# Returns Signal Momentum[☆,☆☆]

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## Abstract

A new type of momentum based on past return signs is introduced, called Returns Signal Momentum. This is mainly driven by sign dependence, which is positively related to average return and negatively related to return volatility. An empirical application using a universe of commodity and financial futures offers supporting evidence to this momentum factor. Investment strategies based on Returns Signal Momentum result in higher returns and Sharpe ratio and lower drawdown when compared to Time Series Momentum and other benchmark strategies. Overall, Returns Signal Momentum can benefit investors as an effective strategy for speculation and hedging.

*Keywords:* Return Sign, Trading Strategies, Market Timing, Time Series Momentum

## 1. Introduction

A wide attention in the academic and professional literature has been paid to the phenomenon of financial market momentum and its implications for investment. A vast number of studies on momentum have been conducted since the seminal paper of Jegadeesh and Titman (1993) who provide evidence that, buying the instruments which have been performing well in the relatively recent past, i.e. winners, and selling those which perform poorly, i.e. losers, produce abnormal returns in the short run[1].

Traditionally, the word "momentum" in finance refers to a market anomaly in which assets with good past performance have a tendency to rise further, and vice versa. Cross-Sectional Momentum strategies (henceforth, XSM) are created ranking the assets based on their performance and investing using this order. Later research has shown that momentum can also be effective in a time series context. Moskowitz et al. (2012) document a new type of momentum across various asset classes based on the individual asset's past performance. This is called Time Series Momentum (henceforth, TSM). Subsequent studies also provide evidence of TSM in portfolios with similar datasets, see, among others, (Baltas and Kosowski, 2013; Hutchinson and O'Brien, 2015; Kim et al., 2016)[2]. This opened the way for further studies in the time series property of momentum effect in financial assets.

In this paper, we introduce a financial market momentum based on the probability of past return signs, called Returns Signal Momentum (henceforth, RSM). Given that RSM generates position signals using the signs of past returns of an individual asset, and does not single out the best or worst performers in a pool of assets, we can argue that it falls ubder the wider range of time series momentum. The key features of RSM, and hence its differences compared to TSM, are mainly two: (i) it takes into

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[1] Evidence of financial market momentum has also been found in international stock markets, see, e.g., Fama and French (1998), emerging markets see, e.g., Rouwenhorst (1999), country indices, see, e.g., Asness et al. (1997), industries, see, e.g., Moskowitz and Grinblatt (1999), size and B/M factors, see, e.g., Lewellen (2002), commodities, see, e.g., Miffre and Rallis (2007) and Shen et al. (2007), and global asset classes, see, e.g., Asness et al. (2013).

[2] TSM has also been documented in global stock markets, see, e.g., Bird et al. (2016), global asset classes in the long run from 1880-2013, see, e.g., Hurst et al. (2012), emerging markets, see, e.g., Georgopoulou and Wang (2016) and currency markets, see, e.g., Menkhoff et al. (2012).

account each of the returns during the look-back period rather than calculating the total period return as in TSM, and (ii) focuses on the signs of past returns regardless of their magnitude. These special characteristics allow us to capture the trend more efficiently avoiding temporary price reversals or other market corrections which might lead to false position signals.

Obviously, a question arises regarding the calculation of the probability of future return signs based on recent past performance. Given that this is a binary outcome, i.e. the sign variable takes the value 0 if the return is negative and 1 if the return is positive, various binary variable forecasting models could be employed. However, in an effort to simplify this research and focus more on the intuition of the suggested momentum factor, we use the economically atheoretical equally weighted average of past returns signs[3]. Our focus is exclusively on the analysis of the momentum caused by sign dependence, therefore we do not introduce new probability estimators. However, Appendix A offers additional econometric motivation in favour of the equally weighted average for the interested reader.

Since RSM is a phenomenon of time series continuation, we expect it is related to both TSM and XSM. Lewellen (2002) provides a theoretical work showing that the returns of XSM strategies can be decomposed by a positive time series autocorrelation term and a negative cross-serial correlation term[4]. In other words, the time series part of the momentum effect is caused by the autocorrelation of an instrument's own past returns. Empirical evidence on positive short-term autocorrelation, or serial correlation in financial asset returns, can also be found in Lo and MacKinlay (1988, 1990) and Campbell et al. (1997) among others.

Moskowitz et al. (2012) claim that the observed phenomenon of TSM challenges

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[3]This can also be further expanded using exponential moving average as well as binary outcome estimation methods such as the probit and logit models. However, given that the main qualitative results do not change significantly, we omit them here. A further problem with probit and logit models would be the instrument selection and the method would be sensitive to that matter.

[4]Jegadeesh and Titman (2002) also attribute momentum profits to both cross-sectional and time series determinants. Berk et al. (1999), Chordia and Shivakumar (2002), Avramov and Chordia (2006) and Liu and Zhang (2008) among others, explain the importance of time-variation in expected returns in the creation of XSM.

the random walk theory. In contrast, RSM, which depends on the signs of returns, does not contradict the random walk theory which focuses on the price returns. Therefore, RSM offers an alternative view and explanation of the momentum effect in the time series context based on sign dependence.

The motivation for returns sign predictability stems from Christoffersen and Diebold (2006) who theoretically show that return sign dependence exists as long as the conditional mean of the returns is not equal to zero. We expect that sign dependence is possible to be detected because the returns of most financial assets are positive in the long run. This is particularly true for stock and commodity markets due to the global expansionary monetary policy. For example, S&P 500 adjusted price index rises from 16.66 in 1950 to 2043.94 in 2015, which yields an annualised average return of 7.68% per year.

Although studies about sign predictability are not as prevalent as those about return mean forecasting, a number of recent papers empirically test sign dependence in various developed stock markets, see, e.g., Leung et al. (2000), Christoffersen et al. (2006), Nyberg (2011) and Chevapatrakul (2013) among others. Moskowitz et al. (2012) also provide evidence that sign dependence exists in a more straightforward way by examining the predictability of the signs of past excess returns on the current price returns. Their regression results show strong momentum effect for the first 12 months.

In our empirical illustration, we carry out a number of regressions which reveal the strong relationship between the signs of past returns and current returns. The results are consistent with Moskowitz et al. (2012) because RSM, as a type of momentum in the time series context, should also display time series autocorrelation. Hence, the behavioural rationale of RSM is attributed to the short-term under-reaction and delayed over-reaction as suggested in the literature[5]. We also control for time series dummies and cross-sectional dummies in the regression analysis finding that the suggested momentum effect does not come from the cross-sectional part of the asset

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[5]Behavioural theories about under-reaction and over-reaction in financial markets can be found in Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) among others.

pool, but mainly comes from the time series part. Finally, regression analysis using the probability of positive signs of the returns, which is an important indicator for RSM, shows more robust short-run continuation and long-run reversal.

We extend our results including market timing investment strategies based on RSM using a portfolio which consists of 55 of the world's most liquid commodity and financial futures. RSM position signals are generated when the equally weighted average of past return signs exceed a certain probability threshold. We consider various fixed and time-varying values for this threshold. The results provide evidence of superior profitability and lower risk characteristics when compared to literature benchmarks such as the buy-and-hold strategy, the simple price moving average and the TSM strategy. The time-varying probability threshold is calculated using a cross-validation exercise and illustrates a strong negative relationship with the market, i.e. the time-varying threshold increases during times of market turbulence, keeping the investor market neutral or short, and decreases in stable times, putting the investor in a long position. Our results are consistent even when transaction costs are taken into account; see Appendix B.

To better understand the risk exposure of RSM, we run a factor regression analysis on RSM strategies returns against a series of financial market risk factors suggested by the literature. We find that RSM is highly related to the global stock market index, MSCI, in spite of the fact that the 55 assets come from different asset classes. Moreover, RSM seems to have a linear relationship with Moskowitz et al. (2012) TSM portfolio strategy. However, there is still some part of the RSM effect which cannot be explained by the existing risk factors providing evidence in favour of the hereby suggested research.

The rest of the paper is organised as follows. In Section 2 we describe our data collection and transformation methodologies. Section 3 presents the regression analysis which motivates RSM. Then, in Section 4 we perform the portfolio strategies based on RSM and compare it to various benchmarks using both fixed and time-varying probability thresholds. We also provide a full risk factor regression analysis in this section. Finally, Section 5 summarises the conclusions.

## 2. Data

### 2.1. Data Collection and Processing

Following the TSM literature, we collect data for 55 of the world's most liquid exchange traded futures instruments. The pool consists of 24 commodity futures, 9 foreign exchange futures for 9 countries against the US dollar, 9 equity indexes of developed countries, and 13 government bonds for 6 developed countries for various maturities. The data has been downloaded using Bloomberg and DataStream[6]. Futures prices of the nearest contracts are concatenated to form long time series for reasons of simplicity. For robustness, we also splice the futures prices based on their trading volume. To mimic a real-life trading situation, once the trading volume of the second nearest contract exceeds the nearest one, we do not allow the nearest contract to be chosen again, even if its trading volume is getting higher. The result is that the descriptives for our spliced data do not vary a lot from those using the nearest contract data.

As in Moskowitz et al. (2012), we compute the daily excess returns for each instrument and calculate its cumulative returns. Then, we can compute our preferred periodic returns, e.g., weekly, monthly and quarterly returns. For the remaining of the paper, we focus on monthly returns which are calculated from the previously mentioned daily excess cumulative return series. The monthly frequency allows us to directly compare our results to the current TSM literature. We also carry out the same quantitative exercises at weekly frequency to check the robustness of the suggested method. The qualitative conclusion is similar, and in some cases more in favour of RSM. Therefore, we omit these results[7].

In Table 1 we summarise the characteristics of the original series. We present the date for the first available data of each series, the annualised arithmetic mean and the annualised standard deviation of the monthly excess returns for each individual instrument. Most futures have positive long term annualised mean, while some of the currency futures exhibit slightly negative values due to the appreciation of the

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[6]More details are provided in Appendix C.

[7] However, they are available on request.

US dollar. Regarding volatility, we find that it varies across different asset classes. The volatility of commodities and equities is much higher than that of currencies and bonds. In particular, the future of Natural Gas presents 54.39% annualised standard deviation and the two-year maturity US bond (US2) offers the lowest volatility of 2.84% standard deviation.

For the factor regression analysis of Section 4, the control variable representing the total market returns is proxied by the MSCI world index downloaded from Bloomberg. The well-known factors of the percentage change of Fama and French (1993) small market capitalisation minus big (SMB), high book-to-market ratio minus low (HML), Carhart (1997) premium on winners minus losers (UMD), as well as the risk free rate, are downloaded from K. French's website[8]. Asness et al. (2013) "Value and Momentum Everywhere" factors and the Moskowitz et al. (2012) TSM factors are available from AQR website[9]. All the above data spans from January, 1985 (where available) to March, 2015 resulting to a number of 361 observations where available.

*2.2. Volatility Adjustment*

Following Moskowitz et al. (2012), we employ the annualised ex ante volatility method to scale the returns of each asset. This method is an annualised exponentially weighted variance of the past returns and is calculated as follows:

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

where the parameter $\delta$ is defined when the center of mass is equal to 60 days, $r_t$ is the period return and $\bar{r}_t$ is the exponentially weighted average return.

There are three reasons why we perform this transformation. The first reason, as mentioned by Moskowitz et al. (2012), is that in order to ensure that the regression results are comparable across different assets, the returns must be adjusted by their volatilities.

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[8]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[9]https://www.aqr.com/

Another reason, which is even more important, is that controlling for risk leads to more profitable investment strategies; this plays a crucial role in adjusting the position size of momentum strategies such as TSM and RSM. We test RSM and TSM strategies using both scaled and unscaled returns. The results suggest that the risk-adjusted investments always perform better than the unadjusted ones, which is consistent with the literature[10].

Finally, the third reason is that sign predictability is negatively related to volatility. Controlling individual instrument's weight to be inversely proportional to its volatility can further improve the portfolio performance. We argue this improvement of performance should distinct from the one in the last point. In other words, the benefit of volatility scaling can be decomposed into two parts: (i) volatility scaling/risk parity approach benefit, and (ii) the benefit from sign dependence. Theoretically, according to Christoffersen and Diebold (2006), sign dependence is caused by volatility dependence. In particular, the higher the volatility, the lower is the sign dependence. RSM is established based on sign dependence, thus RSM effect can also be affected by the volatility of each asset. For those assets with higher volatility where RSM is weaker, we divide the returns $r_t$ by a higher volatility $\sigma_t$ to lower the weight of these assets in the portfolio.

To empirically validate our hypothesis, we apply the most intuitive RSM strategy using a fixed probability which is equal to 0.5, where a long signal is generated when no less than 50% of the returns over the past 12 months are positive, otherwise the position is short. We calculate the Sharpe ratio of RSM strategy returns for individual instruments without volatility adjustment because it removes the benefit from risk parity. Hence, RSM0.5 strategy returns before volatility scaling can be regarded as a proxy of sign dependence. Figure 1 illustrates how the Sharpe ratio

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[10]Similar results can also been found in Ahn et al. (2003), Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), who suggest a risk adjusted momentum portfolio performs better than the unadjusted one, and explains a large part of the momentum profits. Besides, Kim et al. (2016) also highlight the importance of volatility scaling in TSM strategies. Moreover, Baltas and Kosowski (2015) find that an efficient volatility estimates, can reduce the turnover and rebalancing costs of TSM strategies and hence, improve the performance.

of RSM, or the sign dependence, is related to the mean/volatility of the underlying instruments. We find that, the higher the mean, the higher is the performance/sign dependence. However, the higher the volatility, the lower is the performance/sign dependence. This outcome is consistent with the work of Christoffersen and Diebold (2006).

## 3. Regression Analysis

To formally motivate our study we explore the predictive relationship between past, current and future returns as well as past, current and future returns signs. The main regression results in Moskowitz et al. (2012)[11] indicate that the past 12 month period returns, or return signs, have strong positive impact on current asset return predictability. To provide a link with the literature, we perform the same analysis using more recent data from 1 to 60 lags. Our results yield similar findings.

We organise the series in four groups according to their asset class, concatenate them and report the t-statistics obtained from the following predictive regressions:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \frac{r_{t-h}^s}{\sigma_{t-h-1}^s} + \epsilon_t^s, \tag{2}$$

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + \epsilon_t^s, \tag{3}$$

where $r_t^s$ is the excess return of asset $s$ in month $t$ adjusted by its available ex-ante volatility $\sigma_{t-1}^s$. $sign(r_{t-h}^s)$ takes the value $+1$ if $r_{t-h}^s \geqslant 0$ or $-1$ if $r_{t-h}^s < 0$. $h$ is the number of lags used in the regressions and ranges from 1 to 60. Finally, $\epsilon_t^s$ denotes the error term with zero mean and finite variance. In Figure 2, we observe a similar pattern in the t-statistics obtained from Equation 2 and Equation 3 across all horizons. For currency and equity futures the $h = 12$ value, as suggested by the literature, is more evident and is adopted for the remainder of the paper. Our contribution is the use of each month during the period and not just the period

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[11]See Figure 1, Panel A and B therein.

return as in TSM. For example, in equity futures we see that $h = 3$ and $h = 10$ can also contribute to the prediction of current return, however, $h = 12$ is a more suitable choice.

In an effort to provide more details in the effect which causes this positive impact, we extend our analysis using cross-sectional and time series dummy variables. This allows us to separate the signal effect from the cross-sectional and time series momentum effects. We concatenate all the 55 assets monthly returns to run four pooled regressions including the previously mentioned dummy variables. The predictive regressions now become:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + D_t + \epsilon_t^s, \tag{4}$$

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + D_s + \epsilon_t^s, \tag{5}$$

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + D_t + D_s + \epsilon_t^s, \tag{6}$$

where $D_t$ is the time series dummy representing each different time $t$ and $D_s$ is the cross-sectional dummy for each different instrument.

Figure 3 illustrates how past return signs can affect current returns. The predictive regressions results without dummies suggest that most of the 1 to 12 lag return signs have positive impact on current returns. After the first 12 months, there is a long period of reversal[12]. Furthermore, controlling for cross-sectional effect does not change the main result. Thus, we can argue that the 1-12 month positive impact does not come from the cross-sectional property of the dataset. In the bottom left panel of Figure 3, we see that controlling for time series slightly smooths the pattern of the t-statistics across different horizons. For instance, comparing the top left and bottom left panels, which are the t-statistics results with and without time series dummies respectively, we observe that the t-statistic value is not statistically signif-

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[12]See Liu and Papailias (2017) for a full discussion on time series reversal.

icant (positive) for the second month lag before controlling for time series. Finally, looking at the top right and bottom right panels of Figure 3, we see that the predictive regression with the time series dummy variable does not differ greatly from the regression which includes both the cross-sectional and the time series dummy variables.

Having analysed the importance of returns signs in the predictability of future returns direction, we now extend our analysis by including the series of sign probability and not the sign variable, $sign(r_{t-h}^s)$ used so far. As mentioned earlier, we define a binary time series variable $v$ which takes the value 1 if the excess return of an asset is non-negative and 0 otherwise. For a certain look-back period $k$ and a given time $t$, we use a simple moving average[13] method to calculate the probability of positive return signs, $P$, over the past $k$ periods from time $t-k$ to $t-1$ for instrument $s$:

$$P_{t-k,t-1}^s = \frac{1}{k} \sum_{i=t-k}^{t-1} v_i. \tag{7}$$

For further econometric motivation of the equally weighted average method, we refer the interested reader to Appendix A.

Then, we regress the excess risk-adjusted returns on the probability series of positive signs of the past 12 months. The predictive regressions are given by:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h P_{t-h-11,t-h} + \epsilon_t^s. \tag{8}$$

As before, we use lags $h$ from 1 to 60.

Figure 2 presents the predictive power of the probability of positive return signs during the nearest 12 months, $P_{t-12,t-1}$, on future returns. $P_{t-12,t-1}$ have significantly positive impact on, at least, the first 4 period returns. This positive relation gradually vanishes after that. It becomes again strongly negative from months 12 to 24. Looking more into this predictive power by classifying the assets in Figure 5, we

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[13]This can also be further expanded using exponential moving average as well as binary outcome estimation methods such as the probit and logit models. However, given that the main qualitative results do not change significantly, we omit them here.

see that it varies across different classes. For equities, this trend lasts longer and is followed by a long term negative reversal. For the rest of the assets, the positive impact is shorter. However, at least one future period return is responding significantly to the probability $P_{t-12,t-1}$ series.

Finally, we compare the t-statistics when regressing the excess risk-adjusted returns on two indicators: RSM indicator $P^s_{t-12,t-1}$ and TSM indicator $sign(R^s_{t-12,t-1})$, where $sign(R^s_{t-12,t-1})$ represents the sign of the cumulative return of instrument $s$ from $t-12$ to $t-1$. Hence, the TSM predictability regression is:

$$\frac{r^s_t}{\sigma^s_{t-1}} = \alpha + \beta_h sign(R^s_{t-h-12,t-h}) + \epsilon^s_t. \tag{9}$$

Table 2 summarises the t-statistics of the two regressions based on Equation 8 and Equation 9 using the whole dataset and four separate asset classes. It is obvious that the forecastability using RSM indicators, i.e. the probability of past 12 months positive returns, on the first 1-3 lagged month returns is much better than TSM indicators, i.e. the signs of past 12 months period returns. All the t-statistics for different asset classes are at least significant at 5% level using RSM, while the results for TSM are not as clear.

Having analysed the insights that past return signs and the future probability of positive signs have on future return predictability, we are ready to introduce investment strategies to exploit this fact.

## 4. Returns Signal Momentum

To evaluate the profitability of RSM strategies, we form a portfolio using the 55 futures in our data[14]. According to the regression results in Section 3, we choose the look-back period $k$ to be equal to 12 months. For each month, using any investment strategy, RSM, TSM and SMA, a signal is generated for each asset indicating the

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[14]Such a dataset is similar to TSM literature except for some minor differences in currencies, where we use 9 future contracts instead of the cross-rate currency futures. Hutchinson and O'Brien (2015), Kim et al. (2016) and Baltas and Kosowski (2013) also use the same type of future contracts against the USD in their currency portfolio.

investor's position. The holding period is set to one[15], therefore, signals for each asset are renewed every month.

### 4.1. Position Signals & Portfolio Formation

One of the key advantages of RSM compared to TSM or XSM is the use of the full information during the look-back period. Instead of looking at the period return (as in XSM) or return sign (as in TSM) we use all the individual returns during the specified look-back period. Then, using the return signs, which is a binary time series variable, we calculate the probability of positive sign for the next period as mentioned previously. To simplify our analysis, we use the simple average to estimate this probability. Consider an asset $s$, then the signal of RSM strategy is generated when the probability of positive sign exceeds a certain probability threshold. For a given threshold value $q$, if $P_{t-12,t-1} \geqslant q$, then a "buy" signal is generated indicating to enter a long position at time $t$. Otherwise, it indicates to enter a short position. As we discuss later, we propose two types for the probability threshold $q$: (i) a fixed value, and (ii) a time-varying value. The one holding-period position return for instrument $s$ at time $t$ is given by:

$$
R_t^s | P_{t-12,t-1}^s, q = \begin{cases} +r_t^s, & P_{t-12,t-1} \geqslant q \\ -r_t^s, & P_{t-12,t-1} < q \end{cases}.
\tag{10}
$$

To form a portfolio which consists of various instruments we calculate the RSM position signals in the same way as above and allow the portfolio weight for each instrument to be given as a function of its ex-ante realised volatility. Following Moskowitz et al. (2012), we use the same critical value for the annual volatility of 40%. This aligns our results with the current literature and also mimics a real-trading situation with a capital margin of about 5-20%. The RSM return for asset $s$ is given by:

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[15]Moskowitz et al. (2012) also experiment with different look-back and holding periods suggesting that looking-back one year and holding for one month is the optimal setting. This combination is also adopted in our study.

$$R_t^s | P_{t-12,t-1}^s, q = \begin{cases} +r_t^s \frac{40\%}{\sigma_{t-1}^s}, & P_{t-12,t-1} \geqslant q \\ -r_t^s \frac{40\%}{\sigma_{t-1}^s}, & P_{t-12,t-1} < q \end{cases}. \tag{11}$$

Consequently, for a universe of $S$ assets, the RSM portfolio return is calculated as:

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

In order to properly evaluate the result of RSM in individual instrument portfolios we additionally include three well-established benchmarks in the literature: the naïve 1/N, SMA for prices and the TSM. The 1/N indicates the passive buy-and-hold strategy where same weights are assigned across all instruments. In the SMA strategy, a long position for instrument $s$ is generated if the current price is above or equal to the average of the last $k$ periods. In our context, this translates to the last 12 months. Finally, 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 for our $k = 12$ setting, otherwise the investor goes short on instrument $s$. For SMA and TSM the portfolio weights are calculated in the same way as in Equation 11.

### 4.2. Fixed Probability Threshold

The first case we consider is the fixed probability threshold. We report a number of four pre-determined thresholds $q = \{0.2, 0.3, 0.4, 0.5\}$[16]. During the evaluation period the probability threshold values are kept constant. As we see later, the empirical exercise suggests a fixed value of 0.4 which allows the strategy to provide signals that follow the big uptrends in the market and also protect the investor, on average, from downswings.

We report the annualised mean returns, annualised standard deviation, Sharpe ratio, min and max observed returns, cumulative net profits and the maximum draw-

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[16]We also try more thresholds, but omit them here due to they do not add significant value. However, they are available upon request.

down. The formulas for these statistics are provided in Appendix D. First, we study the performance of individual instruments using RSM strategies as well as the benchmark strategies[17]. Results suggest that in most cases, RSM strategies perform better than the benchmarks when the threshold value is no larger than 0.5.

Then, moving to panel A and B of Table 3, we summarise the portfolio performance using the same strategies. At first, comparing the benchmarks, we find that, a TSM exercise works better than the rest. In particular, TSM provides the largest Sharpe ratio, cumulative net profits and the lowest drawdown. Comparing the portfolios which invest based on the suggested RSM strategies, we see that, as long as the threshold is smaller than 0.5, the portfolios perform favourably when compared to TSM. The Sharpe ratio of the best RSM strategy, i.e. using $q = 0.4$, is 20% better compared to that of TSM. All the RSM strategies with a fixed threshold $q < 0.5$ are associated with an annual return which is at least equal to 10% with smaller or similar volatility to the TSM. RSM portfolios also result in larger cumulative net profits and smaller maximum drawdown indicating desirable risk/return characteristics. Specifically, the cumulative net profits of the RSM0.4 portfolio is almost 18% larger than the TSM and the drawdown is almost 44% smaller. It must be highlighted that our comparison is consistent even when transaction costs are included; see Appendix B.

For a more in-depth analysis of how RSM portfolios change throughout time, we graphically depict the evolution of cumulative net profits of the best RSM portfolio with $q = 0.4$ along the three benchmark portfolios. We see in Figure 6 that from January, 1985 to March, 2015, the cumulative net profits of RSM almost doubles the value of TSM. Particularly, the two strategies share a resemblance until 2003, with the equities market[18] outperforming both strategies. However, after 2004, RSM is the best portfolio having a long uptrend until 2008, suffering a 19% loss during and after the crisis, and then rising above 2500%.

We perform a similar graphical investigation by looking into the evolution of

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[17]Details of individual instruments performance are summarised in Appendix E.

[18]As proxied by the S&P 500 index

maximum drawdown across time. In Figure 7, we see that RSM and TSM have the same drawdown, with RSM suffering losses in the mid 1980s. After that, the drawdown risk remains the same with RSM outperforming TSM during the financial crisis in 2008, where the drawdown of the passive long and the S&P 500 is almost 30%.

To conclude the comparison of RSM portfolios and the benchmarks, we also investigate how RSM portfolio returns respond to positive and negative market returns. Figure 8 shows a scatterplot of the quarterly RSM returns against the S&P 500 index returns and TSM portfolio returns[19]. In both cases, we observe that RSM portfolio exhibits positive expected returns based on positive and, most importantly, negative S&P 500 returns, whereas its relationship with TSM is more linear. We also observe that RSM returns are above the regression line indicating a better performance compared to the benchmarks.

### 4.3. Time-Varying Probability Threshold

Having investigated the performance of RSM based on the probability of positive signs using fixed thresholds, we now turn our attention to a time-varying threshold. In the previous subsection, we use a variety of fixed thresholds and the empirical evidence suggests that a value of 0.4 is optimal in the sense that keeps the investor in long positions during market uptrends and protected during crises or market turmoils. However, it would be challenging to evaluate the performance of RSM using a probability threshold which varies across time. There could be a lot of methods to estimate a time varying threshold depending on the investor's preferences. For example, an investor who is cautious with inflation might adopt a threshold as a function of the expected inflation rate. Or, another example is a threshold which is a function of the real effective exchange rate. We suggest a more neutral approach, in terms of preferences, where the probability threshold is chosen using an out-of-sample cross-validation method.

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[19]We also fit some linear regression lines and a polynomial non-linear fit. Following Moskowitz et al. (2012), we use quarterly returns to make the result more comprehensible, however, the same qualitative conclusion is reached when monthly returns are used.

Consider the threshold time series to be denoted by $q_t$. The value at each point in time is calculated by automatically choosing the best threshold value within a rolling 24 months evaluation period. We calculate the cumulative return $R^s_{t-12,t-1}|q$ for the last 12 out of the 24 months span, based on different thresholds $q$ by using the position returns from $R^s_{t-12}|P_{t-24,t-13}, q$ to $R^s_{t-1}|P_{t-13,t-2}, q$. The threshold $q_t$ is chosen when the cumulative return $R^s_{t-12,t-1}|q$ is maximised. The threshold values we use are 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8.

The bottom panel of Table 3 shows the performance of RSM portfolio using the time-varying threshold. When compared to the benchmarks, we see that RSM again provides higher mean returns, Sharpe ratio and lower drawdown. Figure 9 illustrates the cumulative net profits of the RSM time-varying threshold strategy compared to the TSM, the market and the passive long strategy during January, 1985 to March, 2015. As we see, the cumulative net profits of RSM is better compared to the benchmarks and in particular about 1.2 times larger than TSM.

An obvious issue to explore is the behaviour of the threshold value across time. In Panel A of Figure 10 we plot the time series of the probability threshold estimates and compare it to the S&P 500 price index. It is interesting to notice that when the market increases (e.g., during 2000-2002, 2004-2008 and after 2011) the threshold value decreases allowing the investor to enter more long positions as the market expectations are optimistic. However, when the market decreases (e.g., 2003-2004 and 2008-2011), the threshold increases protecting the investor.

Then, we calculate the correlation coefficients of this time-varying threshold value and the price of S&P 500 index using a kernel-based smoothing method[20] and compare it to the NBER-based recession indicators as shown in Panel B of Figure 10. When it comes to the recession periods (early 1990s, 2001 and 2008 global financial crisis), the correlation becomes low at about 0 in the early 1990s recession, around -0.3 for the 2001 crisis and nearly -0.9 for the 2008 crisis. Thus, the time-varying threshold correctly captures the market conditions indicating a more punctual market-timing.

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[20]See Giraitis et al. (2014).

However, for the particular universe of futures used here, we notice that the RSM portfolio with time-varying threshold, although still better than the TSM and the other benchmarks, provides partially smaller cumulative return profits compared to the RSM portfolio with the fixed $q = 0.4$ threshold. This is due to the volatility which is also smaller than the RSM0.4 strategy. Hence, the Sharpe ratio for RSM time-varying threshold strategy (0.916) is very close to RSM0.4 (0.962), which are both higher than the rest RSM strategies ranging and the TSM (0.792). Overall, this exercise sheds additional light in the ways that RSM could be used in practice.

## 4.4. Risk Exposure Analysis

We conclude the main results for the suggested RSM by analysing their risk exposure. To do so, we regress the returns of RSM portfolio on three major classes of market risk factors. These are the Fama-French SMB, HML and UMD factors which represent the size, value and momentum respectively as in Fama and French (1993) and Carhart (1997), the "Value and Momentum Everywhere" factors of Asness et al. (2013) and the TSM factor of Moskowitz et al. (2012). We control the regression models for the market risk by including the monthly returns of the MSCI world index. The regressions output is reported in Table 4.

The results reveal an approximately 40% change in the RSM portfolio which is due to the change of the market. RSM also has strong positive relationship with each of the momentum factors (UMD, Momentum everywhere and TSM) as the beta coefficients are statistically significant at 5% and 1% levels. Despite the fact that all momentum factors and the market change can explain parts of the RSM portfolio returns, there is still a statistically significant intercept for each model which indicates that some part of the returns is due to the RSM effect. The alpha estimate varies from 0.27% to 0.58% at 5% level of significance. Overall, we see that RSM is related to the other momentum factors, as it is also a momentum effect, however a part of RSM cannot be explained by the known factors.

## 5. Conclusions

In this paper we introduce a new type of momentum based on the probability of positive signs of financial asset returns. A comprehensive study on 55 financial instruments across a time span of 30 years illustrates the beneficial risk/return characteristics that are associated with RSM strategies. RSM generates signals using an estimate of the probability with reference to a probability threshold value. Various fixed threshold values are used presenting empirical evidence that RSM portfolios provide larger cumulative net profits, larger Sharpe ratio and lower maximum drawdown compared to the passive long, simple price moving average and time series momentum portfolios. A time-varying probability threshold which is based on cross-validation suggests, that the threshold is negatively correlated with the market. In particular, when the market expectations are positive, the time-varying threshold decreases, allowing the investor to enter more long positions. When the market conditions deteriorate, the time-varying threshold increases, protecting the investor from the upcoming downtrend.

The risk exposure analysis indicates that RSM should not be considered as a financial market risk factor due to its strong relationship with the market and the other momentum factors. However, it does produce significant alpha which cannot be explained by the existing risk factors. Therefore, it can be attributed to the RSM effect. Our research indicates that RSM can be successfully used as an alternative type of momentum for speculation and hedging by market participants.

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## Table 1: Summary statistics.

| Asset | Start Date | Annual Mean | Annual Volatility | Postive Rate |
|---|---|---|---|---|
| **Commodity futures** | | | | |
| Aluminum | 1987/6/2 | 0.0258 | 0.2055 | 0.4835 |
| Brent | 1988/6/24 | 0.1000 | 0.3219 | 0.5389 |
| Cocoa | 1970/1/6 | 0.0810 | 0.3267 | 0.5018 |
| Coffee | 1972/8/17 | 0.0914 | 0.3872 | 0.4814 |
| Copper | 1986/4/2 | 0.0822 | 0.2541 | 0.5303 |
| Corn | 1970/1/6 | 0.0637 | 0.2790 | 0.5000 |
| Cotton | 1970/1/6 | 0.0670 | 0.2973 | 0.5535 |
| Gas Oil | 1989/7/4 | 0.1038 | 0.3313 | 0.5487 |
| Gold | 1975/1/3 | 0.0664 | 0.1956 | 0.5062 |
| Heating Oil | 1980/1/3 | 0.0844 | 0.3564 | 0.5142 |
| Lean Hogs | 1986/4/2 | 0.0725 | 0.3431 | 0.5447 |
| Live Cattle | 1970/1/6 | 0.0567 | 0.1966 | 0.5258 |
| Natural Gas | 1990/4/4 | 0.1646 | 0.5439 | 0.5351 |
| Nickel | 1987/1/6 | 0.1348 | 0.4176 | 0.5118 |
| Platinum | 1984/1/27 | 0.0386 | 0.2288 | 0.5187 |
| RBOB | 1986/8/22 | 0.1304 | 0.4014 | 0.5190 |
| Silver | 1970/1/6 | 0.1035 | 0.3415 | 0.5092 |
| Soy Meal | 1970/1/6 | 0.0883 | 0.3490 | 0.5203 |
| Soy Oil | 1970/1/6 | 0.0738 | 0.3163 | 0.5148 |
| Soybeans | 1970/1/6 | 0.0710 | 0.2909 | 0.5240 |
| Sugar | 1970/1/6 | 0.1231 | 0.4588 | 0.4926 |
| Wheat | 1970/1/6 | 0.0693 | 0.2908 | 0.5037 |
| WTI | 1983/3/31 | 0.0685 | 0.3285 | 0.5365 |
| Zinc | 1989/1/5 | 0.0351 | 0.2436 | 0.5064 |
| **Currency futures** | | | | |
| AUD | 1971/1/6 | -0.0021 | 0.1103 | 0.5057 |
| CAD | 1971/1/6 | -0.0027 | 0.0651 | 0.4887 |
| EUR | 1971/1/6 | -0.0019 | 0.1108 | 0.5208 |
| JPY | 1971/1/6 | 0.0223 | 0.1145 | 0.4962 |
| NZD | 1971/1/6 | -0.0021 | 0.1201 | 0.5189 |
| NOK | 1971/1/6 | 0.0094 | 0.1041 | 0.4962 |
| SEK | 1971/1/6 | 0.0249 | 0.1102 | 0.4717 |
| CHF | 1971/1/6 | 0.0160 | 0.1245 | 0.5170 |
| GBP | 1971/1/6 | -0.0052 | 0.1011 | 0.4887 |
| **Equity index futures** | | | | |
| SPI | 1970/1/6 | 0.0747 | 0.1930 | 0.5793 |
| CAC | 1970/1/6 | 0.0788 | 0.2033 | 0.5517 |
| DAX | 1970/1/6 | 0.0869 | 0.1974 | 0.5849 |
| FTSE/MIB | 1970/1/6 | 0.0744 | 0.2379 | 0.5166 |
| TOPIX | 1970/1/6 | 0.0657 | 0.1868 | 0.5572 |
| AEX | 1970/1/6 | 0.0741 | 0.1917 | 0.5904 |
| IBEX | 1970/1/6 | 0.0700 | 0.2088 | 0.5461 |
| FTSE | 1970/1/6 | 0.0859 | 0.1968 | 0.5812 |
| S&P500 | 1970/1/6 | 0.0796 | 0.1545 | 0.6015 |
| **Bond futures** | | | | |
| AUS3 | 1986/1/2 | 0.0111 | 0.0628 | 0.5629 |
| AUS10 | 1986/1/2 | 0.0089 | 0.0477 | 0.5600 |
| EURO2 | 1986/1/2 | 0.0181 | 0.0811 | 0.5114 |
| EURO5 | 1986/1/2 | 0.0233 | 0.0734 | 0.5771 |
| EURO10 | 1986/1/2 | 0.0373 | 0.0784 | 0.5914 |
| EURO30 | 1986/1/2 | 0.0375 | 0.1236 | 0.5229 |
| CA10 | 1986/1/2 | 0.0232 | 0.0736 | 0.5486 |
| JP10 | 1985/10/22 | 0.0161 | 0.0538 | 0.5949 |
| UK10 | 1982/11/19 | 0.0099 | 0.0914 | 0.5438 |
| US2 | 1986/1/2 | 0.0036 | 0.0284 | 0.5286 |
| US5 | 1986/1/2 | 0.0080 | 0.0469 | 0.5314 |
| US10 | 1982/5/4 | 0.0204 | 0.0737 | 0.5381 |
| US30 | 1977/8/23 | 0.0192 | 0.1176 | 0.5166 |

This table reports the start date, mean, volatility/standard deviation, and the probability of positive signs for the 55 instruments. The arithmetic monthly mean returns and standard deviation are both annualized. The detailed data sources are described in Appendix C.

Table 2: Predictive power of RSM and TSM indicators.

| Lag (Months) | Probability of 12 Month Positive Returns | | | | | Signs of 12 Month Cumulative Returns | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Commodity | Currency | Equity | Bond | All | Commodity | Currency | Equity | Bond | All |
| 1 | **2.151** | **4.091** | **6.693** | **2.579** | **4.823** | **1.783** | -1.250 | 0.664 | 0.706 | 1.531 |
| 2 | 1.588 | **2.699** | **6.553** | 0.838 | **2.850** | 0.126 | -1.152 | 0.710 | 0.829 | 1.478 |
| 3 | 0.567 | **1.668** | **6.263** | 0.801 | **2.412** | 0.253 | 0.022 | 1.477 | -0.870 | 0.106 |
| 4 | -0.349 | 1.368 | **5.858** | 0.693 | **2.119** | -1.197 | -1.393 | 0.419 | **-1.702** | -1.382 |
| 5 | -0.944 | 0.643 | **5.132** | 0.411 | 1.594 | -0.236 | 1.153 | 0.042 | -0.726 | 0.185 |
| 6 | -1.201 | 0.746 | **4.253** | 0.237 | 1.245 | -0.409 | **2.243** | 1.130 | -0.051 | 1.127 |
| 7 | -1.265 | 1.008 | **3.602** | -0.279 | 0.732 | -1.398 | 1.506 | 1.089 | 0.569 | 1.495 |
| 8 | -1.529 | 0.725 | **3.355** | -1.572 | -0.597 | -1.596 | 0.307 | 1.020 | 1.002 | 1.629 |
| 9 | -1.023 | 1.402 | **3.009** | **-2.729** | -1.452 | 0.679 | 0.123 | 1.154 | 0.228 | 1.177 |
| 10 | -0.187 | 1.488 | **1.810** | **-3.312** | **-1.874** | 1.010 | -0.151 | 0.376 | -1.482 | -0.438 |
| 11 | -0.363 | 1.016 | 1.013 | **-3.279** | **-2.051** | 0.099 | -0.603 | 0.483 | **-2.405** | **-1.647** |
| 12 | -1.302 | 0.605 | 0.618 | **-3.271** | **-2.250** | 1.352 | 0.276 | 0.330 | **1.889** | **2.950** |
| 13 | **-1.833** | 0.042 | 0.341 | **-4.176** | **-3.400** | 0.761 | -0.844 | -1.064 | 1.376 | **1.864** |
| 14 | **-2.146** | 0.022 | 0.509 | **-3.737** | **-3.036** | -0.864 | -0.701 | -0.309 | -1.488 | -1.114 |
| 15 | -1.520 | 0.159 | -0.072 | **-3.668** | **-2.934** | -0.663 | **-1.729** | 0.710 | 0.222 | 0.452 |
| 16 | -1.297 | -0.713 | 0.014 | **-4.147** | **-3.523** | -1.195 | -1.177 | -0.729 | -1.330 | -1.131 |
| 17 | -1.056 | -1.177 | 0.050 | **-4.083** | **-3.529** | -1.565 | 0.514 | -0.511 | 0.653 | 1.168 |
| 18 | -1.051 | -1.602 | 0.736 | **-3.933** | **-3.420** | -1.422 | 0.037 | -0.099 | -0.667 | -0.130 |
| 19 | -1.178 | **-2.311** | 0.230 | **-3.456** | **-3.100** | -0.901 | -0.299 | 1.167 | -0.013 | 0.859 |
| 20 | -1.140 | **-1.773** | -0.247 | **-3.157** | **-2.921** | -0.581 | -0.614 | 0.231 | -0.335 | 0.296 |
| 21 | **-1.936** | **-2.686** | -0.229 | **-2.850** | **-2.914** | -1.291 | 0.874 | 1.406 | -0.065 | 1.072 |
| 22 | **-1.986** | **-3.197** | 0.011 | **-2.160** | **-2.369** | -0.961 | 1.230 | 0.052 | 1.017 | **1.791** |
| 23 | **-2.500** | **-2.842** | 0.434 | -1.523 | **-1.744** | **-2.718** | -0.172 | -0.828 | 0.615 | 0.587 |
| 24 | **-2.084** | **-3.143** | -0.042 | -1.461 | **-1.712** | -1.521 | **-1.731** | -0.800 | -1.125 | -1.165 |
| 25 | **-1.677** | **-2.723** | 0.438 | -0.195 | -0.337 | -0.481 | -1.197 | -1.012 | -0.796 | |
| 26 | -0.560 | **-2.531** | -0.526 | -0.020 | -0.081 | -0.633 | 0.504 | 0.119 | 0.413 | 1.398 |
| 27 | -0.793 | **-2.429** | -0.320 | -0.462 | -0.496 | 0.746 | 0.444 | **-2.357** | 0.928 | **1.741** |
| 28 | -0.235 | **-2.400** | -1.133 | -0.906 | -0.823 | -1.432 | -0.123 | **-1.837** | 0.095 | 0.907 |
| 29 | 0.588 | -1.451 | -1.070 | -1.303 | -0.851 | -0.076 | 0.023 | **-1.779** | 1.149 | 1.642 |
| 30 | 1.050 | -1.424 | -1.153 | -0.684 | -0.127 | 0.350 | 0.428 | -1.025 | 1.492 | **2.056** |
| 31 | 0.946 | -0.549 | -0.631 | -0.588 | 0.196 | **1.851** | -0.103 | 0.046 | 0.560 | 1.363 |
| 32 | 1.183 | -0.497 | -0.494 | -0.011 | 0.844 | 0.298 | **-1.842** | 0.166 | -1.643 | -1.372 |
| 33 | 1.542 | -0.472 | -0.403 | 0.296 | 1.219 | **2.016** | **-2.321** | 1.006 | **1.942** | **2.572** |
| 34 | 0.703 | -1.051 | -0.854 | -0.136 | 0.490 | 1.267 | **-1.695** | -0.958 | 1.234 | **1.886** |
| 35 | 1.261 | **-1.797** | **-1.712** | -0.309 | 0.126 | **2.083** | **-1.918** | -0.914 | 0.986 | **1.718** |
| 36 | 0.592 | **-2.499** | -0.922 | -0.826 | -0.554 | **2.115** | -0.248 | **-2.476** | 0.359 | 0.912 |

Reported are the t-statistics of two sets of pooled regressions based on Equation 8 and Equation 9. The regressions are run using the whole dataset and four separated asset classes. The explained variables are the lagged returns of the underlying asset from 1 month to 36 months. A two-sided t-test is employed, and the 10% statistically significant t-statistics are reported in bold.

Table 3: Performance of RSM strategies compared to benchmark.

| Strategies | Average | Volatility | Sharpe Ratio | Maximum | Minimum | Cumulative Net Profits | Maximum Drawdown |
|---|---|---|---|---|---|---|---|
| Panel A: Benchmarks | | | | | | | |
| 1/N | 0.053 | 0.075 | 0.707 | 0.078 | -0.134 | 3.536 | 0.301 |
| SMA | 0.078 | 0.131 | 0.596 | 0.167 | -0.127 | 7.144 | 0.430 |
| TSM | 0.103 | 0.130 | 0.792 | 0.130 | -0.113 | 16.312 | 0.291 |
| Panel B: RSM fixed thresholds | | | | | | | |
| RSM 0.2 | 0.112 | 0.134 | 0.835 | 0.125 | -0.140 | 20.925 | 0.312 |
| RSM 0.3 | 0.114 | 0.129 | 0.881 | 0.126 | -0.126 | 22.872 | 0.269 |
| RSM 0.4 | 0.119 | 0.123 | 0.962 | 0.132 | -0.131 | 27.164 | 0.195 |
| RSM 0.5 | 0.103 | 0.117 | 0.883 | 0.129 | -0.129 | 17.099 | 0.190 |
| Panel C: RSM time-varying threshold | | | | | | | |
| RSM TV | 0.110 | 0.121 | 0.916 | 0.132 | -0.113 | 21.234 | 0.268 |

Reported is a comparison of performance for RSM strategies with different fixed and time-varying thresholds and three benchmarks: 1/N, SMA and TSM from January, 1985 to March, 2015. Strategies evaluation criteria consists of mean, standard deviation, gross Sharpe Ratio, maximum/minimum returns, cumulative net profits and the maximum drawdown. The corresponding formulas of all the evaluation methods are available in Appendix D. All the results are annualized.

Table 4: Returns signal momentum risk exposure.

Panel A: Fama and French factors

|  | MSCI World | SMB | HML | UMD | Intercept | R2 |
|---|---|---|---|---|---|---|
| Coefficient | 0.42 | -0.12 | 0.05 | 0.20 | 0.58% | 27.28% |
| t-Statistic | 10.92 *** | -2.2 ** | 0.80 | 5.57 *** | 3.48 *** | |

Panel B: Value and Momentum factors

|  | MSCI World | VAL Everywhere | MOM Everywhere | Intercept | R2 |
|---|---|---|---|---|---|
| Coefficient | 0.41 | 0.25 | 0.74 | 0.36% | 33.27% |
| t-Statistic | 11.53 *** | 2.06 ** | 7.48 *** | 2.12 ** | |

Panel C: Time series momentum factors

|  | MSCI World | TSM | Intercept | R2 |
|---|---|---|---|---|
| Coefficient | 0.32 | 0.58 | 0.27% | 40.93% |
| t-Statistic | 11.45 *** | 17.46 *** | 2.09 ** | |

This table reports the factor exposure of the monthly returns of RSM0.4 strategies. The regression coefficients are reported in the first row and t-statistics (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$) are reported in the row below. Three sets of regressions are run: Fama-French and Carhart factors(Panel A), "Value and Momentum Everywhere" factors (Panel B) and Time Series Momentum factors (Panel C). The regressions are conducted with the dataset that spans from January, 1985 to March, 2015.

Figure 1: Sign dependence and individual instrument's mean/volatility.
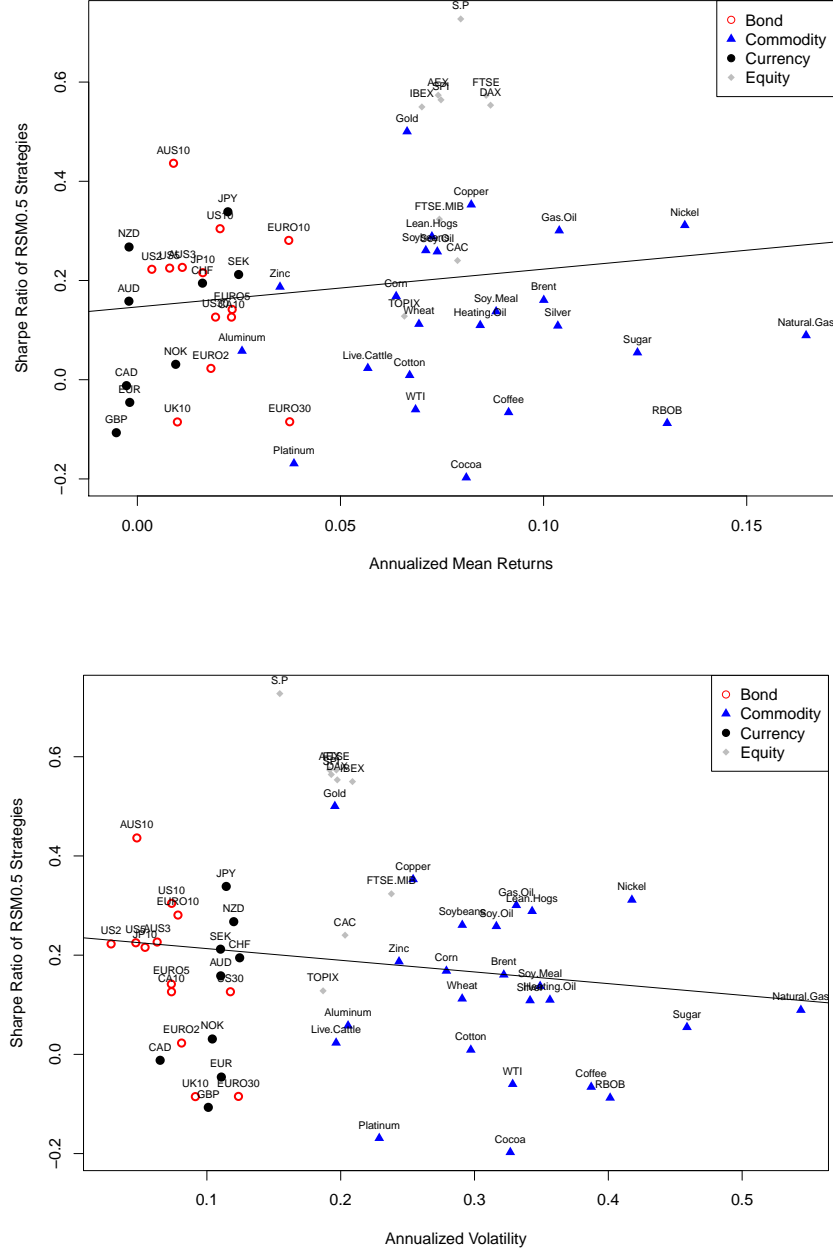


Reported figure illustrates how the Sharpe ratio of RSM before volatility adjustment, or the sign dependence, is related to the mean/volatility of the underlying instruments. Detailed calculation of mean, volatility and Sharpe ratio are listed in Appendix D.

Figure 2: Returns and return signs predictive regressions.
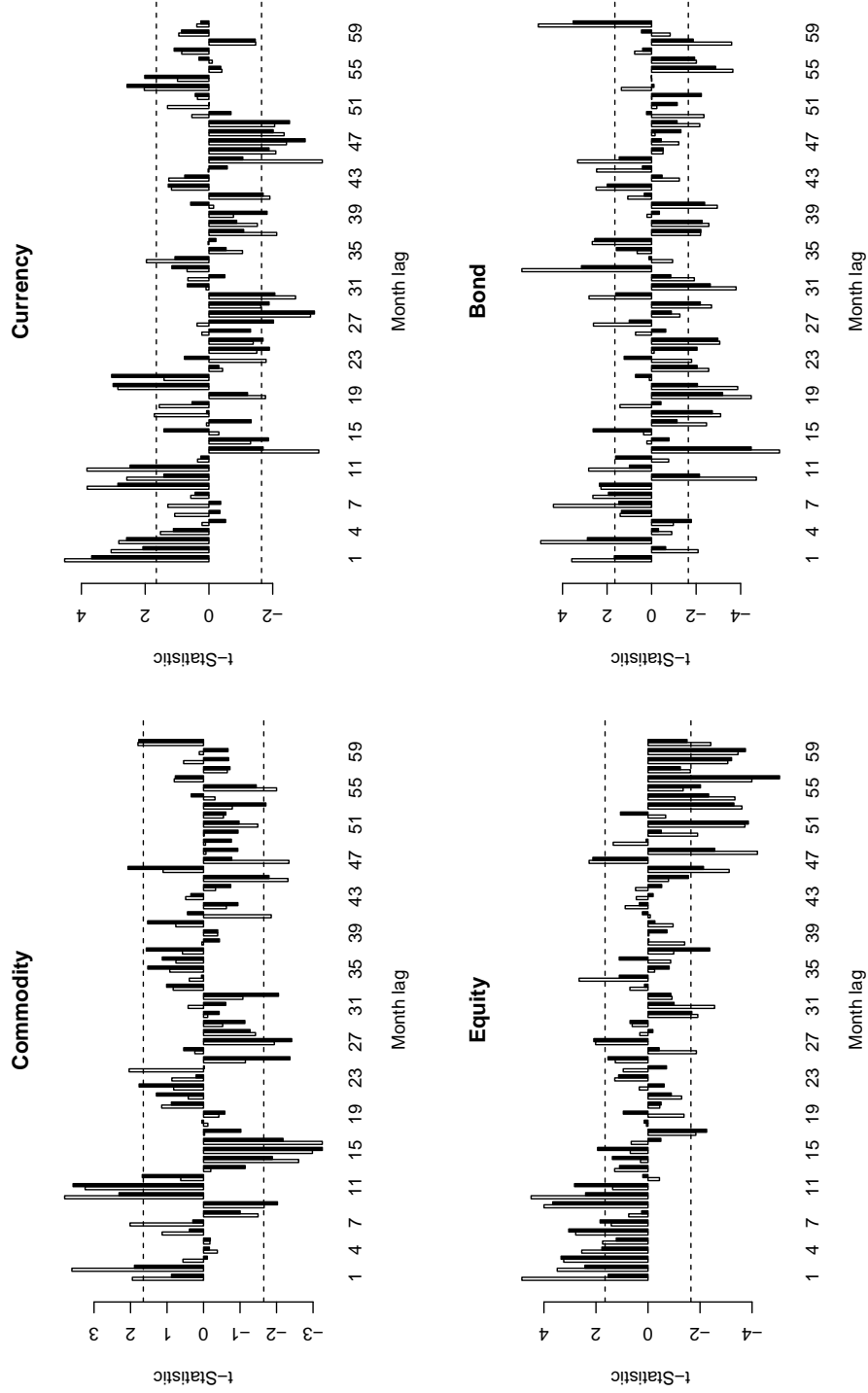
Reported are the $t$-statistics for different lags from $h = 1$ to $h = 60$. White and black bars indicate the $t$-statistics of regressions as in Equation 2 and Equation 3 respectively. Four separated pooled regressions are run representing four asset classes from January, 1985 to March, 2015.

Figure 3: Return signs predictability with and without cross-sectional (CS) and time series (TS) dummies.
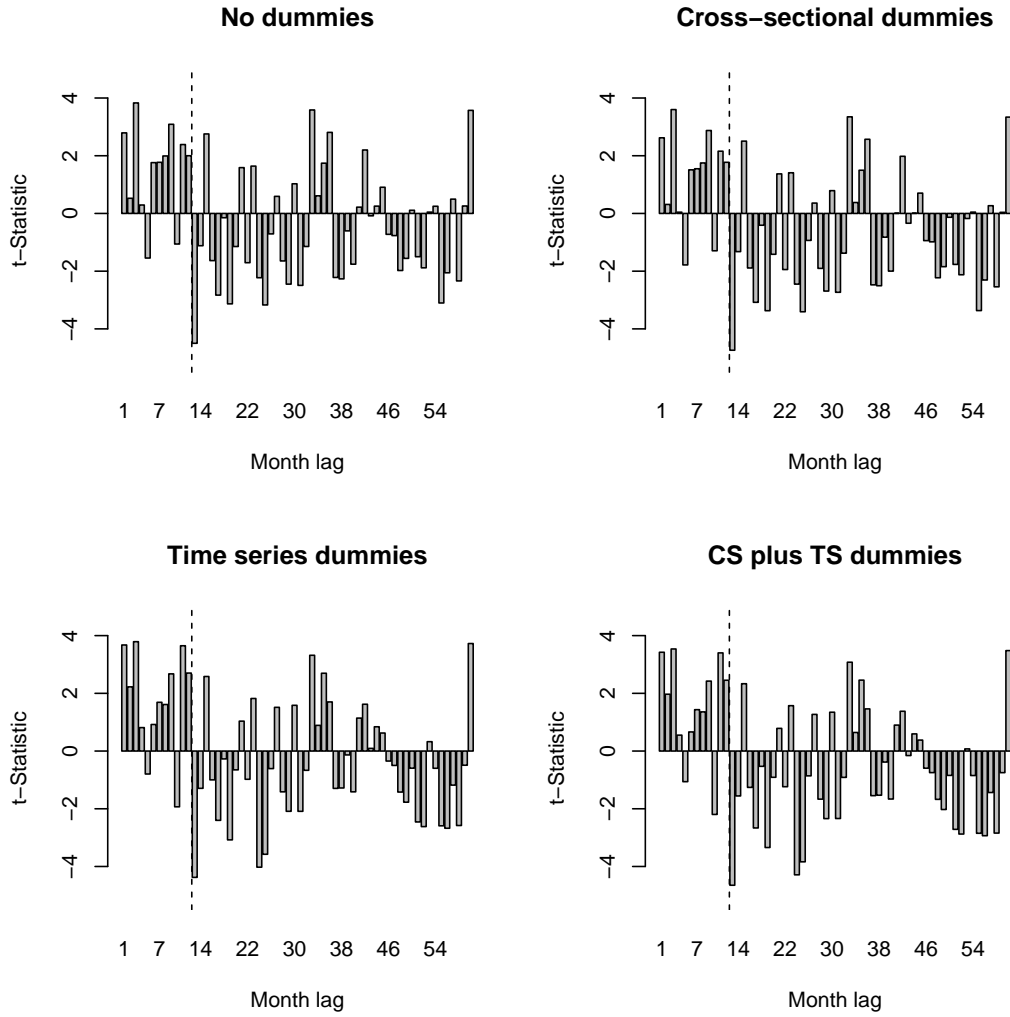
**No dummies**

**Cross−sectional dummies**

**Time series dummies**

**CS plus TS dummies**

Reporting the t-statistics for different lags from $h = 1$ to $h = 60$. Four separated pooled regressions as in Equation 3, Equation 4, Equation 5 and Equation 6 are run.

Figure 4: Predictability of 12 months probability of positive return signs (Total assets).
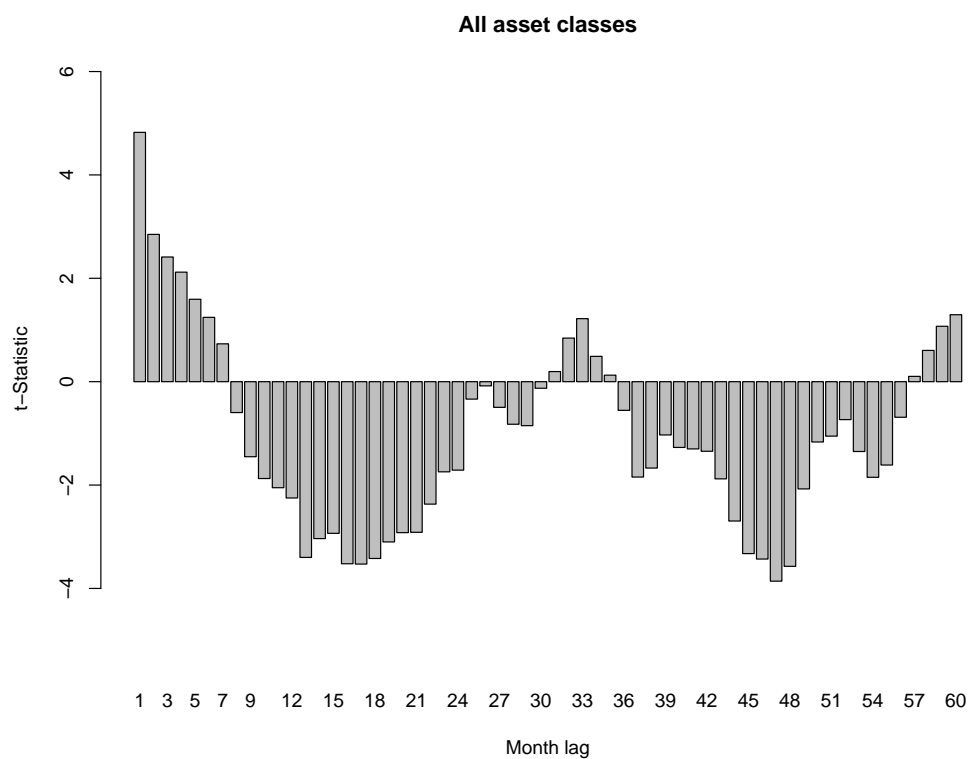
**All asset classes**



Reporting the t-statistics for lags from $h = 1$ to $h = 60$. The pooled regression which consists of all the 55 instruments as in Equation 8 is run.

Figure 5: Predictability of 12 months probability of positive return signs (Asset classifications).
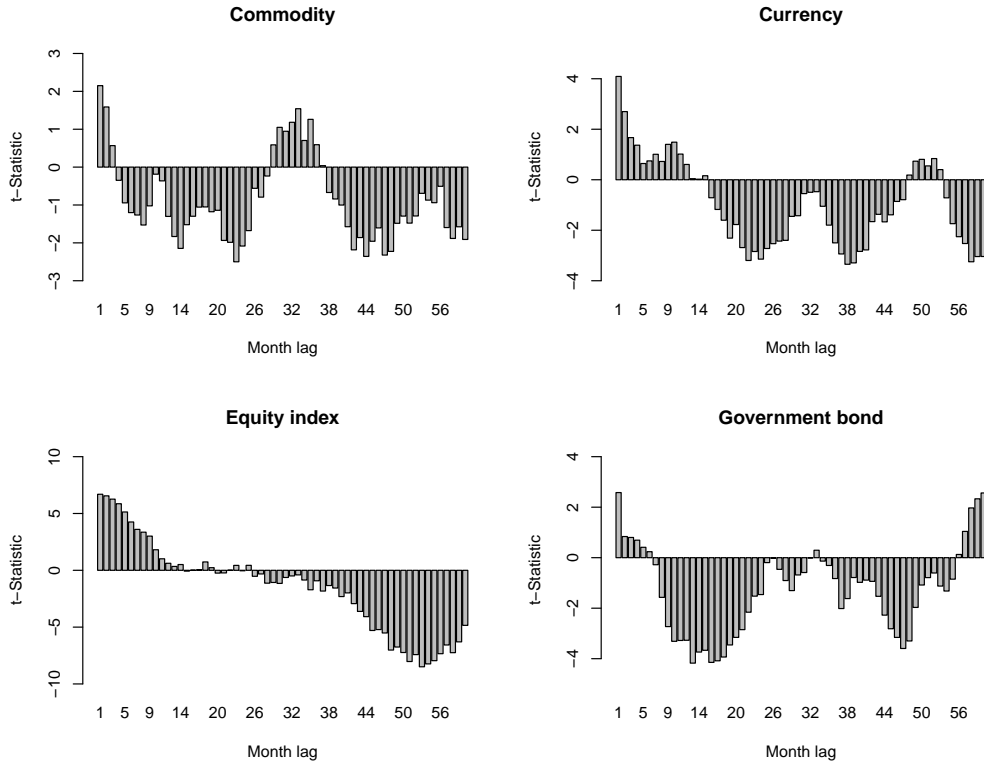


Reporting the t-statistics for lags from $h = 1$ to $h = 60$. Four separated pooled regressions representing four asset classes as in Equation 8 are run.

Figure 6: Returns signal momentum strategy profitability (Fixed threshold).
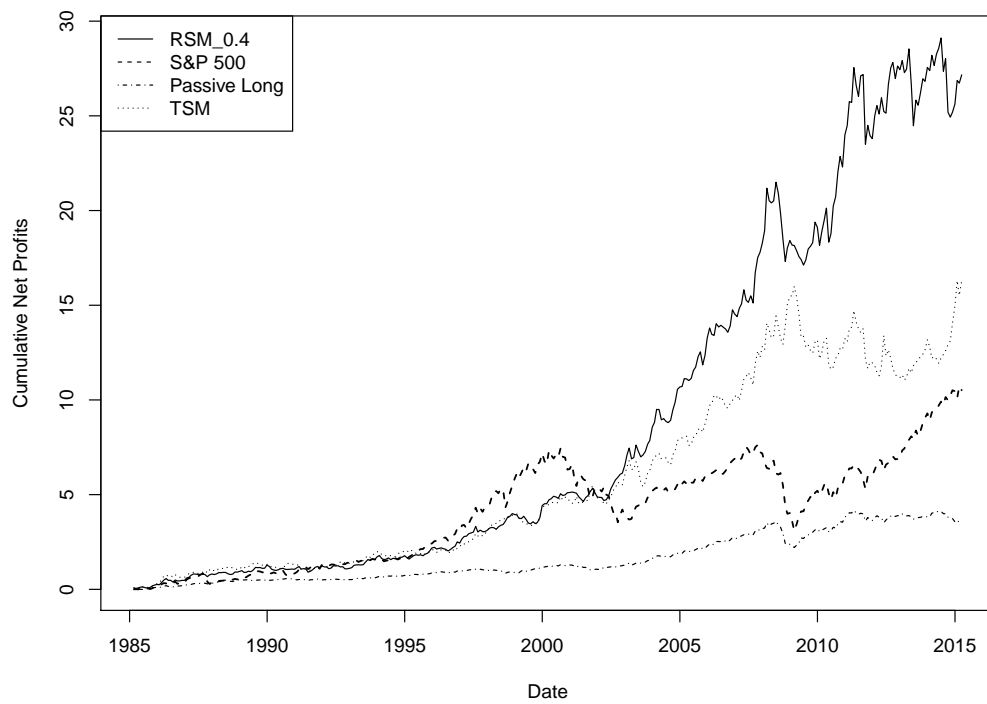


Reported are the cumulative net profits of RSM0.4 strategy and three benchmarks: S&P 500 index, Passive Long (1/N) and TSM from January, 1985 to March, 2015.

Figure 7: Maximum drawdown of returns signal momentum strategy (Fixed threshold).
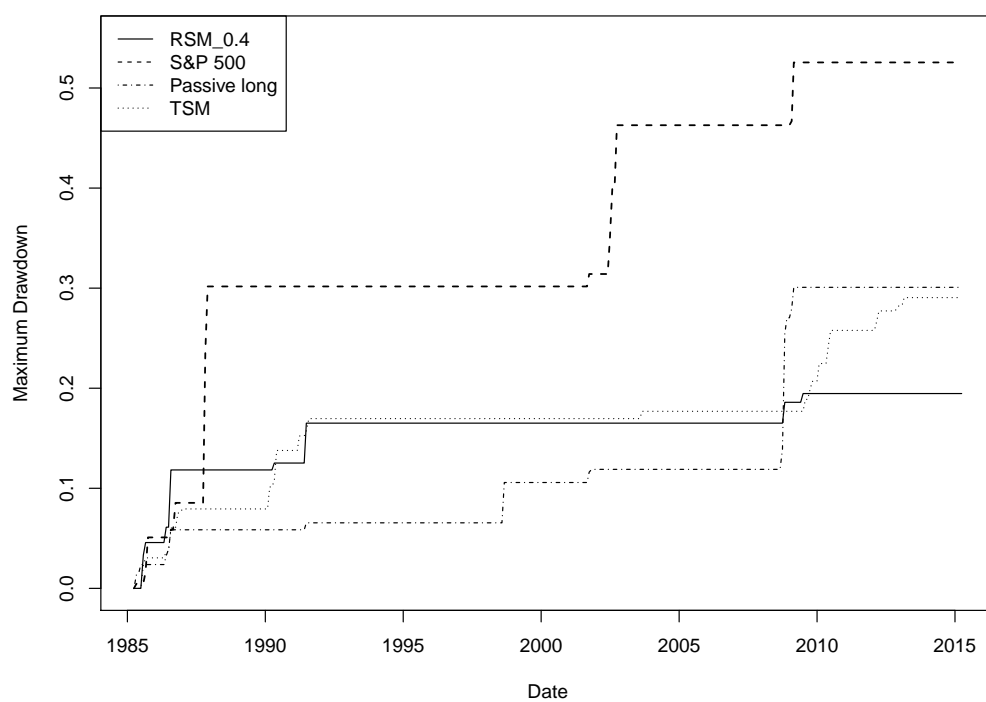


Reported are the Maximum Drawdowns of RSM0.4 strategy and three benchmarks: S&P 500 index, Passive Long (1/N) and TSM from January, 1985 to March, 2015.

Figure 8: RSM versus S&P 500 index and TSM.
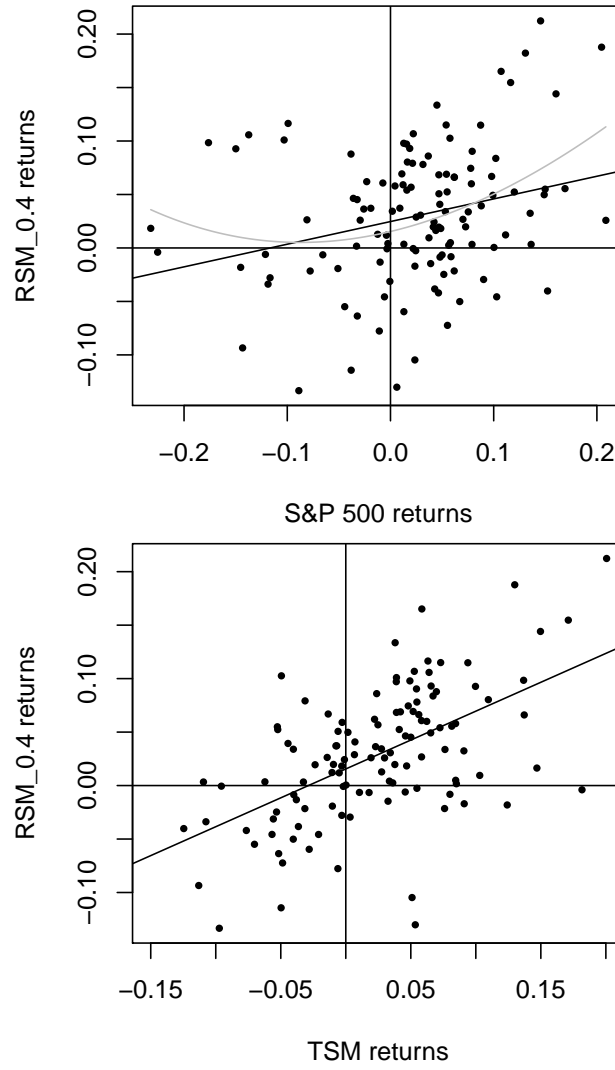


Reported are the scatter plots of quarterly returns of RSM0.4 strategies compared to S&P 500 index and TSM returns.

Figure 9: Returns signal momentum strategy profitability (Time-varying threshold).
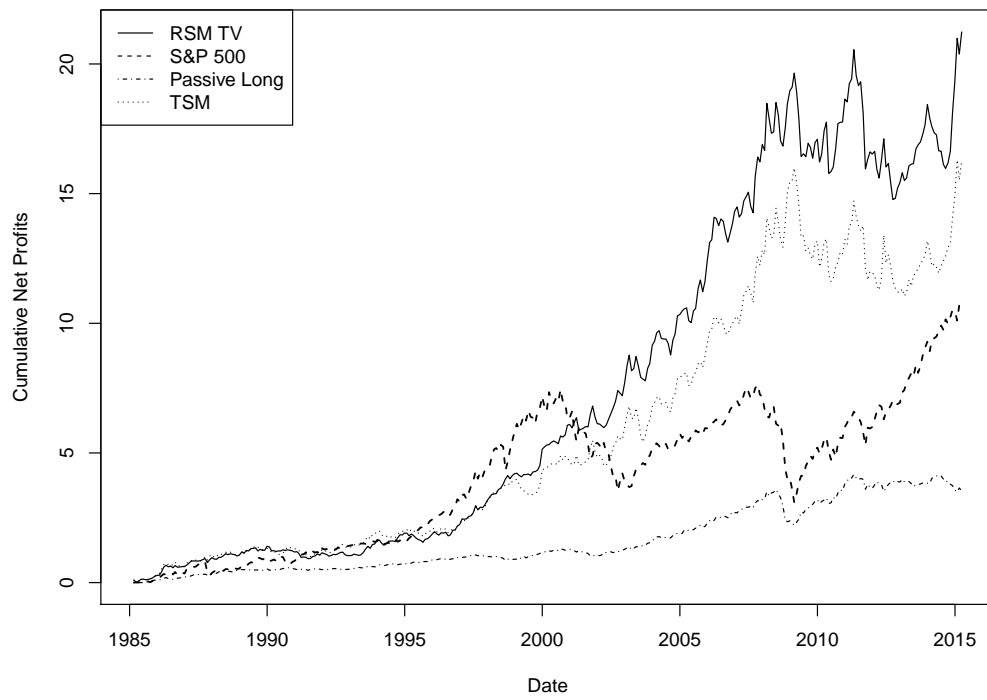


Reported are the cumulative net profits of RSM time-varying threshold strategy and three benchmarks: S&P 500 index, Passive Long (1/N) and TSM from January, 1985 to March, 2015.

Figure 10: Time-varying threshold value using cross validation.

(a) Panel A: Time-varying threshold value and S&P 500 index.
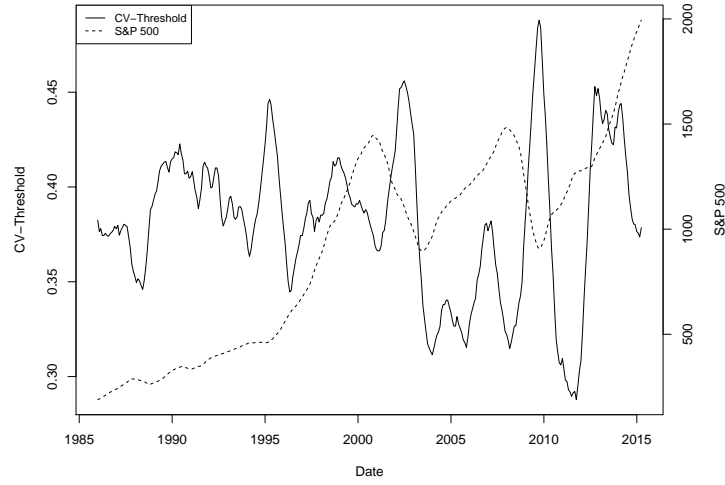


(b) Panel B: Correlation of TV threshold and S&P 500 index.
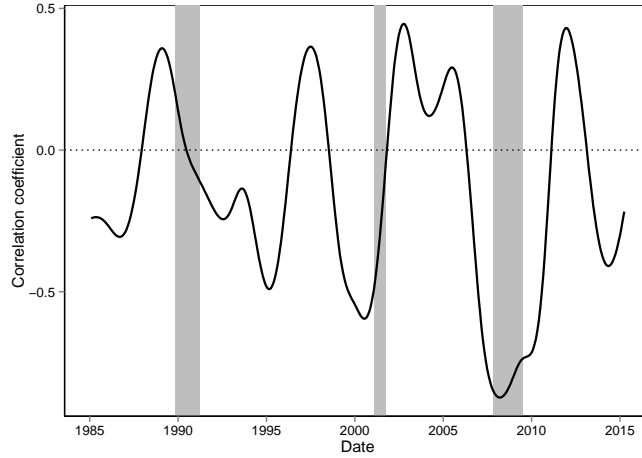


Panel A Reports the time-varying threshold value and S&P 500 index over time. The left hand side axis scales the time-varying threshold value, while the scale on the right hand side is for S&P 500 index. Panel B reports the kernel-based smoothing correlation coefficients between the time-varying threshold value and S&P 500 index. NBER based recession indicators are shown in the shaded area when value equals to 1.

# Appendices

## A. Singular Spectrum Analysis and the Average of Past Returns Signs

In this Appendix, we offer additional motivation for the use of the simple average of past return signs as an estimate of sign probability. As we mention in the main text, our purpose is not to offer new probability estimators, but to illustrate the financial momentum effect caused by sign dependence. Therefore, the use of simple average proves to be an effective and robust estimator, but more advanced binary variable forecasting models could be employed. Below, we offer additional econometric motivation on the use of averaging for the interested reader.

Consider the time series $\{X_t\}_{t \in \mathbb{Z}}$ taking values in $\mathcal{R}_X \in \{0, 1\}$. The Data Generating Process (DGP) of $X_t$ is not explicitly specified but we take it that there is possibly a time-varying probability distribution $p_t \stackrel{\text{def}}{=} \mathbb{P}(X_t = 1)$ underlying the evolution of values of $X_t$. One can make various assumptions as to how $p_t$ is to be modelled: it can be, for example, based on a Non-Homegeneous Markov Chain (NHMC) assumption obeying certain ergodicity conditions. We will illustrate that the application of Singular Spectrum Analysis (SSA) on such a binary time series will lead, under the NHMC assumptions, to an 'optimal' smoother that is of the form of a regular moving average; in the context of the theory of SSA this is equivalent in using the leading eigenvalue and eigenvector for the reconstruction of the time series.

Denote the $(n \times m)$ trajectory matrix of the sample $\{X\}_{t=1}^{N}$, with $n \stackrel{\text{def}}{=} N - m + 1$, as $\mathbf{T}_X$ and write $\mathbf{T}_X \stackrel{\text{def}}{=} [\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m]$ where each $\mathbf{X}_i$, $i = 1, 2, \ldots, m$ is a $(n \times 1)$ column vector. The $(m \times m)$ sample covariance matrix is then given by $\mathbf{C}_n \stackrel{\text{def}}{=} n^{-1} \mathbf{T}_X^\top \mathbf{T}_X$ and the $(i, j)$th element of $\mathbf{C}_n$, with $i \geq j$, is given by $c_{n,ij} \stackrel{\text{def}}{=} n^{-1} \mathbf{X}_i^\top \mathbf{X}_j = n^{-1} \sum_{t=j}^{N-m+j} x_{t+(i-j)} x_t$.

Taking expectations we find that $\mathbb{E}(c_{n,ij}) = n^{-1} \sum_{t=j}^{N-m+j} \mathbb{P}(x_{t+(i-j)} = 1, x_t = 1)$. Under suitable ergodicity conditions for NHMC (see, for example, Anily and Federgruen (1987) and Yang (2009) and the references therein) we can have that:

1. $\lim_{n \to \infty} c_{n,ij} = \mathbb{E}(c_{n,ij}|\mathcal{F})$, a.e, for the appropriate conditioning set $\mathcal{F}$, and more

importantly,

2. $\lim_{n\to\infty} c_{n,ij} = \phi_{ij}(\pi)$, a.e., where $\pi$ is the $(2 \times 1)$ vector of the stationary distribution of the NHMC. In fact,

3. $\lim_{n\to\infty} c_{n,ii} = \phi_0(\pi) \equiv \phi_0$, for all $i$, and $\lim_{n\to\infty} c_{n,ij} = \phi_1(\pi) \equiv \phi_1$, for all $i \neq j$, so that the limit of $\mathbf{C}_n$ is given by $\mathbf{C}$:

4.

$$\mathbf{C} \stackrel{\mathrm{def}}{=} \begin{bmatrix} \phi_0 & \phi_1 & \cdots & \phi_1 \\ \phi_1 & \phi_0 & \cdots & \phi_1 \\ \vdots & \vdots & \vdots & \vdots \\ \phi_1 & \phi_1 & \cdots & \phi_0 \end{bmatrix}$$

Although we already know that the sample covariance matrix $\mathbf{C}_n$, which has all its entries positive, obeys the Perron-Frobenious theorem and has one dominant eigenvalue $\widehat{r}_1$, satisfying:

$$\min_i \sum_j c_{n,ij} \leq \widehat{r}_1 \leq \max_i \sum_j c_{n,ij}$$

it is still useful to compute the eigenvalues and eigenvectors of the limit covariance matrix $\mathbf{C}$:

$$r_1 = \phi_0 + (m-1)\phi_1, \quad r_i = \phi_0 - \phi_1, \quad i = 2, \ldots, m$$

with corresponding dominant eigenvector $\mathbf{V}_1 = \mathbf{J}_m/\sqrt{m}$, where $\mathbf{J}_m$ is an $(m \times 1)$ vector of 1's.

Finally, note that the ratio:

$$\frac{r_1}{\sum_i r_i} = \frac{1}{m} + \frac{m-1}{m} \cdot \frac{\phi_1}{\phi_0}$$

and in the limit, as $m \uparrow$ when $N \to \infty$, it is just $\phi_1/\phi_0$. The higher is thus the degree of persistence $\phi_1$ the higher is the ratio of explained variance by the leading eigenvalue. Thus, under certain conditions on the DGP of $X_t$, the limit SSA decomposition has as dominant eigenvector the first component of the Discrete Cosine Transform – this is the same result as in the case of a random walk/unit root model.

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Thus applying SSA smoothing to $X_t$ we would be approximating the time-varying probability $\widehat{p}_t$.

Since we have that, asymptotically, the dimension of the signal $d$ in the binary time series is known and equals $d = 1$ we have that SSA reconstruction becomes SSA smoothing:

$$\widehat{\mathbf{T}}_X \stackrel{\text{def}}{=} \mathbf{T}_X \mathbf{J}_m \mathbf{J}_m^\top / m$$

and the reconstructed trajectory matrix has rows that are $m$-period rolling averages of the original observations. The $i$th row $\widehat{\mathbf{x}}_i^\top$ is given as $\widehat{\mathbf{x}}_i^\top \stackrel{\text{def}}{=} \left( m^{-1} \sum_{t=i}^{m+i-1} x_t \right) \mathbf{J}_m^\top$, and, applying diagonal averaging $\mathcal{D}(\widehat{\mathbf{T}}_X)$ produces the final smoothed series $\widehat{S}_t$ which takes the form of the moving averages, first given in Thomakos (2008):

$$\widehat{S}_t \stackrel{\text{def}}{=} \left\{ \begin{array}{lr} \frac{1}{tm} \sum_{j=1}^t \sum_{s=j}^{m+(j-1)} x_s, & t \leq m-1 \\ \frac{1}{m^2} \sum_{j=1}^m \sum_{s=t-m+j}^{t+(j-1)} x_s, & m \leq t \leq N-m+1 \\ \frac{1}{(N-t+1)k} \sum_{j=t}^N \sum_{s=j-m+1}^j x_s, & t > N-m+1 \end{array} \right\}$$

We have that the first observation is from a forward moving average, the middle $N - 2(m-1)$ observations are from a symmetric, weighted moving average and the last $N$ observation is from a backward moving average, as in:

$$\begin{array}{rcl} \widehat{S}_1 & = & \frac{1}{m} \sum_{t=1}^m X_t \\ \widehat{S}_t & = & \frac{1}{m} \sum_{j=-m+1}^{m-1} \left( 1 - \frac{|j|}{m} \right) X_{t+j} \\ \widehat{S}_N & = & \frac{1}{m} \sum_{t=N-m+1}^N X_t \end{array}$$

Therefore, we see that there is at least one possible approach for obtaining under certain assumptions the regular moving average smoother we used in the body of the paper.

## B. Transaction Costs

Table B.1 reports the performance of various portfolios when transaction costs are included. Following Marshall et al. (2012), who conclude that the average transaction cost of commodity futures varies from 3.5 to 4.4 basis points (half spread) depending on different trading volume, we use 4 basis points as the transaction cost. We conservatively assume that the strategies are re-balanced every month as most future contracts expire every month. This translates to $2*2*4 = 16$ basis points per month. We find that the RSM strategies using both fixed and time-varying thresholds outperform the benchmarks, as also reported in the main text, and the results are qualitatively consistent with the results in Table 3.

In particular, we see that RSM 0.4 results in 13.882 cumulative return with 21% drawdown. TSM, which is the best of the three benchmarks, offers 7.856 cumulative return with larger drawdown of 34.4%.

## C. Data Sources

The asset pool consists of futures returns of 4 asset classes: commodity, currency, equity index and government bond. It covers 24 commodity futures from different exchanges (CBOT, CME, COMEX, ICE, LME, NYMEX and TOCOM), 9 developed countries currency futures to USD (AUD, CAD, EUR, JPY, NZD, NOK, SEK, CHF and GBP), 9 equity index futures for 9 different countries (Australia, France, Germany, Italy, Japan, Netherlands, Spain, UK and US), and 13 government bond futures of 6 developed economies (Australia, Eurozone, Canada, Japan, UK and US). Majority of the data is downloaded from Bloomberg and DataStream. We use a similar data concatenation policy to those data who has shorter time availability as Moskowitz et al. (2012). The details of all the data sources and splice method is provided in Table C.1.

## D. Strategy Evlaluation

We evaluate the candidate trading strategies by considering both return and risk context. The return measures include average returns, minimize/maximum returns and cumulative net profits. While the risk related measures consists of standard deviation and maximum drawdown. Besides, the Sharpe Ratio (reward-to-risk ratio) is also considered. Let $R_t^s$ denotes the return of strategy $s$ at month $t$ ranging from $m_1$ to $m_n$, the evaluation measures are calculated as follows:

1. The annualized average return

$$AR^s \stackrel{\text{def}}{=} \frac{1}{n} \sum_{t=m_1}^{m_n} R_t^s \tag{13}$$

2. The cumulative net profit

$$CNP^s \stackrel{\text{def}}{=} \left\{ \prod_{t=m_1}^{t=m_n} (1 + R_t^s) \right\} - 1 \tag{14}$$

3. The annualized volatility/standard deviation

$$SD^s \stackrel{\text{def}}{=} \sqrt{\frac{1}{n} \sum_{t=m_1}^{m_n} (R_t^s - AR^s)^2} \tag{15}$$

4. The gross Sharpe Ratio, annualized

$$SR^s \stackrel{\text{def}}{=} \frac{AR^s}{SD^s} \tag{16}$$

5. The maximum drawdown $MDD_t^s$ measures the maximum historical decline over the investment horizon. The maximum value from an arbitrary peak of the cumulative profit to any subsequent cumulative profit from time 0 to time $T$ is calculated. The formula of maximum drawdown can be expressed as:

$$MDD_t^s = \frac{\max_{T \in (0,t)} \{0, \max CNP_T^s - CNP_t^s\}}{\max_{T \in (0,t)} CNP_T^s} \tag{17}$$

where $CNP_t^s$ denote the cumulative profit at time t. $\max_{T \in (0,t)} CNP_T^s$ is the highest cumulative profit from time 0 to time $T$.

## E. Individual Strategy Performance

Tables E.1, E.2 and E.3 provide the annualised mean returns, Sharpe Ratios and maximum drawdowns of different RSM strategies with threshold $q = \{0.2, 0.3, 0.4, 0.5\}$ compared to the buy-and-hold, SMA and TSM strategies as benchmarks. More RSM strategies with different threshold values are omitted from the tables but are available on request. The data for each instrument covers the period January, 1985 to March, 2015 (depending on the data availability of the instruments).

We observe that these RSM strategies outperform (both in terms of annualised mean and Sharpe Ratio) all the other three benchmarks in most cases with the median value being 10.2%, 10.1%, 11.2% and 9.2% respectively. This result is also consistent with the results of portfolio strategy performance in the main paper where RSM shows superior performance when the threshold value is no larger than 0.5. Across all 55 instruments, the vast majority of RSM strategies threshold values generate positive returns.

The positive performance of RSM strategies is further highlighted in terms of risk/return characteristics. RSM yields to large mean returns associated with similar maximum drawdown values to the SMA and TSM. The median maximum drawdowns for RSM0.2 to 0.5 strategies range from 0.888 to 0.938, which is smaller or very close to SMA and TSM. Consequently, RSM strategies produce higher returns on average, even on an individual basis comparison, without carrying higher risk.

Table B.1: Performance of portfolios including transaction costs.

| Strategies | Average | Volatility | Sharpe Ratio | Maximum | Minimum | Cumulative Net Profits | Maximum Drawdown |
|---|---|---|---|---|---|---|---|
| Panel A: Benchmarks | | | | | | | |
| 1/N | 0.035 | 0.075 | 0.462 | 0.077 | -0.135 | 1.597 | 0.310 |
| SMA | 0.056 | 0.130 | 0.430 | 0.165 | -0.128 | 3.178 | 0.484 |
| TSM | 0.081 | 0.129 | 0.626 | 0.129 | -0.114 | 7.856 | 0.343 |
| Panel B: RSM fixed thresholds | | | | | | | |
| RSM 0.2 | 0.094 | 0.133 | 0.707 | 0.123 | -0.142 | 11.940 | 0.325 |
| RSM 0.3 | 0.095 | 0.129 | 0.732 | 0.124 | -0.128 | 12.329 | 0.278 |
| RSM 0.4 | 0.098 | 0.123 | 0.793 | 0.131 | -0.132 | 13.882 | 0.210 |
| RSM 0.5 | 0.081 | 0.116 | 0.701 | 0.128 | -0.130 | 8.402 | 0.201 |
| Panel C: RSM time-varying threshold | | | | | | | |
| RSM TV | 0.088 | 0.120 | 0.738 | 0.130 | -0.114 | 10.391 | 0.288 |

This table reports the performance for RSM strategies with different fixed and time-varying thresholds and three benchmarks: 1/N, SMA and TSM from January, 1985 to March, 2015. Strategies evaluation criteria consists of mean, standard deviation, gross Sharpe Ratio, maximum/minimum returns, cumulative net profits and the maximum drawdown. The corresponding formulas of all the evaluation methods are available in Appendix D. All the results are annualised.

Table C.1: Data Sources.

| Assets | Start Date | Bloomberg Ticker | Splicing Information |
|---|---|---|---|
| **Commodity futures** | | | |
| Aluminum | 1987/6/1 | LMAHDS03 Comdty | |
| Brent | 1988/6/23 | CO1 Comdty | |
| Cocoa | 1959/7/1 | CC1 Comdty | |
| Coffee | 1972/8/16 | KC1 Comdty | |
| Copper | 1986/4/1 | LMCADS03 Comdty | |
| Corn | 1959/7/1 | C 1 Comdty | |
| Cotton | 1959/7/1 | CT1 Comdty | |
| Gas Oil | 1989/7/3 | QS1 Comdty | |
| Gold | 1975/1/2 | GC1 Comdty | |
| Heating Oil | 1980/1/2 | HO1 Comdty | |
| Lean Hogs | 1986/4/1 | LH1 Comdty | |
| Live Cattle | 1964/11/30 | LC1 Comdty | |
| Natural Gas | 1990/4/3 | NG1 Comdty | |
| Nickel | 1987/1/5 | LMNIDS03 Comdty | |
| Platinum | 1984/1/26 | JA1 Comdty | |
| RBOB | 2005/10/3 | XB1 Comdty | Unleaded Gasoline from 21/08/1986 (Bloomberg) |
| Silver | 1964/3/2 | SI1 Comdty | |
| Soy Meal | 1960/1/22 | SM1 Comdty | |
| Soy Oil | 1961/9/1 | BO1 Comdty | |
| Soybeans | 1959/7/1 | S 1 Comdty | |
| Sugar | 1961/1/3 | SB1 Comdty | |
| Wheat | 1959/7/1 | W 1 Comdty | |
| WTI | 1983/3/30 | CL1 Comdty | |
| Zinc | 1989/1/4 | LMZSDS03 Comdty | |
| **Currency futures** | | | |
| AUD/USD | 1987/1/13 | AD1 Curncy | AUD spot from 05/01/1971 (Bloomberg) |
| CAD/USD | 1977/1/18 | CD1 Curncy | CAD spot from 05/01/1971 (Bloomberg) |
| EUR/USD | 1998/5/19 | EC1 Curncy | DEM 04/1986, DEM SPOT 01/1971 (Bloomberg) |
| JPY/USD | 1976/8/3 | JY1 Curncy | JPY spot from 05/01/1971 (Bloomberg) |
| NZD/USD | 1997/5/7 | NV1 Curncy | NZD spot from 05/01/1971 (Bloomberg) |
| NOK/USD | 2002/5/16 | NO1 Curncy | NOK spot from 05/01/1971 (Bloomberg) |
| SEK/USD | 2002/5/16 | SE1 Curncy | SEK spot from 05/01/1971 (Bloomberg) |
| CHF/USD | 1975/2/14 | SF1 Curncy | CHF spot from 05/01/1971 (Bloomberg) |
| GBP/USD | 1975/2/14 | BP1 Curncy | GBP spot from 05/01/1971 (Bloomberg) |
| **Equity index futures** | | | |
| SPI | 2000/5/2 | XP1 Index | MSCI Australia from 01/01/1970 (DataStream) |
| CAC | 1988/12/7 | CF1 Index | MSCI France from 01/01/1970 (DataStream) |
| DAX | 1990/11/23 | GX1 Index | MSCI Germany from 01/01/1970 (DataStream) |
| FTSE MIB | 2004/3/22 | ST1 Index | MSCI Italy from 01/01/1970 (DataStream) |
| TOPIX | 1990/5/16 | TP1 Index | MSCI Japan from 01/01/1970 (DataStream) |
| AEX | 1983/1/3 | FXNL Index | MSCI Netherlands from 01/01/1970 (DataStream) |
| IBEX | 1992/7/21 | IB1 Index | MSCI Spain from 01/01/1970 (DataStream) |
| FTSE | 1988/2/26 | Z 1 Index | MSCI UK from 01/01/1970 (DataStream) |
| S&P 500 | 1982/4/21 | SP1 Index | MSCI USA from 01/01/1970 (DataStream) |
| **Bond futures** | | | |
| AUS 3Y | 1989/12/18 | YM1 Comdty | JPM Australia from 01/01/1986 (DataStream) |
| AUS 10Y | 1987/9/18 | XM1 Comdty | JPM Australia from 01/01/1986 (DataStream) |
| EURO 2Y | 1997/3/7 | DU1 Comdty | JPM Germany from 01/01/1986 (DataStream) |
| EURO 5Y | 1991/10/4 | OE1 Comdty | JPM Germany from 01/01/1986 (DataStream) |
| EURO 10Y | 1990/11/23 | RX1 Comdty | JPM Germany from 01/01/1986 (DataStream) |
| EURO 30Y | 1998/10/2 | UB1 Comdty | JPM Germany from 01/01/1986 (DataStream) |
| CA 10Y | 1989/9/15 | CN1 Comdty | JPM Canada from 01/01/1986 (DataStream) |
| JP 10Y | 1985/10/21 | JB1 Comdty | |
| UK 10Y | 1982/11/18 | G 1 Comdty | |
| US 2Y | 1990/6/25 | TU1 Comdty | JPM USA from 01/01/1986 (DataStream) |
| US 5Y | 1988/5/20 | FV1 Comdty | JPM USA from 01/01/1986 (DataStream) |
| US 10Y | 1982/5/3 | TY1 Comdty | |
| US 30Y | 1977/8/22 | US1 Comdty | |

Reported are the detailed data sources for the 55 instruments. The date of the earliest availability on Bloomberg/DataStream and the corresponding tickers are listed for each future contracts. For those futures which have more than one data source, we provide the splicing information prior to the availability of their latest data sources.

Table E.1: Annualized mean of different strategies for individual assets.

| | Bnh | SMA | TSM | RSM0.2 | RSM0.3 | RSM0.4 | RSM0.5 |
|---|---|---|---|---|---|---|---|
| Aluminum | 0.026 | 0.032 | 0.006 | 0.064 | -0.011 | 0.002 | 0.020 |
| Brent | 0.100 | 0.104 | 0.176 | 0.088 | 0.118 | 0.076 | 0.069 |
| Cocoa | 0.050 | -0.110 | -0.078 | 0.055 | 0.076 | 0.020 | -0.080 |
| Coffee | 0.067 | 0.020 | 0.036 | 0.109 | 0.147 | 0.160 | -0.031 |
| Copper | 0.082 | 0.169 | 0.175 | 0.086 | 0.044 | 0.112 | 0.151 |
| Corn | 0.053 | 0.065 | 0.051 | 0.124 | 0.054 | -0.021 | 0.092 |
| Cotton | 0.052 | -0.046 | -0.034 | 0.018 | 0.023 | -0.029 | -0.037 |
| Gas.Oil | 0.104 | 0.093 | 0.227 | 0.107 | 0.113 | 0.149 | 0.137 |
| Gold | 0.057 | 0.129 | 0.168 | 0.102 | 0.058 | 0.107 | 0.181 |
| Heating.Oil | 0.097 | 0.042 | 0.149 | 0.087 | 0.073 | 0.090 | 0.106 |
| Lean.Hogs | 0.073 | -0.165 | -0.034 | 0.081 | 0.085 | 0.125 | 0.130 |
| Live.Cattle | 0.043 | -0.182 | 0.023 | 0.095 | 0.083 | 0.108 | 0.019 |
| Natural.Gas | 0.165 | -0.070 | 0.072 | 0.134 | 0.050 | 0.101 | 0.082 |
| Nickel | 0.135 | 0.251 | 0.129 | 0.010 | 0.060 | 0.112 | 0.160 |
| Platinum | 0.048 | -0.044 | 0.076 | 0.095 | 0.059 | 0.027 | -0.024 |
| RBOB | 0.130 | -0.109 | 0.056 | 0.099 | 0.142 | 0.121 | -0.038 |
| Silver | 0.071 | -0.029 | 0.060 | 0.086 | 0.074 | 0.117 | 0.043 |
| Soy.Meal | 0.070 | -0.074 | 0.029 | 0.176 | 0.165 | 0.179 | 0.078 |
| Soy.Oil | 0.036 | 0.026 | 0.088 | 0.128 | 0.061 | 0.121 | 0.157 |
| Soybeans | 0.047 | 0.045 | -0.020 | 0.137 | 0.150 | 0.156 | 0.164 |
| Sugar | 0.107 | -0.002 | 0.077 | 0.093 | 0.037 | 0.065 | 0.082 |
| Wheat | 0.053 | -0.150 | 0.076 | 0.070 | 0.036 | -0.008 | 0.046 |
| WTI | 0.076 | 0.089 | 0.093 | 0.043 | 0.063 | 0.113 | 0.028 |
| Zinc | 0.035 | 0.039 | 0.101 | 0.123 | 0.146 | 0.124 | 0.032 |
| AUD | 0.006 | 0.064 | 0.064 | -0.006 | 0.010 | 0.022 | 0.055 |
| CAD | 0.004 | 0.120 | 0.222 | -0.015 | 0.041 | 0.122 | 0.006 |
| EUR | -0.001 | 0.233 | 0.051 | 0.0003 | 0.056 | 0.024 | 0.011 |
| JPY | 0.032 | 0.232 | 0.298 | 0.065 | 0.148 | 0.217 | 0.159 |
| NZD | 0.023 | 0.140 | 0.094 | 0.055 | 0.087 | 0.034 | 0.161 |
| NOK | 0.004 | 0.094 | 0.021 | 0.024 | -0.013 | 0.067 | 0.054 |
| SEK | 0.016 | 0.153 | 0.048 | 0.078 | 0.101 | 0.149 | 0.147 |
| CHF | 0.041 | 0.108 | 0.066 | 0.145 | 0.084 | 0.110 | 0.115 |
| GBP | 0.015 | 0.023 | -0.015 | 0.030 | 0.039 | -0.009 | 0.014 |
| SPI | 0.085 | 0.154 | 0.181 | 0.250 | 0.248 | 0.255 | 0.247 |
| CAC | 0.084 | 0.243 | 0.145 | 0.179 | 0.197 | 0.189 | 0.141 |
| DAX | 0.111 | 0.233 | 0.270 | 0.262 | 0.249 | 0.288 | 0.280 |
| FTSE.MIB | 0.075 | 0.216 | 0.325 | 0.145 | 0.211 | 0.222 | 0.190 |
| TOPIX | 0.036 | 0.170 | 0.259 | 0.127 | 0.087 | 0.022 | 0.072 |
| AEX | 0.076 | 0.246 | 0.247 | 0.205 | 0.211 | 0.238 | 0.296 |
| IBEX | 0.099 | 0.239 | 0.237 | 0.210 | 0.210 | 0.234 | 0.274 |
| FTSE | 0.069 | 0.119 | 0.148 | 0.199 | 0.216 | 0.225 | 0.251 |
| S.P | 0.093 | 0.260 | 0.262 | 0.270 | 0.273 | 0.304 | 0.306 |
| AUS3 | 0.011 | 0.126 | 0.060 | 0.134 | 0.120 | 0.090 | 0.076 |
| AUS10 | 0.009 | 0.114 | 0.066 | 0.141 | 0.153 | 0.125 | 0.135 |
| EURO2 | 0.018 | 0.068 | -0.026 | 0.115 | 0.075 | 0.083 | 0.027 |
| EURO5 | 0.023 | 0.095 | -0.034 | 0.126 | 0.106 | 0.088 | 0.097 |
| EURO10 | 0.037 | 0.104 | 0.123 | 0.210 | 0.184 | 0.178 | 0.159 |
| EURO30 | 0.037 | 0.079 | 0.012 | 0.146 | 0.113 | 0.052 | 0.012 |
| CA10 | 0.023 | 0.058 | 0.006 | 0.094 | 0.160 | 0.106 | 0.058 |
| JP10 | 0.016 | 0.022 | 0.124 | 0.144 | 0.183 | 0.147 | 0.127 |
| UK10 | 0.009 | -0.031 | 0.012 | 0.031 | 0.027 | 0.019 | -0.041 |
| US2 | 0.004 | 0.160 | 0.184 | 0.119 | 0.170 | 0.175 | 0.188 |
| US5 | 0.008 | 0.047 | 0.084 | 0.041 | 0.112 | 0.099 | 0.099 |
| US10 | 0.017 | 0.003 | 0.092 | 0.076 | 0.142 | 0.162 | 0.124 |
| US30 | 0.033 | 0.049 | 0.091 | 0.188 | 0.201 | 0.188 | 0.091 |
| Median | 0.047 | 0.079 | 0.077 | 0.102 | 0.101 | 0.112 | 0.092 |

This table reports annualized mean returns of all the 55 individual instruments using buy-and-hold, SMA, TSM and RSM0.2-0.5 strategies from January, 1985 to March, 2015 (depending on the data availability of the instruments). The monthly mean returns are calculated in the same way as in Appendix D. The median returns of all the instruments are summarised in the last line.

Table E.2: Annualized sharpe ratio of different strategies for individual assets.

| | Bnh | SMA | TSM | RSM0.2 | RSM0.3 | RSM0.4 | RSM0.5 |
|---|---|---|---|---|---|---|---|
| Aluminum | 0.125 | 0.079 | 0.015 | 0.157 | -0.027 | 0.005 | 0.050 |
| Brent | 0.311 | 0.261 | 0.444 | 0.220 | 0.296 | 0.190 | 0.173 |
| Cocoa | 0.166 | -0.268 | -0.191 | 0.134 | 0.186 | 0.050 | -0.195 |
| Coffee | 0.172 | 0.043 | 0.078 | 0.235 | 0.318 | 0.346 | -0.066 |
| Copper | 0.323 | 0.383 | 0.397 | 0.194 | 0.100 | 0.253 | 0.342 |
| Corn | 0.182 | 0.139 | 0.109 | 0.265 | 0.115 | -0.045 | 0.196 |
| Cotton | 0.165 | -0.089 | -0.066 | 0.034 | 0.044 | -0.055 | -0.072 |
| Gas.Oil | 0.314 | 0.210 | 0.523 | 0.244 | 0.258 | 0.343 | 0.314 |
| Gold | 0.366 | 0.299 | 0.391 | 0.236 | 0.134 | 0.247 | 0.421 |
| Heating.Oil | 0.258 | 0.089 | 0.315 | 0.184 | 0.154 | 0.192 | 0.224 |
| Lean.Hogs | 0.211 | -0.368 | -0.075 | 0.181 | 0.190 | 0.279 | 0.291 |
| Live.Cattle | 0.264 | -0.446 | 0.055 | 0.231 | 0.201 | 0.262 | 0.046 |
| Natural.Gas | 0.303 | -0.167 | 0.170 | 0.319 | 0.119 | 0.240 | 0.195 |
| Nickel | 0.323 | 0.555 | 0.283 | 0.022 | 0.131 | 0.244 | 0.350 |
| Platinum | 0.207 | -0.105 | 0.181 | 0.227 | 0.140 | 0.063 | -0.058 |
| RBOB | 0.325 | -0.243 | 0.125 | 0.220 | 0.317 | 0.270 | -0.085 |
| Silver | 0.252 | -0.070 | 0.144 | 0.205 | 0.178 | 0.282 | 0.103 |
| Soy.Meal | 0.242 | -0.165 | 0.065 | 0.399 | 0.373 | 0.405 | 0.175 |
| Soy.Oil | 0.141 | 0.057 | 0.193 | 0.283 | 0.135 | 0.266 | 0.346 |
| Soybeans | 0.191 | 0.106 | -0.048 | 0.327 | 0.358 | 0.372 | 0.390 |
| Sugar | 0.266 | -0.004 | 0.179 | 0.215 | 0.085 | 0.151 | 0.191 |
| Wheat | 0.185 | -0.365 | 0.184 | 0.168 | 0.087 | -0.020 | 0.111 |
| WTI | 0.224 | 0.238 | 0.247 | 0.114 | 0.167 | 0.302 | 0.073 |
| Zinc | 0.144 | 0.094 | 0.241 | 0.295 | 0.351 | 0.298 | 0.076 |
| AUD | 0.048 | 0.151 | 0.150 | -0.014 | 0.023 | 0.051 | 0.129 |
| CAD | 0.059 | 0.275 | 0.513 | -0.035 | 0.095 | 0.280 | 0.014 |
| EUR | -0.011 | 0.552 | 0.120 | 0.001 | 0.130 | 0.056 | 0.027 |
| JPY | 0.274 | 0.535 | 0.691 | 0.148 | 0.340 | 0.499 | 0.364 |
| NZD | 0.183 | 0.341 | 0.228 | 0.133 | 0.212 | 0.082 | 0.392 |
| NOK | 0.034 | 0.230 | 0.050 | 0.057 | -0.032 | 0.164 | 0.130 |
| SEK | 0.137 | 0.370 | 0.116 | 0.188 | 0.243 | 0.362 | 0.355 |
| CHF | 0.339 | 0.258 | 0.159 | 0.348 | 0.201 | 0.264 | 0.274 |
| GBP | 0.142 | 0.055 | -0.037 | 0.073 | 0.095 | -0.022 | 0.033 |
| SPI | 0.522 | 0.338 | 0.401 | 0.554 | 0.551 | 0.567 | 0.547 |
| CAC | 0.421 | 0.596 | 0.353 | 0.437 | 0.481 | 0.461 | 0.344 |
| DAX | 0.512 | 0.547 | 0.636 | 0.616 | 0.586 | 0.681 | 0.661 |
| FTSE.MIB | 0.323 | 0.473 | 0.719 | 0.316 | 0.462 | 0.486 | 0.416 |
| TOPIX | 0.180 | 0.397 | 0.612 | 0.297 | 0.204 | 0.051 | 0.168 |
| AEX | 0.388 | 0.574 | 0.575 | 0.476 | 0.490 | 0.553 | 0.693 |
| IBEX | 0.446 | 0.530 | 0.526 | 0.465 | 0.465 | 0.518 | 0.610 |
| FTSE | 0.438 | 0.298 | 0.372 | 0.504 | 0.548 | 0.569 | 0.637 |
| S.P | 0.610 | 0.727 | 0.732 | 0.754 | 0.763 | 0.855 | 0.863 |
| AUS3 | 0.176 | 0.308 | 0.146 | 0.325 | 0.291 | 0.218 | 0.184 |
| AUS10 | 0.187 | 0.303 | 0.176 | 0.376 | 0.408 | 0.332 | 0.361 |
| EURO2 | 0.223 | 0.160 | -0.062 | 0.274 | 0.179 | 0.197 | 0.064 |
| EURO5 | 0.318 | 0.223 | -0.081 | 0.297 | 0.251 | 0.208 | 0.230 |
| EURO10 | 0.475 | 0.241 | 0.285 | 0.491 | 0.429 | 0.414 | 0.369 |
| EURO30 | 0.303 | 0.172 | 0.025 | 0.320 | 0.248 | 0.114 | 0.027 |
| CA10 | 0.315 | 0.127 | 0.012 | 0.210 | 0.359 | 0.237 | 0.129 |
| JP10 | 0.299 | 0.050 | 0.287 | 0.332 | 0.423 | 0.340 | 0.293 |
| UK10 | 0.101 | -0.064 | 0.024 | 0.064 | 0.055 | 0.039 | -0.084 |
| US2 | 0.125 | 0.372 | 0.429 | 0.276 | 0.395 | 0.406 | 0.437 |
| US5 | 0.170 | 0.106 | 0.188 | 0.092 | 0.252 | 0.221 | 0.221 |
| US10 | 0.248 | 0.007 | 0.206 | 0.171 | 0.318 | 0.364 | 0.277 |
| US30 | 0.299 | 0.108 | 0.202 | 0.421 | 0.451 | 0.422 | 0.203 |
| Median | 0.248 | 0.172 | 0.184 | 0.235 | 0.243 | 0.264 | 0.203 |

This table reports annualized gross Sharpe ratios of all the 55 individual instruments using buy-and-hold, SMA, TSM and RSM0.2-0.5 strategies from January, 1985 to March, 2015 (depending on the data availability of the instruments). The gross Sharpe ratios are calculated in the same way as in Appendix D. The median Sharpe ratios of all the instruments are summarised in the last line.

Table E.3: Maximum drawdown of different strategies for individual assets.

| | Bnh | SMA | TSM | RSM0.2 | RSM0.3 | RSM0.4 | RSM0.5 |
|---|---|---|---|---|---|---|---|
| Aluminum | 0.616 | 0.933 | 0.922 | 0.794 | 0.927 | 0.900 | 0.896 |
| Brent | 0.732 | 0.893 | 0.756 | 0.881 | 0.881 | 0.874 | 0.806 |
| Cocoa | 0.715 | 0.997 | 0.996 | 0.909 | 0.886 | 0.964 | 0.996 |
| Coffee | 0.846 | 0.990 | 0.957 | 0.856 | 0.765 | 0.830 | 0.995 |
| Copper | 0.641 | 0.867 | 0.894 | 0.966 | 0.990 | 0.976 | 0.924 |
| Corn | 0.651 | 0.960 | 0.986 | 0.844 | 0.959 | 0.995 | 0.975 |
| Cotton | 0.737 | 1.623 | 1.405 | 2.812 | 2.551 | 2.725 | 3.264 |
| Gas.Oil | 0.723 | 0.887 | 0.603 | 0.904 | 0.912 | 0.817 | 0.858 |
| Gold | 0.477 | 0.934 | 0.905 | 0.973 | 0.996 | 0.978 | 0.972 |
| Heating.Oil | 0.702 | 0.967 | 0.828 | 0.947 | 0.905 | 0.899 | 0.907 |
| Lean.Hogs | 0.663 | 1.000 | 0.987 | 0.769 | 0.729 | 0.693 | 0.826 |
| Live.Cattle | 0.299 | 1.000 | 0.980 | 0.832 | 0.900 | 0.800 | 0.980 |
| Natural.Gas | 0.847 | 0.988 | 0.903 | 0.913 | 0.938 | 0.835 | 0.901 |
| Nickel | 0.794 | 0.714 | 0.896 | 0.987 | 0.923 | 0.935 | 0.716 |
| Platinum | 0.659 | 0.995 | 0.854 | 0.925 | 0.958 | 0.987 | 0.977 |
| RBOB | 0.712 | 0.999 | 0.962 | 0.888 | 0.791 | 0.887 | 0.984 |
| Silver | 0.681 | 0.998 | 0.950 | 0.895 | 0.938 | 0.872 | 0.990 |
| Soy.Meal | 0.586 | 0.998 | 0.962 | 0.711 | 0.728 | 0.669 | 0.938 |
| Soy.Oil | 0.583 | 0.990 | 0.979 | 0.843 | 0.925 | 0.861 | 0.842 |
| Soybeans | 0.573 | 0.957 | 0.993 | 0.812 | 0.781 | 0.678 | 0.765 |
| Sugar | 0.708 | 0.988 | 0.919 | 0.880 | 0.932 | 0.940 | 0.938 |
| Wheat | 0.637 | 1.000 | 0.951 | 0.859 | 0.869 | 0.953 | 0.953 |
| WTI | 0.716 | 0.850 | 0.728 | 0.869 | 0.832 | 0.898 | 0.965 |
| Zinc | 0.749 | 0.887 | 0.883 | 0.803 | 0.767 | 0.896 | 0.990 |
| AUD | 0.450 | 0.955 | 0.936 | 0.962 | 0.938 | 0.978 | 0.952 |
| CAD | 0.296 | 0.943 | 0.815 | 0.987 | 0.972 | 0.890 | 0.966 |
| EUR | 0.418 | 0.660 | 0.960 | 0.952 | 0.955 | 0.976 | 0.981 |
| JPY | 0.418 | 0.717 | 0.577 | 0.989 | 0.932 | 0.878 | 0.831 |
| NZD | 0.440 | 0.850 | 0.922 | 0.940 | 0.898 | 0.914 | 0.804 |
| NOK | 0.392 | 0.894 | 0.978 | 0.930 | 0.971 | 0.867 | 0.948 |
| SEK | 0.430 | 0.855 | 0.958 | 0.949 | 0.909 | 0.844 | 0.890 |
| CHF | 0.373 | 0.801 | 0.929 | 0.874 | 0.850 | 0.874 | 0.842 |
| GBP | 0.311 | 0.953 | 0.978 | 0.922 | 0.934 | 0.977 | 0.945 |
| SPI | 0.512 | 1.469 | 1.809 | 6.966 | 6.966 | 6.850 | 5.519 |
| CAC | 0.607 | 0.837 | 0.959 | 0.837 | 0.794 | 0.893 | 0.963 |
| DAX | 0.683 | 0.873 | 0.859 | 0.851 | 0.879 | 0.823 | 0.853 |
| FTSE.MIB | 0.702 | 0.954 | 0.771 | 0.930 | 0.810 | 0.897 | 0.933 |
| TOPIX | 0.758 | 0.909 | 0.685 | 0.981 | 0.996 | 0.999 | 0.992 |
| AEX | 0.685 | 0.821 | 0.909 | 0.867 | 0.839 | 0.920 | 0.838 |
| IBEX | 0.618 | 0.867 | 0.857 | 0.884 | 0.920 | 0.945 | 0.903 |
| FTSE | 0.494 | 0.930 | 0.951 | 0.807 | 0.807 | 0.740 | 0.756 |
| S.P | 0.528 | 0.744 | 0.620 | 0.724 | 0.724 | 0.630 | 0.567 |
| AUS3 | 0.262 | 0.777 | 0.931 | 0.850 | 0.936 | 0.954 | 0.944 |
| AUS10 | 0.262 | 0.819 | 0.845 | 0.756 | 0.756 | 0.791 | 0.751 |
| EURO2 | 0.243 | 0.876 | 0.985 | 0.906 | 0.923 | 0.826 | 0.944 |
| EURO5 | 0.243 | 0.755 | 0.984 | 0.818 | 0.853 | 0.893 | 0.745 |
| EURO10 | 0.243 | 0.925 | 0.786 | 0.763 | 0.814 | 0.883 | 0.772 |
| EURO30 | 0.334 | 0.982 | 0.994 | 0.954 | 0.965 | 0.990 | 0.996 |
| CA10 | 0.235 | 0.889 | 0.954 | 0.963 | 0.706 | 0.780 | 0.920 |
| JP10 | 0.251 | 0.985 | 0.961 | 0.875 | 0.901 | 0.918 | 0.941 |
| UK10 | 0.394 | 1.096 | 0.997 | 1.180 | 1.180 | 1.099 | 1.080 |
| US2 | 0.113 | 0.832 | 0.821 | 0.824 | 0.714 | 0.791 | 0.858 |
| US5 | 0.157 | 0.930 | 0.822 | 0.979 | 0.826 | 0.820 | 0.860 |
| US10 | 0.220 | 0.990 | 0.821 | 0.984 | 0.768 | 0.835 | 0.898 |
| US30 | 0.308 | 0.983 | 0.938 | 0.604 | 0.591 | 0.620 | 0.948 |
| Median | 0.573 | 0.933 | 0.931 | 0.888 | 0.901 | 0.893 | 0.938 |

This table reports maximum drawdowns of all the 55 individual instruments using buy-and-hold, SMA, TSM and RSM0.2-0.5 strategies from January, 1985 to March, 2015 (depending on the data availability of the instruments). The maximum drawdowns are calculated in the same way as in Appendix D. The median drawdowns of all the instruments are summarised in the last line.