	0.114	0.480	5.175
NZD	1971-01-06	-0.002	0.120	-0.403	9.870
NOK	1971-01-06	0.009	0.104	0.081	4.571
SEK	1971-01-06	0.025	0.110	0.927	7.294
CHF	1971-01-06	0.016	0.124	0.076	4.301
GBP	1971-01-06	-0.005	0.101	-0.078	5.153
Equity index futures					
SPI	1970-01-06	0.075	0.193	-0.670	10.241
CAC	1970-01-06	0.079	0.203	-0.114	3.911
DAX	1970-01-06	0.087	0.197	-0.506	5.119
FTSE/MIB	1970-01-06	0.074	0.238	0.409	4.169
TOPIX	1970-01-06	0.066	0.187	-0.172	4.279
AEX	1970-01-06	0.074	0.192	-0.556	5.474
IBEX	1970-01-06	0.070	0.209	-0.092	4.544
FTSE	1970-01-06	0.086	0.197	1.172	17.689
S&P 500	1970-01-06	0.080	0.154	-0.463	4.773
Bond futures					
AUS3	1986-01-02	0.011	0.063	-3.391	37.454
AUS10	1986-01-02	0.009	0.048	-4.970	85.085
EURO2	1986-01-02	0.018	0.081	0.213	8.129
EURO5	1986-01-02	0.023	0.073	-0.002	9.478
EURO10	1986-01-02	0.037	0.078	0.235	5.771
EURO30	1986-01-02	0.037	0.124	-0.672	10.224
CA10	1986-01-02	0.023	0.074	-1.347	13.016
JP10	1985-10-22	0.016	0.054	-0.323	8.357
UK10	1982-11-19	0.010	0.091	-1.687	16.211
US2	1986-01-02	0.004	0.028	-0.053	8.363
US5	1986-01-02	0.008	0.047	-0.668	8.046
US10	1982-05-04	0.020	0.074	-0.305	6.311
US30	1977-08-23	0.019	0.118	-0.048	6.306

Table 2: Post TSM and RSM holding period performance $(12, 12)$.

Reported is the performance of 12 months holding period post trend-following strategies for the 4 sub-portfolios during 13-60 months after the formation of the signals, i.e. 13-24 months, 25-36 months, 37-48 months and 49-60 months. Decomposition method of the 4 sub-portfolios can be seen in Figure 1. Each subgroup is constructed by evaluating whether the underlying trend-following profit is realised or not under a (j, h) scheme, where $j = 12$, is the trend-following look-back period and $h = 12$ is the trend-following holding period. The post trend-following holding period is equally divided into 4 sub-periods which are shown in different panels. We compute the annualised mean, Newey-West t-statistics (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$), annualised volatility/standard error, Sharpe Ratio and maximum drawdown for each strategy which are detailed in Section G of the Online Appendix. The performance is evaluated based on a dataset spanning January, 1985 to March 2015.

	TSM				RSM			
	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser
Panel A: 13-24 months								
Annualised Mean	0.044	0.042	0.007	0.084	0.040	0.039	-0.002	0.087
Newey-West t-statistics	1.906*	1.680*	0.163	3.964***	1.612	1.338	0.019	3.702***
Annualised Volatility	0.028	0.031	0.042	0.027	0.030	0.030	0.034	0.030
Sharpe Ratio	1.535	1.352	0.177	3.139	1.324	1.285	-0.049	2.880
Maximum Drawdown	0.160	0.150	0.420	0.129	0.188	0.163	0.413	0.118
Panel B: 25-36 months								
Annualised Mean	0.009	0.076	0.056	0.057	0.014	0.063	0.052	0.051
Newey-West t-statistics	0.259	2.511**	2.469**	0.854	0.334	3.463***	2.023**	0.655
Annualised Volatility	0.030	0.034	0.030	0.041	0.033	0.026	0.032	0.038
Sharpe Ratio	0.310	2.235	1.871	1.387	0.430	2.389	1.640	1.328
Maximum Drawdown	0.265	0.111	0.152	0.301	0.332	0.080	0.163	0.286
Panel C: 37-48 months								
Annualised Mean	0.019	0.057	0.055	0.043	0.029	0.037	0.056	0.030
Newey-West t-statistics	0.585	1.374	0.899	1.254	0.833	0.979	0.911	0.858
Annualised Volatility	0.030	0.034	0.037	0.033	0.031	0.029	0.041	0.032
Sharpe Ratio	0.637	1.686	1.482	1.310	0.947	1.297	1.390	0.939
Maximum Drawdown	0.255	0.165	0.134	0.203	0.243	0.172	0.178	0.197
Panel D: 49-60 months								
Annualised Mean	0.036	0.059	0.040	0.041	0.042	0.057	0.043	0.035
Newey-West t-statistics	0.601	1.375	1.298	1.516	0.673	1.802*	1.840*	1.915*
Annualised Volatility	0.038	0.033	0.031	0.027	0.038	0.029	0.029	0.026
Sharpe Ratio	0.944	1.763	1.296	1.499	1.110	1.937	1.474	1.336
Maximum Drawdown	0.236	0.112	0.249	0.148	0.215	0.086	0.122	0.154

Table 3: Performance of trend-following reversal strategies.

Reported is the performance of 4 sub-portfolios sorted by both time series continuation and reversal using volatility scaling to determine the weight. Decomposition method of the 4 sub-portfolios can be seen in Figure 1. The strategy signals are renewed every month and the holding period is 1 month. Each subgroup is constructed by evaluating whether the underlying trend-following profit is realised or not under a (j, h) scheme, where $j = 12$, is the trend-following look-back period and $h = 1, 3, 6, 12$ denotes the trend-following holding periods shown in different panels. We compute the annualised mean, Newey-West t-statistics (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$), annualised volatility/standard error, Sharpe Ratio and maximum drawdown for each strategy. The performance is evaluated based on a dataset spanning from January, 1985 to March 2015. The realised winner and contrarian loser exhibit strong performance with the t-statistics being significant at the 1% level across different (j, h) schemes.

	TSM				RSM			
	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser
Panel A: (12,1)								
Annualised Mean	0.218	0.044	0.151	0.098	0.220	0.041	0.141	0.105
Newey-West t-statistics	5.842***	0.899	4.061***	2.944***	5.510***	0.883	3.709***	2.584***
Annualised Volatility	0.200	0.224	0.200	0.211	0.204	0.233	0.209	0.235
Sharpe Ratio	1.087	0.195	0.754	0.465	1.080	0.176	0.678	0.444
Maximum Drawdown	0.294	0.770	0.515	0.458	0.297	0.755	0.528	0.673
Panel B: (12,3)								
Annualised Mean	0.265	0.074	0.036	0.165	0.262	0.085	0.054	0.155
Newey-West t-statistics	7.454***	1.780*	1.008	4.019***	7.216***	2.000**	1.344	3.571***
Annualised Volatility	0.209	0.219	0.190	0.221	0.213	0.227	0.199	0.224
Sharpe Ratio	1.269	0.338	0.187	0.749	1.231	0.376	0.272	0.693
Maximum Drawdown	0.213	0.517	0.614	0.472	0.267	0.530	0.492	0.548
Panel C: (12,6)								
Annualised Mean	0.177	0.060	0.092	0.150	0.204	0.028	0.104	0.088
Newey-West t-statistics	4.027***	1.532	2.705***	4.283***	4.781***	0.678	2.632***	2.103**
Annualised Volatility	0.217	0.221	0.195	0.207	0.225	0.223	0.217	0.216
Sharpe Ratio	0.815	0.273	0.473	0.726	0.907	0.124	0.477	0.406
Maximum Drawdown	0.363	0.558	0.432	0.378	0.448	0.661	0.409	0.527
Panel D: (12,12)								
Annualised Mean	0.193	0.031	0.007	0.207	0.189	0.049	-0.002	0.183
Newey-West t-statistics	4.969***	0.738	0.151	5.313***	5.063***	1.157	-0.053	4.462***
Annualised Volatility	0.212	0.230	0.221	0.216	0.211	0.225	0.228	0.229
Sharpe Ratio	0.911	0.137	0.034	0.958	0.899	0.220	-0.010	0.799
Maximum Drawdown	0.365	0.705	0.776	0.332	0.349	0.596	0.791	0.486

Table 4: Factor exposure of trend-following reversal strategies $(12, 12)$ I.

This table reports the factor exposure of different sub-portfolios decomposed from TSM and RSM strategies, namely realised winner, realised loser, contrarian winner and contrarian loser. Decomposition method of the 4 sub-portfolios can be seen in Figure 1. The regression coefficients are reported in the first row and t-statistics (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$) in the row below. Panel A and B summarise the results of Fama-French three and five factor models, respectively. Small Minus Big (SMB), High Minus Low (HML), Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA) represent size, value, profitability and investment factors, respectively. The regressions are conducted with the monthly returns that span the period from January, 1985 to March 2015. The alphas of realised winner and contrarian loser are statistically significant at the 1% level in both factor models.

	TSM				RSM			
	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser
Panel A: Fama and French three factors								
Intercept	0.014	-0.001	-0.002	0.016	0.013	0.001	-0.003	0.014
	4.514***	-0.303	-0.736	4.676***	4.400***	0.227	-0.868	3.859***
MSCI	0.485	0.482	0.429	0.260	0.536	0.414	0.422	0.232
	7.008***	6.219***	5.718***	3.447***	7.912***	5.423***	5.425***	2.891***
SMB	-0.238	0.082	-0.004	0.002	-0.247	0.161	-0.122	0.013
	-2.375**	0.731	-0.037	0.018	-2.527**	1.454	-1.081	0.116
HML	-0.298	0.230	0.146	-0.012	-0.286	0.256	0.093	0.012
	-2.781***	1.916*	1.257	-0.100	-2.728***	2.161**	0.769	0.098
R^2	0.156	0.105	0.087	0.035	0.184	0.089	0.080	0.024
Panel B: Fama and French five factors								
Intercept	0.014	-0.001	-0.001	0.012	0.013	0.001	-0.001	0.011
	4.338***	-0.417	-0.170	3.496***	4.164***	0.191	-0.154	2.934***
MSCI	0.489	0.493	0.368	0.380	0.546	0.418	0.340	0.329
	6.598***	5.962***	4.585***	4.796***	7.525***	5.159***	4.100***	3.860***
SMB	-0.207	0.014	-0.106	0.134	-0.203	0.030	-0.195	0.095
	-1.854*	0.109	-0.874	1.117	-1.855*	0.248	-1.558	0.739
HML	-0.279	0.101	0.320	-0.496	-0.275	0.105	0.381	-0.400
	-1.909*	0.620	2.022**	-3.182***	-1.924*	0.660	2.339**	-2.386**
RMW	0.091	-0.163	-0.232	0.439	0.131	-0.292	-0.211	0.310
	0.635	-1.019	-1.490	2.864***	0.931	-1.864*	-1.314	1.881*
CMA	-0.114	0.418	-0.292	0.731	-0.108	0.518	-0.549	0.658
	-0.559	1.837*	-1.320	3.350***	-0.541	2.321**	-2.408**	2.807***
R^2	0.163	0.120	0.096	0.083	0.192	0.116	0.097	0.053

Table 5: Factor exposure of trend-following reversal strategies (12, 12) II.

This table reports the factor exposure of the four sub-portfolios decomposed from TSM and RSM strategies, namely realised winner, realised loser, contrarian winner and contrarian loser. Decomposition method of the 4 sub-portfolios can be seen in Figure 1. The regression coefficients are reported in the first row and t-statistics (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$) in the row below. Panel A and B summarise the results of global asset class factor model and value and Momentum Everywhere factor model, respectively. The regressions are conducted with the monthly returns that span the period from January, 1985 to March 2015. The alphas of the realised winner and contrarian loser are strongly significant in the Value and Momentum Everywhere model, whereas they are mostly insignificant in the global asset class model.

	TSM				RSM			
	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser	Realised Winner	Realised Loser	Contrarian Winner	Contrarian Loser
Panel A: Global asset class factors								
Intercept	0.002	-0.005	-0.007	0.006	0.001	-0.003	-0.010	0.004
	0.562	-1.452	-2.087**	1.729*	0.429	-0.676	-2.605**	1.147
MSCI	0.359	0.385	0.293	0.141	0.412	0.354	0.283	0.139
	5.405***	4.807***	3.825***	1.892*	6.332***	4.412***	3.575***	1.715*
GSCI	0.208	0.234	0.224	0.142	0.188	0.182	0.227	0.093
	4.122***	3.842***	3.859***	2.503**	3.803***	2.990***	3.780***	1.509
BOND	1.962	0.817	0.922	1.711	1.942	0.645	1.170	1.694
	7.971***	2.753***	3.255***	6.180***	8.055***	2.173**	4.000***	5.656***
USDI	-0.131	0.065	-0.146	-0.172	-0.141	0.126	-0.100	-0.111
	-1.083	0.446	-1.051	-1.266	-1.190	0.865	-0.700	-0.754
R^2	0.306	0.147	0.155	0.159	0.328	0.106	0.153	0.120
Panel B: Value and Momentum Everywhere factors								
Intercept	0.012	0.001	0.004	0.010	0.011	0.002	0.003	0.008
	3.950***	0.276	1.123	3.092***	3.810***	0.705	0.796	2.270**
MSCI	0.478	0.480	0.393	0.279	0.527	0.415	0.382	0.253
	7.505***	6.638***	5.639***	3.966***	8.526***	5.693***	5.235***	3.361***
VAL	-0.882	0.792	-0.763	0.703	-0.876	0.707	-0.735	0.886
	-3.484***	2.758***	-2.757***	2.515***	-3.566***	2.443***	-2.535***	2.958***
MOM	0.948	-0.957	-1.633	1.573	1.000	-0.745	-1.574	1.584
	4.273***	-3.805***	-6.733***	6.423***	4.650***	-2.937***	-6.201***	6.039***
R^2	0.263	0.199	0.190	0.139	0.301	0.148	0.167	0.117

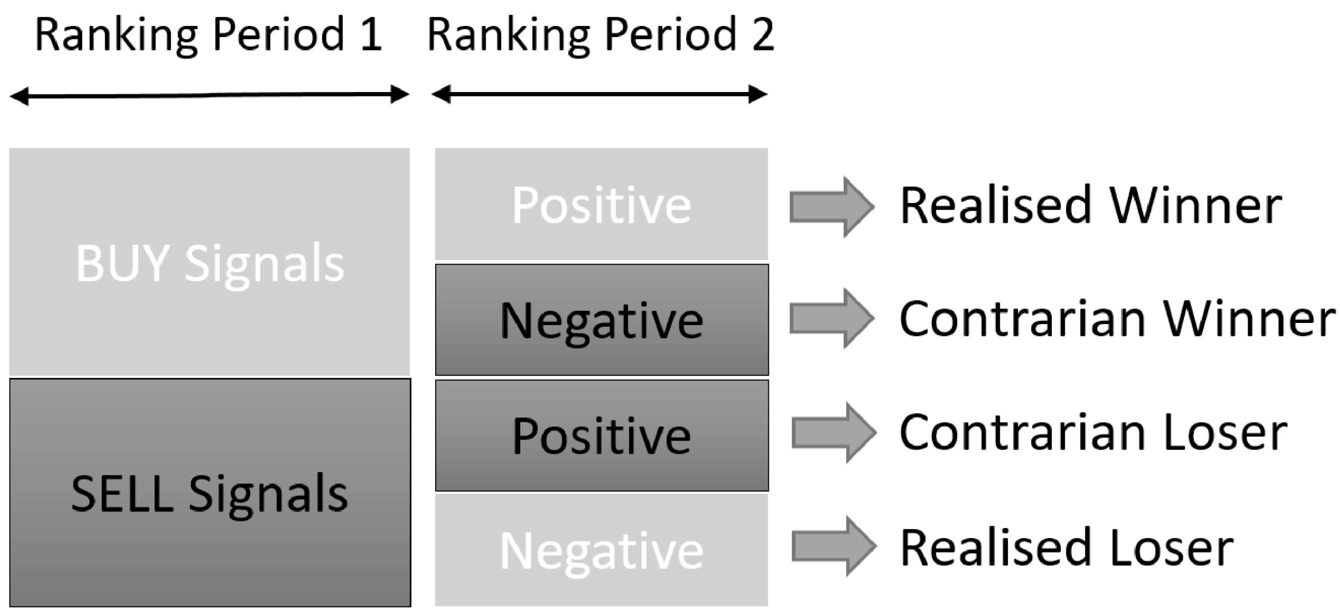


Figure 1: Decomposition of trend-following strategies.

This figure illustrates how the four sub-portfolios of trend-following strategies: realised winner, realised loser, contrarian winner and contrarian loser are constructed. Ranking period 1 refers to the conventional trend-following look-back period j. Ranking period 2 is the trend-following holding period, which examines whether these winner/loser signals generated from ranking period 1 are realised or not.

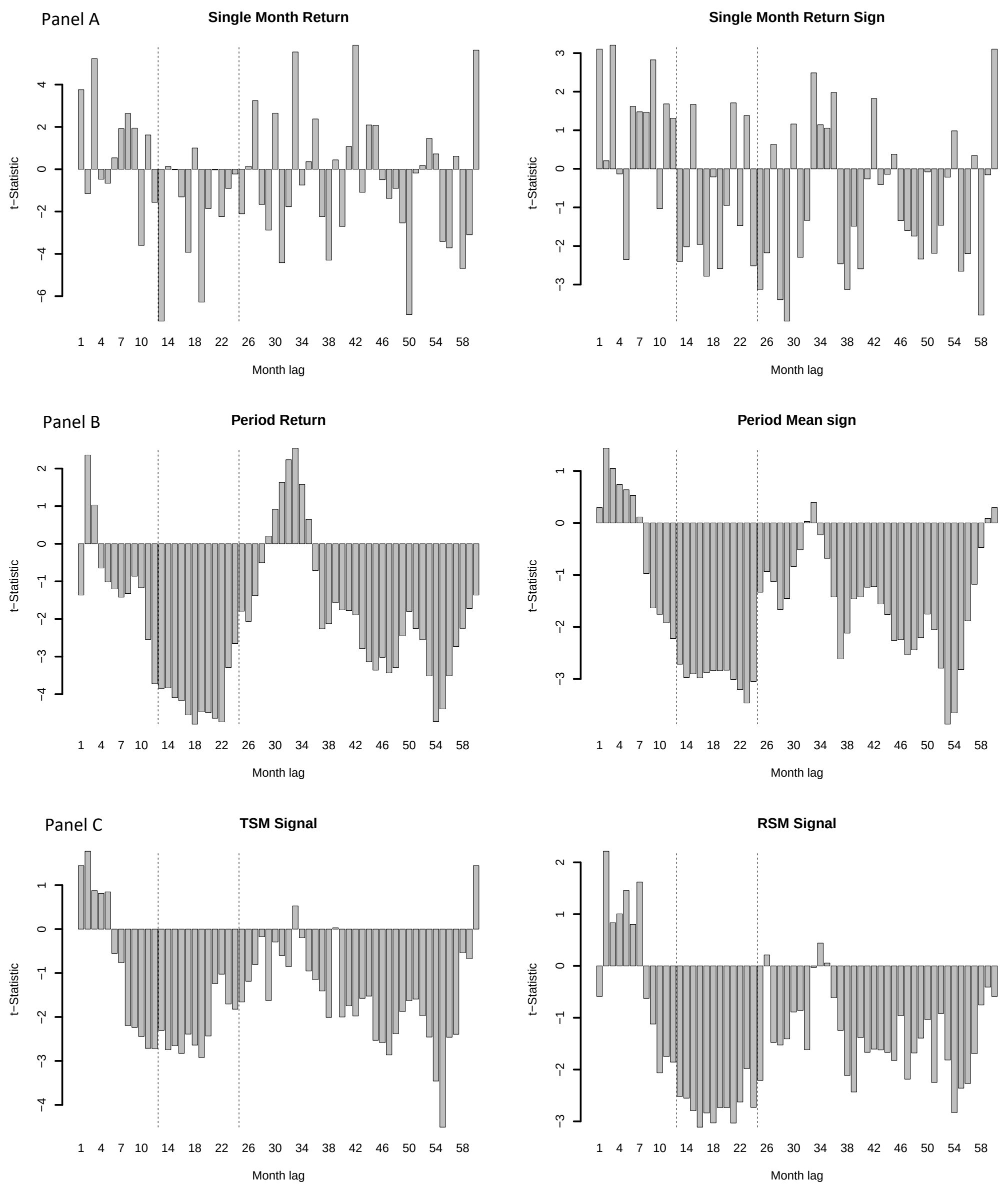


Figure 2: Time series predictability of 12 months TSM and RSM signals.

Reporting the t-statistics of β_h for lags from $h = 1$ to $h = 60$ based on three sets of panel regressions across all assets. In Panel A, we regress the volatility-scaled return r_t^s/σ_{t-1}^s on lagged signal month return $r_{t-h}^s/\sigma_{t-h-1}^s$ and lagged sign of return, $sign(r_{t-h}^s)$, as seen in Equation 7 and 8, respectively. Panel B reports the regression results by using i) 12 months period return $PR_{t-h-11,t-h}$ and ii) 12 months mean return sign $P_{t-h-11,t-h}$ as the explanatory variables. In Panel C, the TSM and RSM signals, namely $S_{t-h-11,t-h}^{TSM}$ and $S_{t-h-11,t-h}^{RSM}$, are used as the regressors. The t-statistics are calculated based on the robust standard errors of Thompson (2011).

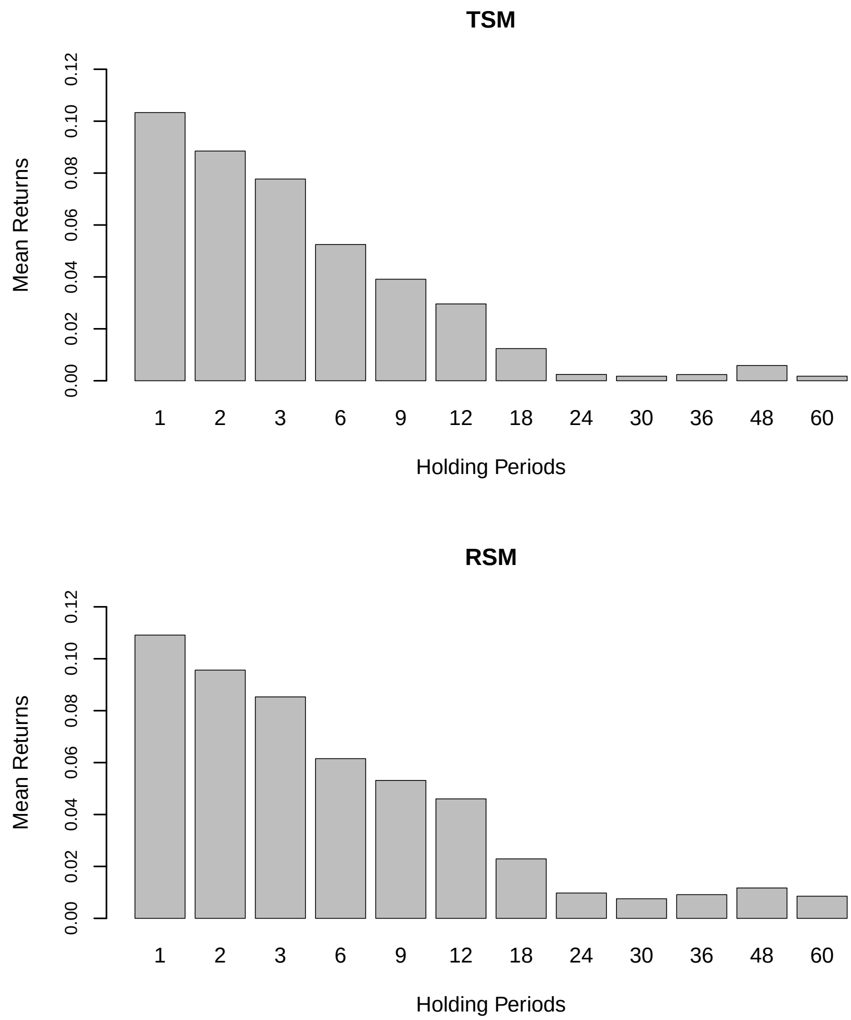
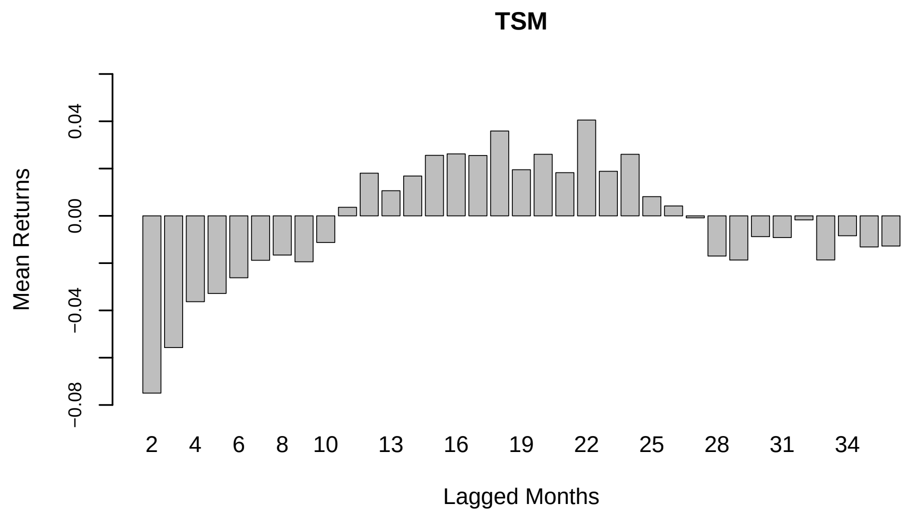


Figure 3: Return decays of trend-following strategies.

Reported are the annualised mean returns of TSM and RSM strategies with different holding periods h(1,2,3,6,9,12,18,24,30,36,48,60 months). The strategies are performed using an asset pool with 55 futures from January, 1985 to March, 2015. The trend-following profit declines as the holding period increases. The decays stop at about holding period of 24 months and keep constant afterwards.



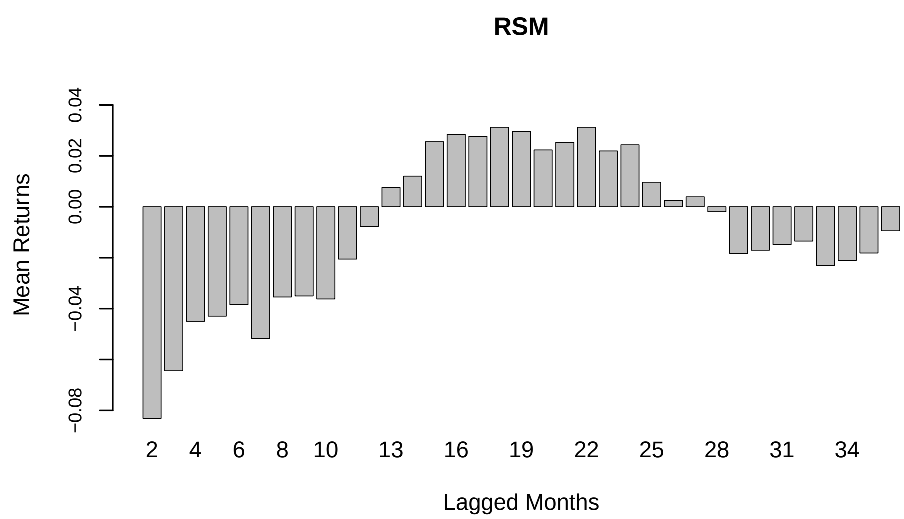


Figure 4: Timing of time series reversal.

Reported are the annualised mean returns of the contrarian TSM and RSM strategies, which is short the assets that have a buy signal and long the assets that have a sell signal. Each contrarian portfolio is hold for one month with different time lags from $h = 2$ to $h = 36$. The strategies are performed using an asset pool with 55 futures from January, 1985 to March, 2015. The contrarian profit mainly appears during 12-24 months after the trend-folling signal is formed.

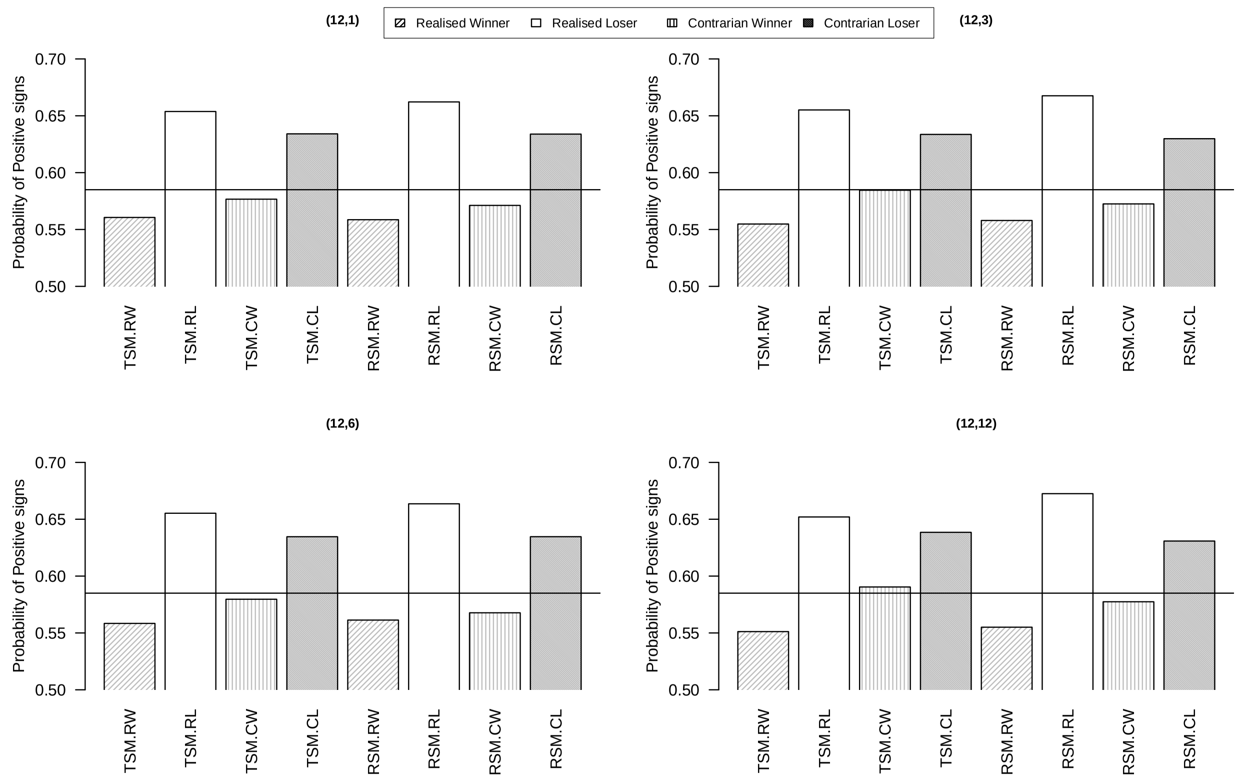


Figure 5: Sign analysis of post TSM and RSM holding period performance (month 13-24).

Reported figure shows the probability of positive signs of the realised winner (RW), realised loser (RL), contrarian winner (CW), and contrarian loser (CL) sub-portfolios during the post holding period (month 13-24). Decomposition method of the 4 sub-portfolios can be seen in Figure 1. The baseline, TSM and RSM strategies, are performed using an asset pool with 55 futures from January, 1985 to March, 2015. Different panels represent different (j, h) schemes in constructing trend-following strategies, where j is the 12-month look-back period and h is the holding period ranging from month 1–12. The horizontal line denotes the unconditional average of the entire sample.

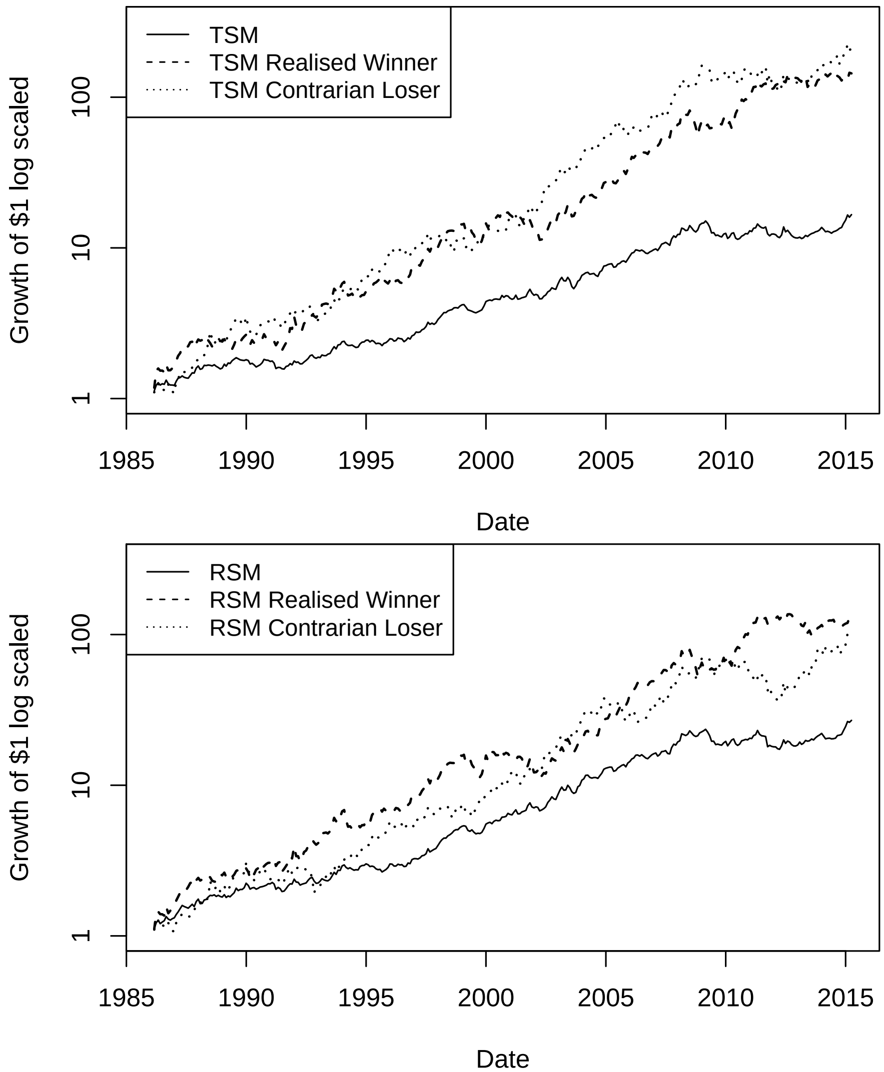


Figure 6: Cumulative returns of different $(12, 12)$ trend-following reversal strategies.

Plotted are the cumulative returns of trend-following reversal realised winner and contrarian loser strategies compared to their corresponding trend-following strategies (TSM and RSM) using $(12, 12)$ scheme. The cumulative returns are calculated as shown in Section G of the Online Appendix. The strategies are performed using an asset pool with 55 futures from January, 1985 to March, 2015. Logarithmic scaling is applied to the y-axes, i.e. growth of $1. As shown in both panels, the realised winner and contrarian loser substantially outperform their baseline strategies.

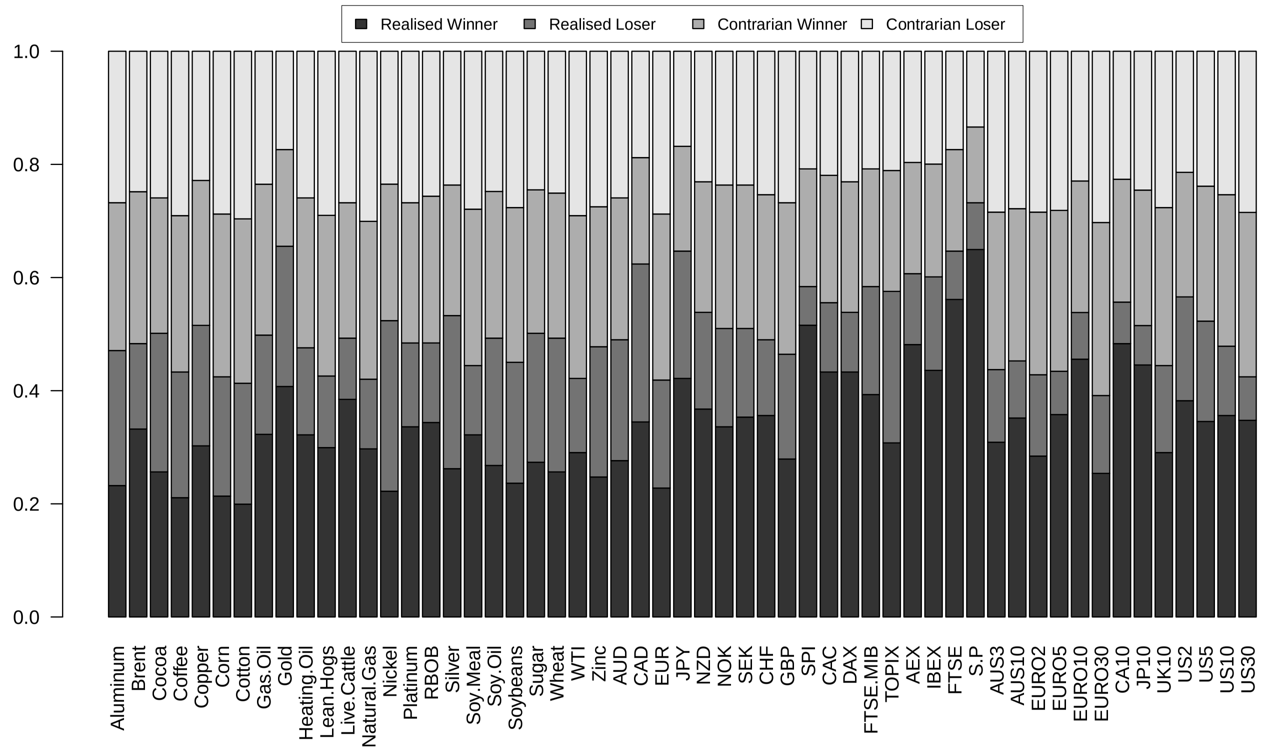


Figure 7: Proportions of TSM trend-following reversal signals for individual instruments $(12, 12)$.

This bar chart reports the aggregated frequency for each of the individual instruments to be assigned to the 4 sub-portfolios under a TSM strategy using $(12, 12)$ scheme. Decomposition method of the 4 sub-portfolios can be seen in Figure 1. The frequency is aggregated across the entire sample period ranging from January, 1985 to March, 2015, based on the portfolio comprised of a total of 55 futures.