Return Signal Momentum[☆,☆☆]

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Abstract

A new type of momentum based on the signs of past returns is introduced. This momentum is driven primarily 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 for the existence of such momentum. Investment strategies based on return signal momentum result in higher returns and Sharpe ratios and lower drawdown relative to time series momentum and other benchmark strategies. Overall, return signal momentum can benefit investors as an effective strategy for speculation and hedging.

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

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1. Introduction

The academic and professional literatures have devoted considerable attention 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 instruments that have performed well in the relatively recent past (i.e., winners) and selling those that have performed poorly (i.e., losers) produces abnormal returns in the short run[1].

Traditionally, the word "momentum" in finance refers to a market anomaly whereby assets with good past performance have a tendency to rise further, and vice versa. Cross-sectional momentum (henceforth, XSM) strategies have been created that rank assets based on their performance and advise investing according to this ranking. Subsequent 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 an 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]. These efforts opened the way for further studies on the time series property of momentum effects for financial assets.

In this paper, we introduce financial market momentum based on the probability of the signs of past returns, called return signal momentum (henceforth, RSM). As RSM generates position signals using the signs of the past returns of an individual asset and does not identify the best or worst performers in a pool of assets, we argue

[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)), commodities (see, e.g., Bianchi et al. (2016)) and currency markets (see, e.g., Menkhoff et al. (2012)).

that it can be classified within the wider range of TSM. The key features of RSM, and hence its differences from TSM, are two: (i) it takes into account each of the returns during the look-back period rather than calculating the total period return as in TSM, and (ii) it focuses on the signs of past returns regardless of their magnitude. These special characteristics allow us to more efficiently capture the trend while avoiding temporary price reversals or other market corrections that might lead to false position signals.

Obviously, a question arises regarding the calculation of the probability of the signs of future returns based on recent past performance. As this is a binary outcome, i.e., the sign variable takes 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 signs of returns[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 for the interested reader that is in favour of the equally weighted average.

Since RSM is a phenomenon of time series continuation, we expect that it is related to both TSM and XSM. Lewellen (2002) provides a theoretical work showing that the returns of XSM strategies can be decomposed into a positive time series autocorrelation term and a negative cross-serial correlation term[4]. In other words, the time series component 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

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

[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.

Lo and MacKinlay (1988, 1990) and Campbell et al. (1997), among others.

Moskowitz et al. (2012) claim that the observed phenomenon of TSM challenges the random walk theory. In contrast, RSM, which depends on the signs of returns, does not contradict random walk theory, which focuses on price returns. Therefore, RSM offers an alternative view and explanation of the momentum effect in the time series context based on sign dependence.

Our motivation for assuming that signs of returns are predictable stems from Christoffersen and Diebold (2006), who demonstrate theoretically that return sign dependence exists as long as the conditional mean of the returns is not equal to zero. We expect that sign dependence can be detected because the returns of most financial assets are positive in the long run. This is particularly true for stock and commodity markets. For example, the S&P 500 adjusted price index rose from 16.66 in 1950 to 2043.94 in 2015, which yields an annualised average return of 7.68% per year. Although studies on sign predictability are not as common as those on 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). Moskowitz et al. (2012) also more straightforwardly provide evidence that sign dependence exists by examining the predictive power of the signs of past excess returns for current returns. Their regression results reveal a strong momentum effect for the first 12 months.

In our empirical illustration, we estimate a number of regressions that reveal a 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 exhibit time series autocorrelation. Hence, the behavioural rationale for RSM is attributed to the short-term under-reaction and delayed over-reaction suggested in the literature[5]. We also control for time series dummies and cross-sectional dummies in the regression analysis, finding that the

[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. He and Li (2015) specify the time horizons of this theory using an agent based model.

suggested momentum effect does not come from the cross-sectional part of the asset pool but mainly from the time series part. Finally, regression analysis using the probability of positive signs of the returns, which is an important indicator of RSM, shows more robust short-run continuation and long-run reversal[6].

We extend our results by including market timing investment strategies based on RSM using a portfolio that 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 exceeds 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 relative to benchmarks in the literature such as the buy-and-hold strategy, the simple price moving average strategy and the TSM strategy. The time-varying probability threshold is calculated using a cross-validation exercise and evinces a strong negative relationship with the market, i.e., the time-varying threshold increases during periods of market turbulence, keeping the investor market neutral or short, and decreases in stable times, placing 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 of 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, despite 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 that cannot be explained by the existing risk factors, thereby providing evidence in favour of our approach.

The remainder of the paper is organised as follows. Section 2 presents the theoretical and empirical motivation for why sign predictability should be stronger than return predictability. Section 3 describes our data collection and transformation

[6]Momentum and reversal are often considered to be a chain effect and are documented in numerous studies, see, e.g., Vayanos and Woolley (2013), Conrad and Yavuz (2017) and Andrei and Cujean (2017).

methodologies. Then, in Section 4, we implement the portfolio strategies based on RSM and compare the outcome 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. Is Sign Predictability Stronger than Return Predictability?

In this section, we provide a clear motivation for our research by theoretically and empirically exploring the reasons that sign predictability is stronger than return predictability. We begin with a simple model/data generating process that maintains sign predictability without return predictability.

2.1. Sign Predictability

Let Y_t be a binary time series taking values $\{0, 1\}$ with stationary probabilities $(1-\pi, \pi)$. Here, Y_t represents the sign of past returns. We have that $\mathsf{E}[Y_t] = \pi$ and $\mathsf{Var}[Y_t] = \pi(1-\pi)$. Our aim is to find the first-order serial correlation by calculating $\mathsf{E}[Y_t Y_{t-1}]$. Using the Law of Iterated Expectations, we have:

$$\mathsf{E}[Y_t Y_{t-1}] = \mathsf{E}[\mathsf{E}[Y_t Y_{t-1} | \mathcal{F}_{t-1}]] = \mathsf{E}[Y_{t-1} \mathsf{E}[Y_t | \mathcal{F}_{t-1}]] \tag{1}$$

The conditional mean is a determining factor in the above correlation. It is easy to illustrate that if $\mathsf{E}[Y_t|\mathcal{F}_{t-1}] = Y_{t-1}$, which is a random walk for Y_t (see also the discussion below), then the correlation is identically 1 and if $\mathsf{E}[Y_t|\mathcal{F}_{t-1}] = \pi$ (i.e., under independence), the correlation is identically 0. It is useful to not confuse these assumptions with a data generating process per se, although we can always derive one, and we do in what follows. Finally, note that it is easy to verify that $\mathsf{E}[\mathsf{E}[Y_t|\mathcal{F}_{t-1}]] = \pi$, the unconditional mean. Now, taking the case of $\mathsf{E}[Y_t|\mathcal{F}_{t-1}] = Y_{t-1}$ we immediately have that $\mathsf{E}[Y_{t-1}\mathsf{E}[Y_t|\mathcal{F}_{t-1}]] = \mathsf{E}\left[Y_{t-1}^2\right] = \pi$, and therefore, the covariance becomes the variance itself as follows:

$$\mathsf{E}[Y_t Y_{t-1}] - \mathsf{E}[Y_t]\,\mathsf{E}[Y_{t-1}] = \pi - \pi^2 = \pi(1-\pi) = \mathsf{Var}[Y_t], \tag{2}$$

and thus the first-order autocorrelation would be identically $\rho(1) = 1$, irrespective of the value of π. If, on the other hand, $\mathsf{E}\left[\mathsf{E}\left[Y_t|\mathcal{F}_{t-1}\right]\right] = \pi$ we have that $\mathsf{E}\left[Y_t Y_{t-1}\right] = \pi^2$ and therefore the autocovariance and autocorrelation are identically 0.

Our main argument above is that even when our original series, i.e., asset returns, are iid[7], if the signs have any degree of predictability, then they will show the corresponding serial correlation and will thus be "more" predictable. This implies that a rule based on signs can be more successful, as we show later, than a rule based on returns (i.e., RSM vs TSM)[8].

Because we can indeed have a situation like the one we describe above, we can design a proper probabilistic model for a binary random walk for the signs of the returns even under the chance rule that the probabilities of positive and negative returns are the same. Let us now model the data generating process of the binary variable Y_t as:

$$Y_t = Y_{t-1} + \epsilon_t, \tag{3}$$

where ϵ_t is a 3-valued discrete random variable with conditional distribution defined as

$$\epsilon_t|Y_{t-1} = \left\{ \begin{array}{cc} -1, & p_{-1} \\ 0, & p_0 \\ +1, & p_1 \end{array} \right\} \tag{4}$$

which also corresponds to the conditional expectation of ϵ_t. In particular, we have that $\mathsf{E}\left[\epsilon_t|Y_{t-1}\right] = \mathsf{P}\left[\epsilon_t|Y_{t-1}\right]$. We could require that the unconditional mean of ϵ_t is zero, and in that case, we require symmetry in $p_{-1} = p_1$ since:

$$\mathsf{E}\left[\epsilon_t\right] = \mathsf{E}\left[\mathsf{E}\left[\epsilon_t|Y_{t-1}\right]\right] = -1 \cdot p_{-1} + 0 \cdot p_0 + 1 \cdot p_1, \tag{5}$$

which is zero if $p_1 - p_{-1} = 0$, i.e., when $p_1 = p_{-1} = p$. Notice that we also have

[7]This means that it has zero serial correlation and that the probability of having a positive return is the same that of a negative return under a symmetric error distribution.

[8]The authors are aware that in Moskowitz et al. (2012), TSM signals are generated based on the direction-of-change of k-period returns. TSM focuses on time series return predictability; however, in this paper, we focus on the predictability of return signs.

$p_{-1} + p_0 + p_1 = 1$ or, equivalently, under symmetry $2p_1 + p_0 = 1$.

We can now compute the transition probabilities to calculate the unconditional probabilities to match our previous discussion. Straightforward calculations lead to the following:

$$
\begin{aligned}
\mathsf{P}\left[Y_t = 1 | Y_{t-1} = 1\right] &= \mathsf{P}\left[\epsilon_t = 0 | Y_{t-1} = 1\right] = p_0 \\
\mathsf{P}\left[Y_t = 0 | Y_{t-1} = 1\right] &= \mathsf{P}\left[\epsilon_t = -1 | Y_{t-1} = 1\right] = p_{-1} \\
\mathsf{P}\left[Y_t = 1 | Y_{t-1} = 0\right] &= \mathsf{P}\left[\epsilon_t = +1 | Y_{t-1} = 0\right] = p_1 \\
\mathsf{P}\left[Y_t = 0 | Y_{t-1} = 0\right] &= \mathsf{P}\left[\epsilon_t = 0 | Y_{t-1} = 0\right] = p_0
\end{aligned} \tag{6}
$$

from which we can easily obtain the stationary probabilities as

$$
\begin{aligned}
\mathsf{P}\left[Y_1 = 1\right] &= p_0 + p_1 = \pi \\
\mathsf{P}\left[Y_1 = 0\right] &= p_0 + p_{-1} = 1 - \pi.
\end{aligned} \tag{7}
$$

These are, under chance, equal since we have $p_{-1} = p_1 = p$ and satisfy by construction that $\mathsf{P}\left[Y_t = 1\right] + \mathsf{P}\left[Y_t = 0\right] = 1$ from the requirements of the conditional distribution of ϵ_t.

Consequently, it is possible to have a probabilistic model for the signs of the returns that reflects our discussion above, even under the assumption that the probability of a positive or negative return is actually the same. Therefore, signs can have greater persistence than returns themselves and be more predictable[9].

The theoretical motivation presented in this section is well reflected in Tables 1 and 2. In Table 1, we present the first-order sample autocorrelation coefficient for the mean signs, the annual returns, the proposed RSM and the TSM (the latter two are the corresponding signals when the momenta are active). There is a positive difference in favour of RSM being more persistent than TSM, not only in the magnitude of the average difference that is presented at the bottom of the table (which is statistically significant with a robust t-test of 4.15) but also from the fact

[9]Similar conclusions have been drawn in the other works; see, e.g., Leung et al. (2000); Hong and Chung (2003); Christoffersen and Diebold (2006).

that 71% of all assets examined have higher autocorrelation estimates for their RSM signals than for their TSM signals. Furthermore, in Table 2, we perform some more exploratory analysis, presenting regressions of the mean signs, the annual returns, and the signals from the two strategies. These dynamic regressions are particularly relevant, especially those in Panel B of the table. There, we use logit-type regressions of the binary signals that generate the two strategies on their lags and the lags of return signs. The results here are again supportive of our arguments, both thus far and to be made below, that the persistence in the RSM approach is higher than that of the TSM approach. Note that estimate of the lagged signals for RSM is double the size of the estimate of TSM, and furthermore, the pseudo-R^2 of the former is approximately 10% larger than that of the latter. Thus, our conjecture can be summarised as follows: (i) signs of returns are more persistent, and thus predictable, than the returns themselves, and (ii) the signs forming the RSM are, on average, more persistent than the signs forming the TSM; thus, over a long period of trading where local trends are present, we anticipate that RSM will outperform TSM, as the former is better able to capture the relevant trends.

2.2. Regression Analysis

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

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

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

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + \epsilon_t^s, \tag{9}$$

where r_t^s is the excess return of asset s in month t adjusted by its available ex ante volatility σ_{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, ϵ_t^s denotes the error term, which has zero mean and finite variance. In Figure 1, we observe a similar pattern in the t-statistics obtained from Equation 8 and Equation 9 across all horizons. For currency and equity futures, setting $h = 12$, as suggested by the literature, is a clearer choice 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 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 returns; however, $h = 12$ is a better choice.

In an effort to provide further details on the effect responsible for 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 TSM effects. We concatenate all 55 assets' monthly returns to run four pooled regressions while including the previously mentioned dummy variables. The predictive regressions are now as follows:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + D_t + \epsilon_t^s, \tag{10}$$

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + D_s + \epsilon_t^s, \tag{11}$$

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + D_t + D_s + \epsilon_t^s, \tag{12}$$

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 2 illustrates how the signs of past returns can affect current returns. The results of the predictive regressions without dummies suggest that most of the 1 to

12 lagged return signs have a positive impact on current returns. After the first 12 months, there is a long period of reversal. Furthermore, controlling for cross-sectional effects does not change the main result. Thus, we 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 2, we see that controlling for time series effects 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 with and without time series dummies, respectively, we observe that the t-statistic value is not statistically significant (positive) for the second month lag before controlling for time series effects. Finally, in the top-right and bottom-right panels of Figure 2, we see that the results predictive regression with the time series dummy variable do not differ substantially from the regression that includes both the cross-sectional and the time series dummy variables.

Having analysed the importance of the signs of returns in the prediction of the direction of future returns, we now extend our analysis by including a series of sign probability instead of the sign variable, $sign(r^s_{t-h})$, used thus far. As noted above, we define a binary time series variable v that takes 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[10] 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:

$$P^s_{t-k,t-1} = \frac{1}{k}\sum_{i=t-k}^{t-1} v_i. \tag{13}$$

For further econometric motivation for employing 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 for the past 12 months. The predictive regressions are given by:

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

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h P_{t-h-11,t-h} + \epsilon_t^s. \tag{14}$$

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

Figure 3 presents the predictive power of the probability of positive return signs during the previous 12 months $P_{t-12,t-1}$ on future returns. $P_{t-12,t-1}$ have significantly positive impacts on, at least, the first 4 periods of returns. This positive relationship gradually vanishes thereafter. It becomes strongly negative from months 12 to 24. Examining this predictive power in greater detail by classifying the assets in Figure 4, we see that it varies across different classes. For equities, this trend lasts longer and is followed by a negative long-term reversal. For the rest of the assets, the positive impact is shorter. However, at least one future period return responds 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: an RSM indicator $P_{t-12,t-1}^s$ and a TSM indicator $sign(R_{t-12,t-1}^s)$, where $sign(R_{t-12,t-1}^s)$ represents the sign of the cumulative return of instrument s from $t-12$ to $t-1$. Hence, the TSM predictability regression is:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(R_{t-h-12,t-h}^s) + \epsilon_t^s. \tag{15}$$

Table 3 summarises the t-statistics of the two regressions based on Equation 14 and Equation 15 using the full dataset and four separate asset classes. It is obvious that the forecastability using RSM indicators, i.e., the probability of positive returns over the past 12 months, on the first 1-3 lagged month returns is much better than that of TSM indicators, i.e., the signs of the returns over the past 12 months. All the t-statistics for different asset classes are significant at least at the 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 provide about future return predictability, we are prepared to introduce investment strategies to exploit these insights.

3. Data

3.1. 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 with various maturities. The data were downloaded from Bloomberg and DataStream[11]. For simplicity, futures prices of the nearest contracts are concatenated to form long time series. 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 that of the nearest contract, we do not allow the nearest contract to be chosen again, even if its trading volume is increasing. The result is that the descriptives for our spliced data do not vary substantially 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 remainder of the paper, we focus on monthly returns that 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 perform the same quantitative exercises at a weekly frequency to check the robustness of the suggested method. The qualitative conclusions are similar and in some cases more in favour of RSM. Therefore, we omit these results[12]. Christoffersen and Diebold (2006) demonstrate that sign dependence is strongest in intermediate frequencies such as weekly and monthly. It becomes weaker when frequency is lowered to quarterly and annually, thereby supporting our finding that RSM outperforms TSM.

In Table 4, we summarise the characteristics of the original series. We present the date for the first available data of each series and the annualised arithmetic mean and

[11] Further details are provided in Appendix C.

[12] However, they are available on request.

the annualised standard deviation of the monthly excess returns for each individual instrument. Most futures have a positive long-term annualised mean, while some of the currency futures exhibit slightly negative values due to the appreciation of the US dollar. We find that volatility varies across different asset classes. The volatility of commodities and equities is much higher than that of currencies and bonds. In particular, the natural gas futures exhibit a 54.39% annualised standard deviation and the two-year maturity US bond (US2) offers the lowest volatility of 2.84% of a standard deviation.

For the factor regression analysis in 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 in 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), and the risk free rate are downloaded from K. French's website[13]. Asness et al. (2013) "Value and Momentum Everywhere" factors and the Moskowitz et al. (2012) TSM factors are available from the AQR website[14]. All the above data spans from January 1985 (where available) to March 2015, resulting in 361 observations where available.

3.2. Volatility Adjustment

Following Moskowitz et al. (2012), we employ the annualised ex ante volatility method to scale the returns of each asset. This scaling approach is used throughout the paper to transform the excess returns of a certain instrument into risk-adjusted excess returns. An ex ante volatility approach is an annualised exponentially weighted variance in the past returns and is calculated as follows:

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2, \tag{16}$$

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

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

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

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

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[15].

Finally, the third reason is that sign predictability is negatively related to volatility. Requiring an individual instrument's weight to be inversely proportional to its volatility can further improve portfolio performance. We argue that this improvement in performance should be distinct from that highlighted in the previous point. In other words, the benefit of volatility scaling can be decomposed into two parts: (i) the benefit from the volatility scaling/risk parity approach 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 is, the lower the sign dependence. RSM is established based on sign dependence; thus, the 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 σ_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 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 the RSM strategy returns for individual

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

instruments without volatility adjustment because it removes the benefit from risk parity. Hence, the returns of the RSM0.5 strategy before volatility scaling can be regarded as a proxy for sign dependence. Figure 5 illustrates how the Sharpe ratio of RSM, or the sign dependence, is related to the mean/volatility of the underlying instruments. We find that the higher the mean is, the higher the performance/sign dependence. However, the higher the volatility is, the lower the performance/sign dependence. This outcome is consistent with the work of Christoffersen and Diebold (2006).

4. Return Signal Momentum

To evaluate the profitability of RSM strategies, we form a portfolio using the 55 futures in our data[16]. According to the regression results in Section 3, we set the look-back period k to 12 months. For each month, using any investment strategy, RSM, TSM or SMA, a signal is generated for each asset indicating the investor's position. The holding period is set to one;[17] therefore, the signals for each asset are renewed every month.

4.1. Position Signals & Portfolio Formation

One of the key advantages of RSM compared with TSM or XSM is the use of all of the information available during the look-back period. Instead of considering 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 signs of the returns, which is a binary time series variable, we calculate the probability of a 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; the signal of the

[16]This dataset is similar to those used in the 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 portfolios.

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

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 that suggest taking a long position at time t. Otherwise, it indicates that the investor should take a short position. As we discuss below, 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:

$$R_t^s|P_{t-12,t-1}^s, q = \begin{cases} +r_t^s, & P_{t-12,t-1} \geqslant q \\ -r_t^s, & P_{t-12,t-1} < q \end{cases}. \tag{17}$$

To form a portfolio that 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 of 40% for the annual volatility. This aligns our results with the current literature and mimics a real trading situation with a capital margin of approximately 5-20%. The RSM return for asset s is given by:

$$R_t^s|P_{t-12,t-1}^s, q = \begin{cases} +r_t^s \frac{40\%}{\sigma_{t-1}^s}, & P_{t-12,t-1} \geqslant q \\ -r_t^s \frac{40\%}{\sigma_{t-1}^s}, & P_{t-12,t-1} < q \end{cases}. \tag{18}$$

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

$$R_t^p = \frac{1}{S} \sum_{s=1}^{S} R_t^s|P_{t-12,t-1}^s, q. \tag{19}$$

To properly evaluate the results of RSM in individual instrument portfolios, we additionally include four well-established benchmarks from the literature: the naïve 1/N, SMA for prices, XSM, and TSM strategies. The 1/N represents 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. Next, we also apply the conventional XSM strategy, where we divide the entire portfolio into quantiles[18] according to monthly performance. The XSM return is calculated by longing the top-performing quintile and shorting the bottom-performing quintile. 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, XSM, and TSM, the portfolio weights are calculated in the same way as in Equation 18.

4.2. Fixed Probability Threshold

The first case we consider is the fixed probability threshold. We report a number of four pre-determined thresholds $q = \{0.2, 0.3, 0.4, 0.5\}$[19]. During the evaluation period, the probability threshold values are held constant. As we see later, the empirical exercise suggests a fixed value of 0.4, which allows the strategy to provide signals that follow large uptrends in the market and 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 drawdown. The formulas for these statistics are provided in Appendix D. First, we study the performance of individual instruments using RSM strategies and the benchmark strategies[20]. The results suggest that in most cases, RSM strategies perform better than the benchmarks when the threshold value is no larger than 0.5.

Then, turning to Panels A and B of Table 5, we summarise the portfolio performance using the same strategies. First, when comparing the benchmarks, we find that the TSM approach performs better than the other methods (1/N, SMA and XSM strategies). In particular, TSM provides the largest Sharpe ratio and cumula-

[18] As the total number of instruments in our asset pool is relatively small, we select the top 20% and bottom 20% following Novy-Marx (2012) and Kim et al. (2016). XSM strategies using other percentages show similar results and are available upon request.

[19] We also considered further thresholds but omit them here because they do not add significant value. However, they are available upon request.

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

tive net profits and the lowest drawdown. Comparing the portfolios that invest based on the suggested RSM strategies, we see that, as long as the threshold is smaller than 0.5, the portfolios perform favourably compared with TSM. The Sharpe ratio of the best RSM strategy, i.e., using $q = 0.4$, is 20% better than that of TSM. All the RSM strategies with a fixed threshold $q < 0.5$ are associated with an annual return that is at least equal to 10% with lower 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 are almost 18% larger than those of TSM and the drawdown is almost 44% smaller. Note 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 over time, we graphically depict the evolution of cumulative net profits of the best RSM portfolio with $q = 0.4$ and the three benchmark portfolios. We see in Figure 6 that from January 1985 to March 2015, the cumulative net profits of RSM are almost twice the value obtained using TSM. The two strategies are similar until 2003, with the equities market[21] outperforming both strategies. However, after 2004, RSM is the best portfolio, exhibiting 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 examining the evolution of maximum drawdown over time. In Figure 7, we see that RSM and TSM have the same drawdown, with RSM suffering losses in the mid-1980s. Thereafter, the drawdown risk remains the same, with RSM outperforming TSM during the financial crisis in 2008, when 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[22]. In both cases, we observe that the RSM

[21] As proxied by the S&P 500 index.

[22] We also fit some linear regression lines and a polynomial non-linear fit. Following Moskowitz

portfolio exhibits positive expected returns based on positive and, most important, negative S&P 500 returns, whereas its relationship with TSM is more linear. We also observe that RSM returns are above the regression line, thus indicating better performance than 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 it keeps the investor in long positions during market uptrends and protected during crises or market turmoil. However, it would be challenging to evaluate the performance of RSM using a probability threshold that varies over time. There are numerous possible methods to estimate a time-varying threshold depending on the investor's preferences. For example, an investor who is cautious about inflation might adopt a threshold as a function of the expected inflation rate. Another example is a threshold that 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.

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-month evaluation period. We calculate the cumulative return $R^s_{t-12,t-1}|q$ for the last 12 months of the 24-month period, 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 5 shows the performance of the RSM portfolio using the time-varying threshold. Compared with the benchmarks, we see that RSM again provides higher mean returns, a higher Sharpe ratio and lower drawdown. Figure

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.

9 illustrates the cumulative net profits of the RSM time-varying threshold strategy compared to the TSM, the market and the passive long strategy from January 1985 to March 2015. As we see, the cumulative net profits of RSM are higher than those of the benchmarks and in particular are approximately 1.2 times larger than those of 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. Interestingly, when the market increases (e.g., during the periods 2000-2002 and 2004-2008 and after 2011), the threshold value decreases and thus allows 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, thereby 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[23] and compare it to the NBER-based recession indicators as shown in Panel B of Figure 10. During the recession periods (the early 1990s, 2001 and the 2008 global financial crisis), the correlation becomes low, at approximately 0 during the early-1990s recession, approximately -0.3 during the 2001 crisis and nearly -0.9 during the 2008 crisis. Thus, the time-varying threshold correctly captures the market conditions, indicating that it has better market timing.

However, for the particular universe of futures used here, the RSM portfolio with a time-varying threshold, although still better than the TSM and the other benchmarks, provides somewhat lower 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 that in the RSM0.4 strategy. Hence, the Sharpe ratio for RSM time-varying threshold strategy (0.916) is very close to that of RSM0.4 (0.962), which are both higher than the rest of the RSM strategies and the TSM (0.792). Overall, this exercise sheds additional light on the ways that RSM could be used in practice.

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

4.4. Risk Exposure Analysis and Performance Robustness

We conclude our discussion of the main results for the suggested RSM by analysing their risk exposure. To do so, we regress the returns of the RSM portfolio on three major classes of market risk factors. These are the Fama-French SMB, HML and UMD factors, which represent 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), the TSM factor of Moskowitz et al. (2012) and the XSM returns calculated from our sample dataset. The regression models controls for market risk by including the monthly returns of the MSCI world index. The regression results are reported in Table 6.

The results reveal an approximately 35-40% change in the RSM portfolio, which is due to the change in the market. RSM also has a strong positive relationship with each of the momentum factors (UMD, Momentum Everywhere and TSM) and the XSM returns, as the beta coefficients are statistically significant at the 5% and 1% levels. Despite that all of the 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 the 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 currently known factors.

Note further that the correlation coefficient between the RSM0.4 returns and the XSM returns is only 0.416, which is significantly lower than that between TSM and XSM returns (0.790). This means that the RSM strategy is qualitatively different from TSM and XSM. However, TSM and XSM are quite similar.

Finally, to check for the robustness of the performance of the RSM-based portfolios, we examine the performance of the portfolios across different sub-periods and study the distribution of the decomposed returns.

Table 7 provides the same performance evaluation statistics reported in Table 5 but for different sub-periods. In particular, we examine (i) three ten-year periods (1985-1995, 1996-2005, and 2006-2015) and (ii) two fifteen-year periods (1985-2000, 2001-2015). It is again evident that even across different periods of time, the RSM portfolios result in higher Sharpe ratios, larger cumulative net profits and smaller drawdowns. For example, we can see that during the ten-year period if we start investing just before the crisis (i.e., 2006-2015), the TSM portfolio features a Sharpe ratio of 0.475, cumulative net profits of 0.684 and a maximum drawdown of 0.291. The investor is better off with the RSM0.4 portfolio, which has a Sharpe ratio of 0.619 and greater cumulative net profits of 0.973, which come with a lower level of drawdown at 0.195.

Finally, we conduct a performance attribution analysis and split the returns of each portfolio into four components:

D1 The vector of returns when a positive signal is generated and a positive return is obtained.

D2 The vector of returns when a positive signal is generated but a negative return is obtained.

D3 The vector of returns when a negative signal is generated and a positive return is obtained.

D4 The vector of returns when a negative signal is generated but a negative return is obtained.

Figure 11 provides the estimated densities of the returns of each of these components. The black solid line refers to the distribution of the returns of the TSM portfolio, whereas the blue dashed lines refers to the distribution of returns of the RSM0.4 portfolio. At a first glance, we see that the results are decisively in favour of RSM.

For the cases of D1 and D4, which correspond in making the right choice based on the underlying signal, the RSM distribution is either shifted to the right (D1, blue line, higher positive mean than the TSM) or has a smaller variance (D4, blue line, higher peak, lower dispersion) and, thus, the average positive return is greater, and the average return on the different types of RSM is much more consistent (lower mean return but smaller variance). For the cases where a wrong choice is made, D2 and D3, we can see that only for D2 is RSM possibly worse than TSM (in terms of both a lower negative mean and higher dispersion), but in the case of D3, the outperformance of RSM is clearly visible – the RSM obtains consistently higher returns on its D3 errors.

In Figure 12, where we plot the densities of all the RSM and TSM returns, similar conclusions can be drawn: (i) first, we observe that the RSM density (blue line) is shifted to the right on the ascending part of the density from the negative side and is shifted right also on the descending part of the density from the positive side; (ii) second, it can be seen that the RSM distributions have lighter tails than the corresponding TSM tails; and (iii) third, it is important to highlight that the RSM distribution of returns has a plateau in the area around zero – this plateau indicates that the concentration of RSM returns is on a wider area in the middle of the distribution and, thus, occurrences outside this plateau are less frequent than in the corresponding TSM distribution. This final comment tallies precisely with the results of the decomposition of the returns presented in Figure 11 above.

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 of 55 financial instruments over a period 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, and we find empirical evidence that RSM portfolios provide larger cumulative net profits, a higher Sharpe ratio and a lower maximum drawdown compared to the passive long, simple price moving average and time series momentum portfolios. A time-varying probability threshold that is based on cross-validation suggests that the threshold is negatively correlated with the market. In particular, when market expectations are positive, the time-varying threshold decreases, allowing the investor to take more long positions. When the market conditions deteriorate, the time-varying threshold increases, protecting the investor from the coming 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 a significant alpha that cannot be explained by the existing risk factors. Therefore, it can be attributed to the RSM effect. A performance robustness analysis highlights the favourable risk/return characteristics of the proposed method. Overall, our research indicates that market participants can successfully apply RSM as an alternative type of momentum for both speculation and risk management purposes.

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Table 1: First order autocorrelation of RSM and TSM signals.

	Mean Signs	Annual Returns	Mean Signs - Annual Return	RSM Signal	TSM Signal	RSMS - TSMS
Aluminum	0.920	0.908	0.013	0.782	0.773	0.009
Brent	0.890	0.884	0.006	0.810	0.617	0.192
Cocoa	0.891	0.856	0.035	0.702	0.589	0.113
Coffee	0.909	0.898	0.011	0.758	0.738	0.019
Copper	0.926	0.927	-0.001	0.725	0.756	-0.031
Corn	0.914	0.909	0.005	0.750	0.777	-0.027
Cotton	0.907	0.880	0.026	0.732	0.744	-0.012
Gas.Oil	0.909	0.892	0.017	0.758	0.686	0.072
Gold	0.901	0.900	0.001	0.818	0.739	0.079
Heating.Oil	0.924	0.858	0.066	0.812	0.669	0.143
Lean.Hogs	0.909	0.836	0.073	0.769	0.709	0.059
Live.Cattle	0.892	0.808	0.084	0.700	0.658	0.042
Natural.Gas	0.926	0.765	0.160	0.782	0.610	0.171
Nickel	0.928	0.923	0.005	0.771	0.770	0.000
Platinum	0.903	0.888	0.014	0.796	0.747	0.049
RBOB	0.901	0.803	0.098	0.661	0.679	-0.018
Silver	0.907	0.888	0.019	0.754	0.711	0.043
Soy.Meal	0.907	0.886	0.021	0.743	0.735	0.007
Soy.Oil	0.936	0.911	0.025	0.802	0.749	0.052
Soybeans	0.926	0.903	0.023	0.845	0.678	0.167
Sugar	0.920	0.881	0.039	0.808	0.721	0.087
Wheat	0.917	0.896	0.021	0.783	0.771	0.012
WTI	0.897	0.875	0.022	0.741	0.693	0.047
Zinc	0.931	0.944	-0.014	0.798	0.700	0.099
AUD	0.934	0.911	0.023	0.795	0.798	-0.003
CAD	0.929	0.916	0.012	0.823	0.832	-0.008
EUR	0.927	0.912	0.015	0.794	0.793	0.001
JPY	0.930	0.931	-0.001	0.812	0.848	-0.037
NZD	0.935	0.907	0.029	0.809	0.791	0.019
NOK	0.911	0.885	0.026	0.781	0.733	0.048
SEK	0.916	0.919	-0.002	0.822	0.730	0.093
CHF	0.922	0.909	0.013	0.743	0.753	-0.010
GBP	0.911	0.904	0.008	0.830	0.741	0.089
SPI	0.922	0.890	0.031	0.755	0.732	0.023
CAC	0.923	0.932	-0.009	0.798	0.826	-0.028
DAX	0.935	0.932	0.004	0.831	0.861	-0.029
FTSE.MIB	0.945	0.946	-0.001	0.838	0.801	0.038
TOPIX	0.932	0.942	-0.011	0.760	0.787	-0.028
AEX	0.933	0.936	-0.003	0.828	0.806	0.022
IBEX	0.938	0.925	0.013	0.822	0.830	-0.008
FTSE	0.929	0.893	0.036	0.829	0.782	0.047
S.P	0.918	0.917	0.001	0.828	0.816	0.012
AUS3	0.937	0.872	0.065	0.746	0.771	-0.024
AUS10	0.927	0.913	0.014	0.762	0.763	-0.001
EURO2	0.916	0.862	0.055	0.812	0.719	0.093
EURO5	0.897	0.851	0.046	0.779	0.712	0.067
EURO10	0.898	0.870	0.028	0.821	0.748	0.073
EURO30	0.917	0.882	0.035	0.791	0.733	0.058
CA10	0.901	0.882	0.019	0.756	0.658	0.097
JP10	0.936	0.888	0.048	0.850	0.695	0.155
UK10	0.886	0.885	0.001	0.730	0.755	-0.025
US2	0.953	0.915	0.038	0.782	0.833	-0.051
US5	0.937	0.915	0.022	0.785	0.781	0.004
US10	0.916	0.909	0.008	0.794	0.764	0.029
US30	0.900	0.887	0.013	0.763	0.746	0.017
Average	0.918	0.894	0.024	0.783	0.745	0.038

This table reports first order autocorrelation of the annual returns, TSM signals, mean of return signs, and RSM signals for each of the individual instruments. The difference of autocorrelation between mean of return signs and annual returns, and the RSM signals and TSM signals are calculated in the last two columns.

Table 2: Return sign and return persistence comparison.

	Explanatory Variable	Coefficient	Standard Error	t Value	R2/PS-R2
Panel A: Linear Regressions					
LM Model1 Y: Mean Signs	L1 Return Signs	0.018	0.002	8.256	0.003
LM Model2 Y: Mean Signs	L1 Mean Signs	0.927	0.003	357.986	0.859
LM Model3 Y: Mean Signs	L1 Return Signs	-0.083	0.001	-132.626	0.923
	L1 Mean Signs	1.012	0.002	502.164	
LM Model4 Y: Annual Returns	L1 Returns	0.060	0.028	2.150	0.000
LM Model5 Y: Annual Returns	L1 Annual Returns	0.894	0.003	288.914	0.799
LM Model6 Y: Annual Returns	L1 Returns	-1.214	0.010	-118.301	0.879
	L1 Annual Returns	0.989	0.003	391.203	
Panel B: Logit Regressions					
Logit Model 1 Y: RSM Signals	L1 Return Signs	0.228	0.030	7.609	0.002
Logit Model 2 Y: RSM Signals	L1 RSM Signals	4.438	0.049	91.007	0.524
Logit Model 3 Y: RSM Signals	L1 Return Signs	-5.788	0.501	-11.558	0.593
	L1 RSM Signals	9.176	0.501	18.322	
Logit Model 4 Y: TSM Signals	L1 Returns	1.030	0.212	4.867	0.001
Logit Model 5 Y: TSM Signals	L1 TSM Signals	3.982	0.043	92.767	0.467
Logit Model 6 Y: TSM Signals	L1 Returns	-7.329	0.318	-23.038	0.487
	L1.TSM Signals	4.335	0.049	89.305	

We compare regression results of 12 models to measure the sign and return persistence. In Panel A, we regress mean of signs or annual returns on the lagged return signs, lagged mean of signs, lagged returns, and lagged annual returns. The coefficients, standard error, t value and adjusted R square are reported. In Panel B, we perform logit regressions, where the dependent variables are RSM signals or TSM signals. The explanatory variables are lagged return signs, lagged RSM signals, lagged returns, and lagged lagged TSM signals. The coefficients, standard error, t value and McFadden pseudo R square are summarised.

Table 3: Predictive power of RSM and TSM indicators.

	Probability of 12 Month Positive Returns					Signs of 12 Month Cumulative Returns				
Lag (Months)	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	-0.197	-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 the beta coefficients in two sets of pooled regressions based on Equation 14 and Equation 15. 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 4: 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 5: 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
XSM	0.102	0.175	0.588	0.165	-0.188	13.019	0.392
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, XSM, 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 6: Return 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 **	
Panel D: XSM factors						
	MSCI World			XSM	Intercept	R2
Coefficient	0.34			0.27	0.52%	34.53%
t-Statistic	9.85 ***			9.07 ***	3.37 ***	

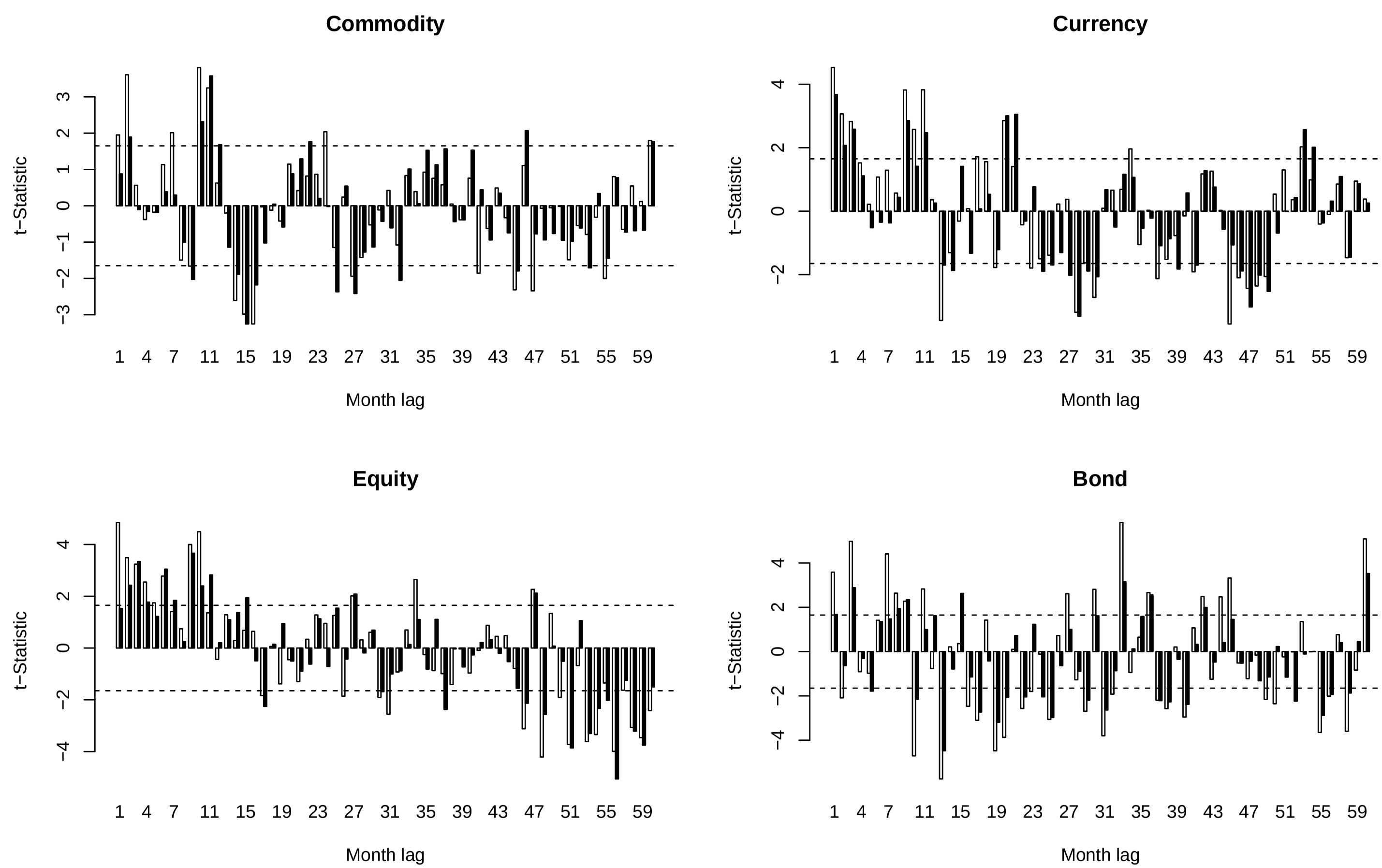
This table reports the factor exposure of the monthly returns of RSM0.4 strategies. The regression coefficients are reported in the first row and t-statistics (*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$) are reported in the row below. Four sets of regressions are run: Fama-French and Carhart factors(Panel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

Table 7: Performance of RSM strategies compared to benchmark (sub-periods).

Strategies	Average	Volatility	Sharpe Ratio	Maximum	Minimum	Cumulative Net Profits	Maximum Drawdown
				1985-1995			
TSM	0.112	0.129	0.868	0.130	-0.088	2.093	0.170
RSM 0.4	0.114	0.122	0.932	0.098	-0.082	2.186	0.165
RSM 0.5	0.095	0.121	0.782	0.101	-0.096	1.593	0.133
				1996-2005			
TSM	0.127	0.124	1.027	0.125	-0.094	2.289	0.177
RSM 0.4	0.157	0.115	1.369	0.132	-0.067	3.480	0.108
RSM 0.5	0.144	0.113	1.279	0.129	-0.066	2.951	0.131
				2006-2015			
TSM	0.066	0.139	0.475	0.125	-0.113	0.684	0.291
RSM 0.4	0.083	0.133	0.619	0.112	-0.131	0.973	0.195
RSM 0.5	0.068	0.116	0.591	0.101	-0.129	0.767	0.190
				1985-2000			
TSM	0.116	0.122	0.955	0.130	-0.088	4.643	0.170
RSM 0.4	0.121	0.118	1.023	0.132	-0.082	5.111	0.165
RSM 0.5	0.108	0.115	0.940	0.129	-0.096	4.002	0.133
				2001-2015			
TSM	0.088	0.139	0.630	0.125	-0.113	2.035	0.291
RSM 0.4	0.116	0.129	0.898	0.112	-0.131	3.609	0.195
RSM 0.5	0.098	0.119	0.818	0.101	-0.129	2.619	0.190

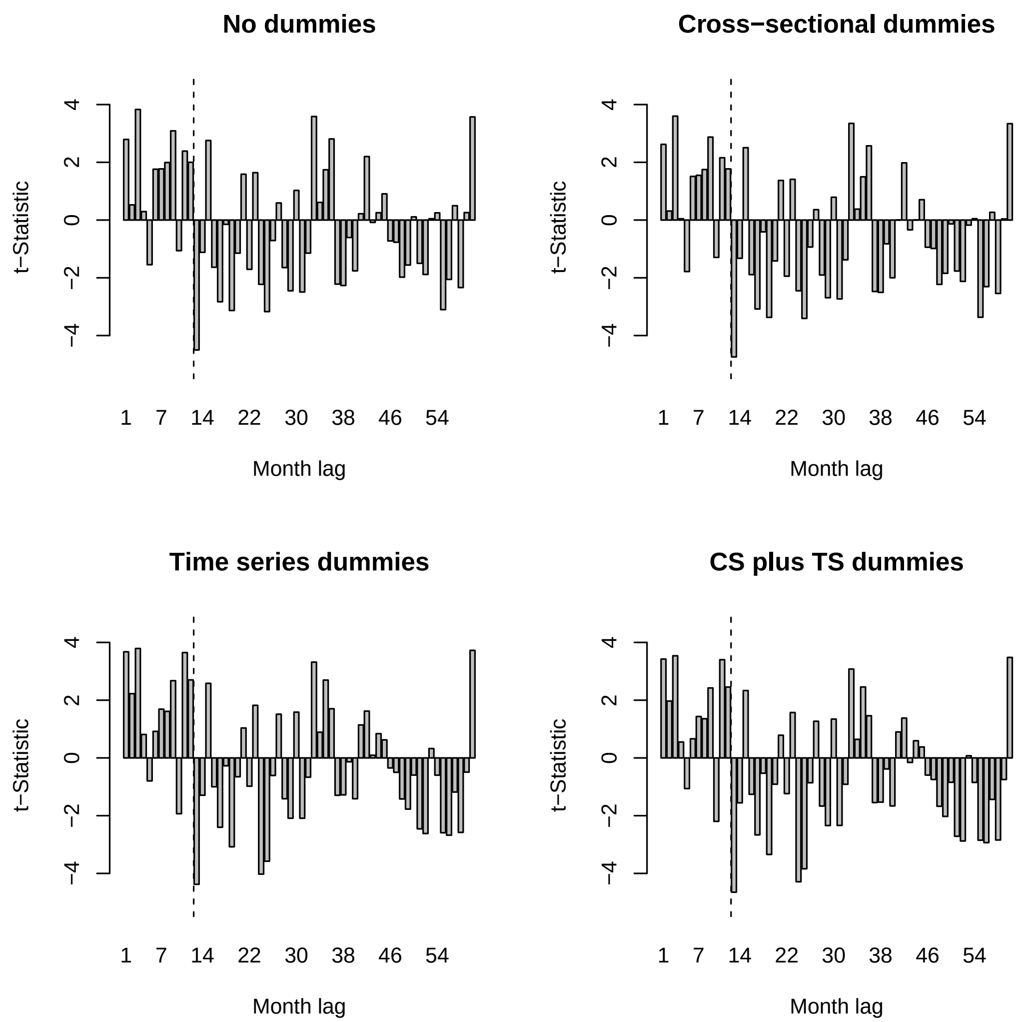
Reported is a comparison of performance between RSM and TSM strategies with during different sub-periods. The performance evaluation statistics are the same as reported in Table 5.

Figure 1: Returns and return signs predictive regressions.



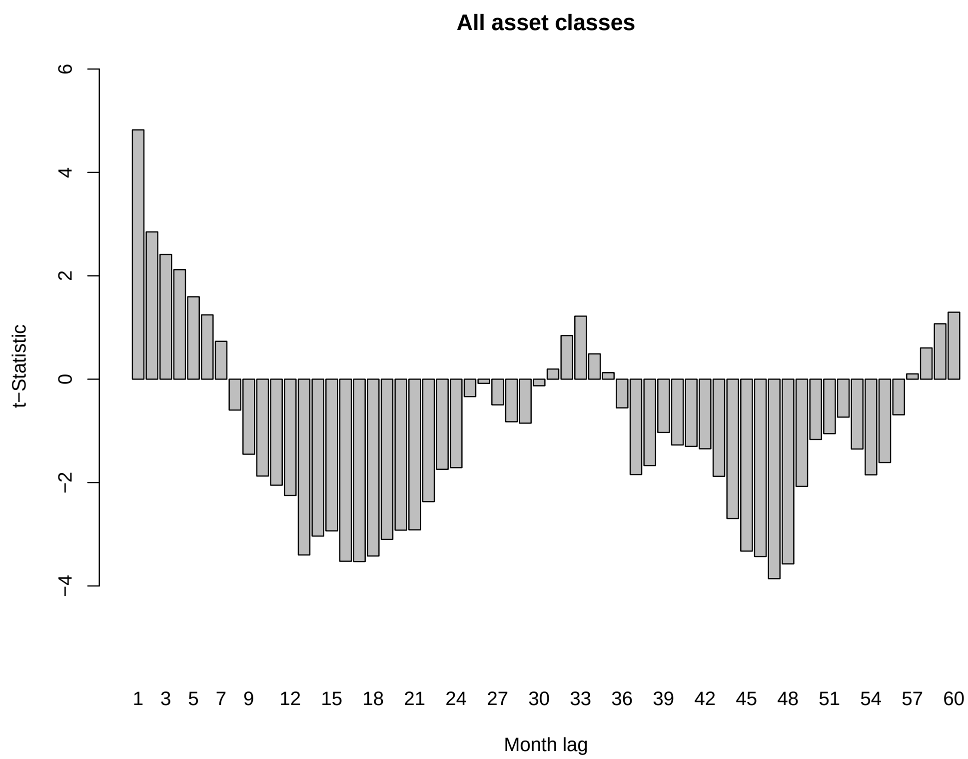
Reported are the t-statistics of the explanatory variables in different models with lags from $h = 1$ to $h = 60$. White and black bars indicate the t-statistics of the beta coefficients as in Equation 8 and Equation 9 respectively. Four separated pooled regressions are run representing four asset classes from January, 1985 to March, 2015.

Figure 2: Return signs predictability with and without cross-sectional (CS) and time series (TS) dummies.



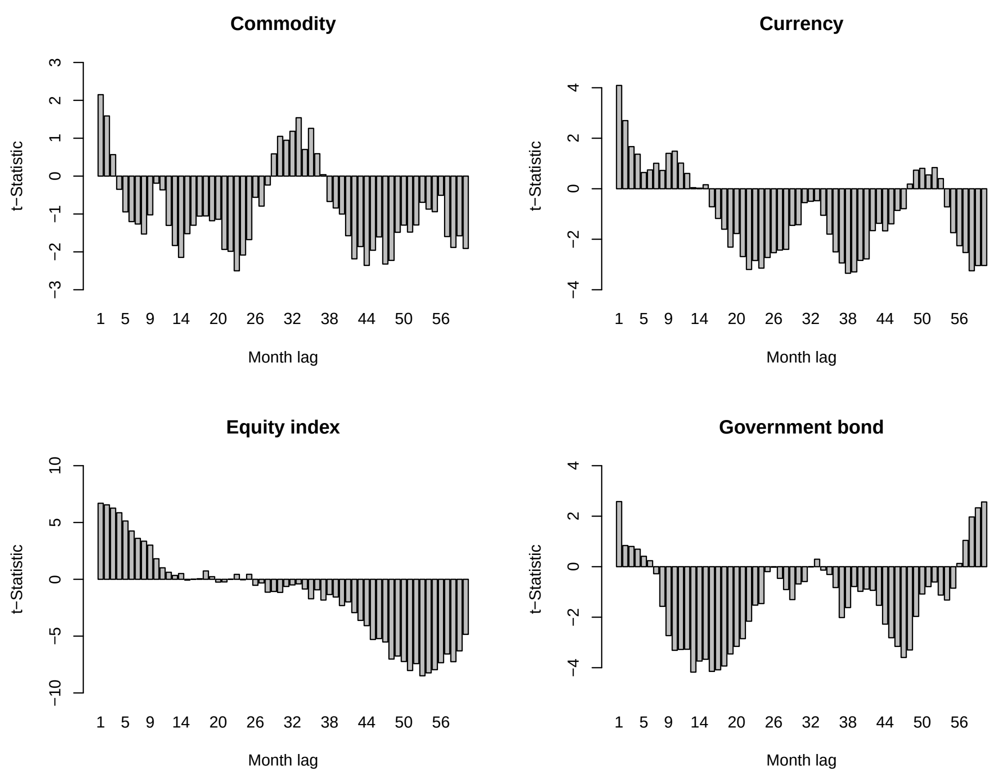
Reporting the t-statistics of the explanatory variables in different models with lags from $h = 1$ to $h = 60$. Four separated pooled regressions as in Equation 9, Equation 10, Equation 11 and Equation 12 are run.

Figure 3: Predictability of 12 months probability of positive return signs (Total assets).



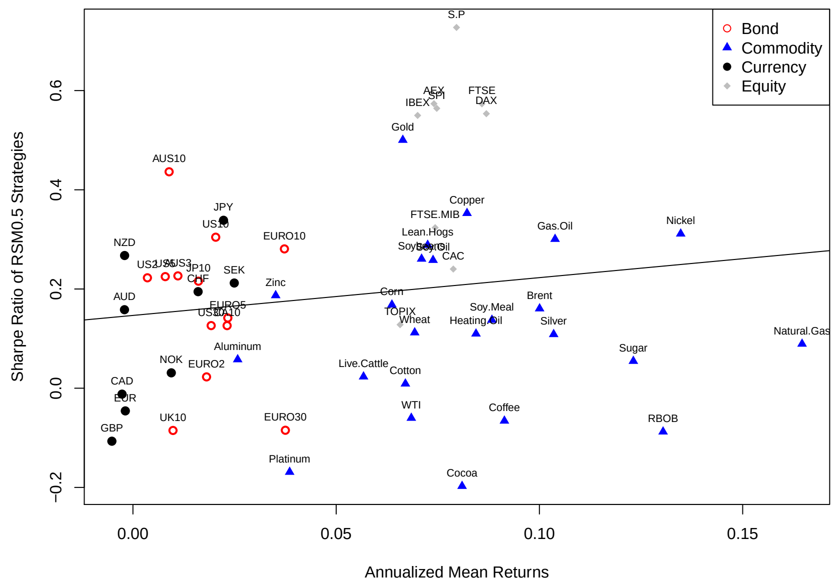
Reporting the t-statistics of the explanatory variables in different models with lags from $h = 1$ to $h = 60$. The pooled regression which consists of all the 55 instruments as in Equation 14 is run.

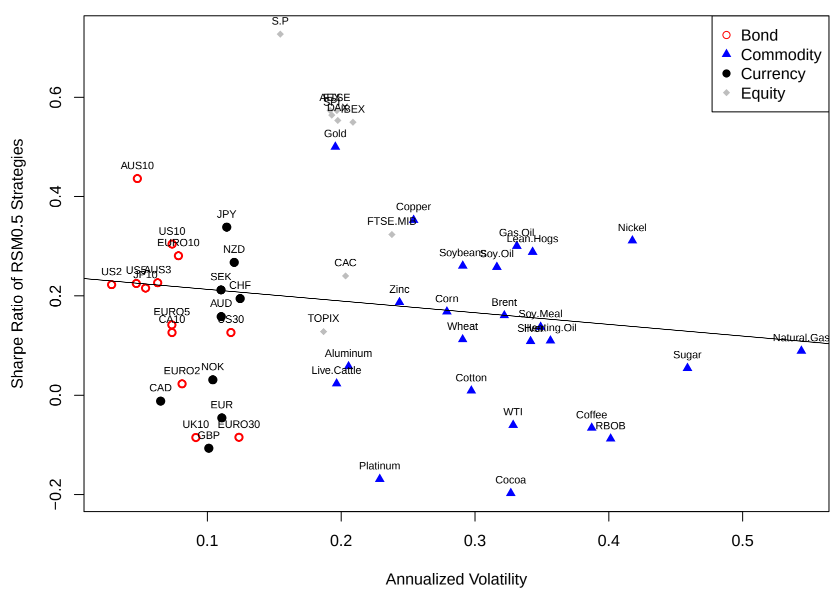
Figure 4: Predictability of 12 months probability of positive return signs (Asset classifications).



Reporting the t-statistics of the explanatory variables in different models with lags from $h = 1$ to $h = 60$. Four separated pooled regressions representing four asset classes as in Equation 14 are run.

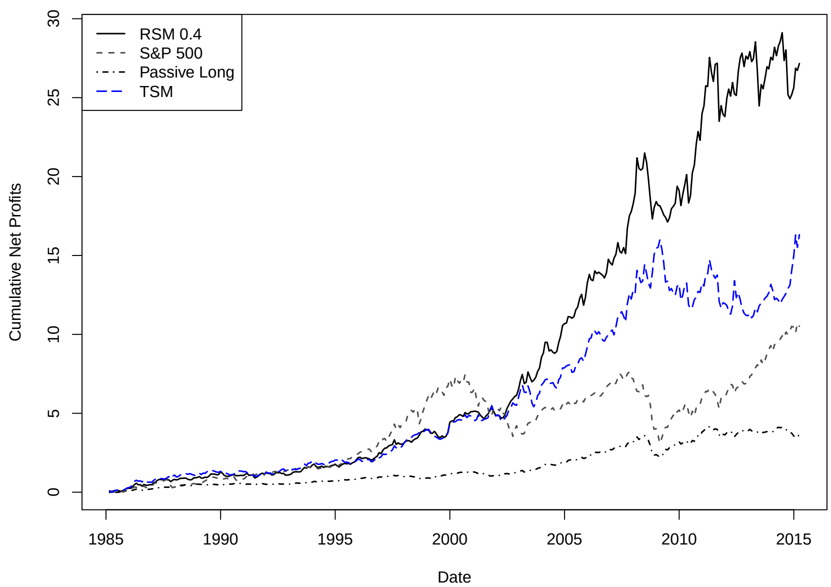
Figure 5: Sign dependence and individual instrument's mean/volatility.





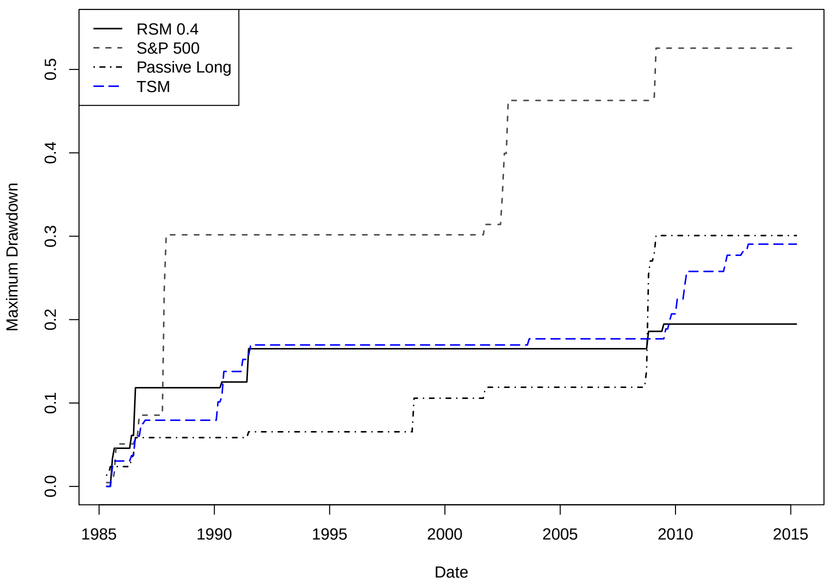
Reported figure illustrates how the Sharpe ratio of RSM before volatility adjustment, or the sign dependence, is related to the mean/volatility of the underlying instruments. Detailed calculation of mean, volatility and Sharpe ratio are listed in Appendix D.

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



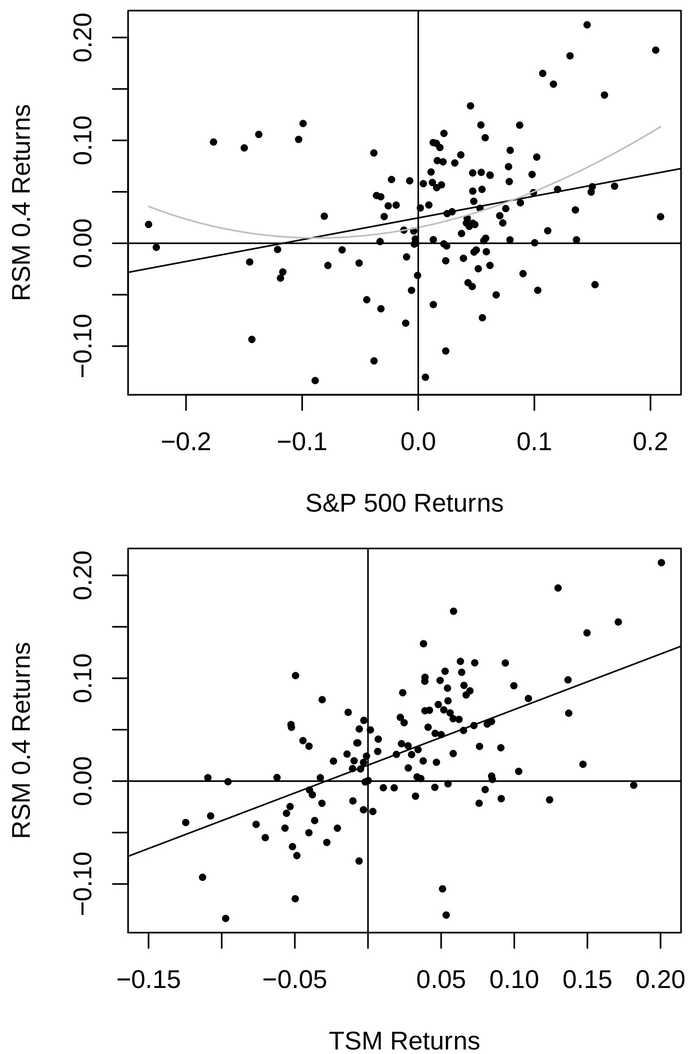
Reported are the cumulative net profits of RSM0.4 strategy and three benchmarks: S&P 500 index, Passive Long (1/N) and TSM from January, 1985 to March, 2015.

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



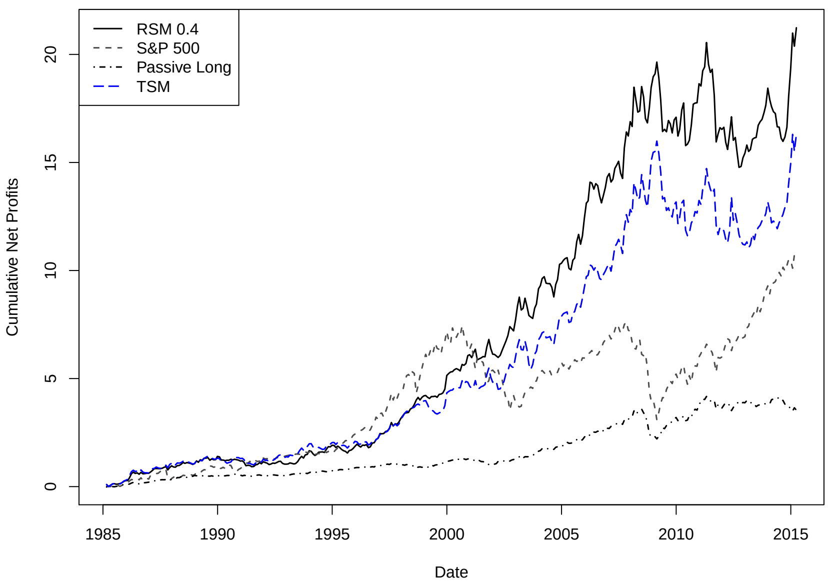
Reported are the Maximum Drawdowns of RSM0.4 strategy and three benchmarks: S&P 500 index, Passive Long (1/N) and TSM from January, 1985 to March, 2015.

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.

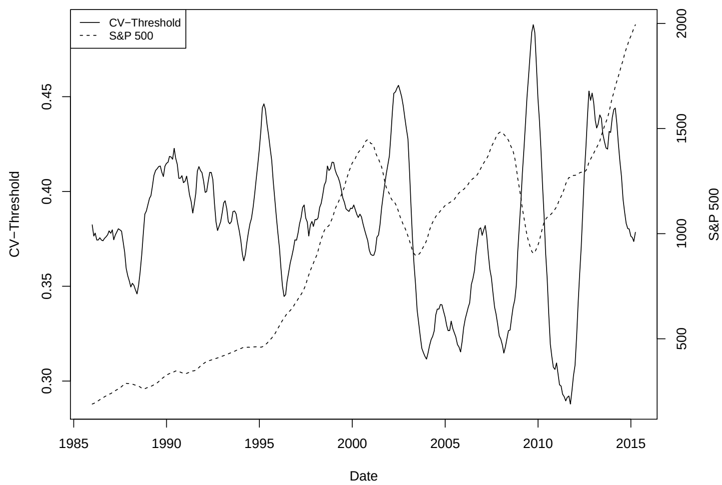
Figure 9: Return signal momentum strategy profitability (Time-varying threshold).



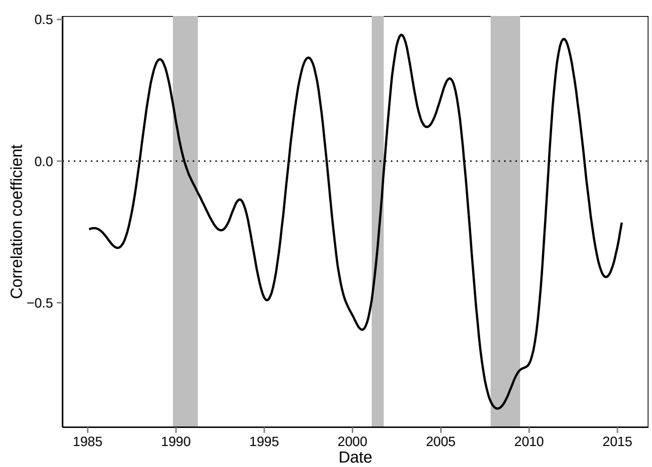
Reported are the cumulative net profits of RSM time-varying threshold strategy and three benchmarks: S&P 500 index, Passive Long (1/N) and TSM from January, 1985 to March, 2015.

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

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

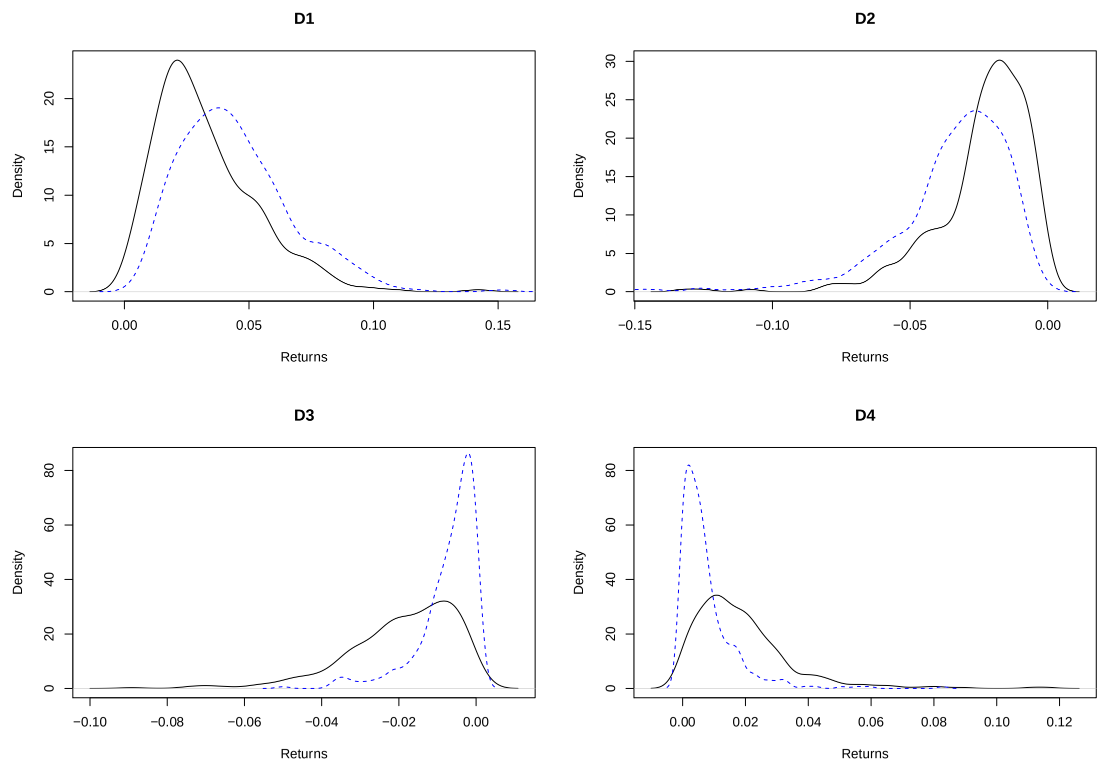


(b) Panel B: Correlation of TV threshold and S&P 500 index.



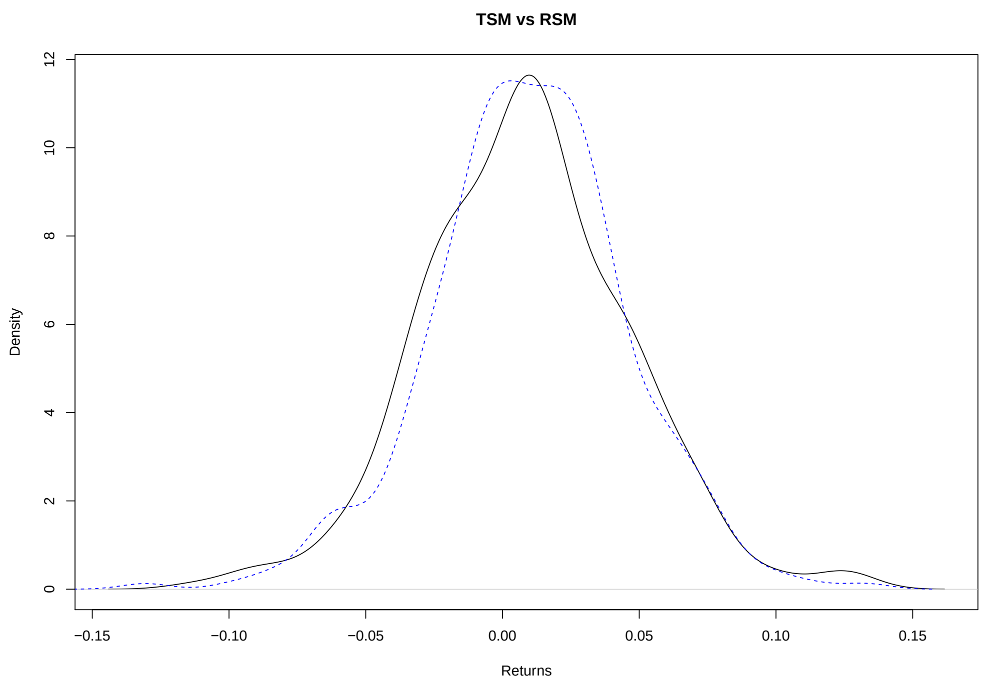
Panel A Reports the time-varying threshold value and S&P 500 index over time. The left hand side axis scales the time-varying threshold value, while the scale on the right hand side is for S&P 500 index. Panel B reports the kernel-based smoothing correlation coefficients between the time-varying threshold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

Figure 11: Return densities of RSM and TSM strategies (all components).



This figures reports the return densities of decomposed RSM0.4 and TSM strategies. In different panels, we decompose each of the strategy into four components: [D1] the vector of returns when a positive signal is generated and a positive return is obtained; [D2] the vector of returns when a positive signal is generated but a negative return is obtained; [D3] the vector of returns when a negative signal is generated and a positive return is obtained; and [D4] the vector of returns when a negative signal is generated but a negative return is obtained.

Figure 12: Return densities of RSM and TSM strategies.



This figures reports the return densities of RSM0.4 and TSM portfolios. The sample used in calculating the return densities spans from January, 1985 to March, 2015.

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

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 π is the (2×1) 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 $\boldsymbol{C}_n$ is given by $\boldsymbol{C}$:
4. $$\boldsymbol{C} \stackrel{\text{def}}{=} \begin{bmatrix} \phi_0 & \phi_1 & \dots & \phi_1 \\ \phi_1 & \phi_0 & \dots & \phi_1 \\ \vdots & \vdots & \vdots & \vdots \\ \phi_1 & \phi_1 & \dots & \phi_0 \end{bmatrix}$$

Although we already know that the sample covariance matrix $\boldsymbol{C}_n$, 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 $\boldsymbol{C}$:

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

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

Finally, note that the ratio:

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

and in the limit, as $m \uparrow$ when $N \to \infty$, it is just ϕ_1/ϕ_0. The higher is thus the degree of persistence ϕ_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.

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:

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

and the reconstructed trajectory matrix has rows that are m-period rolling averages of the original observations. The ith row $\widehat{\boldsymbol{x}}_i^\top$ is given as $\widehat{\boldsymbol{x}}_i^\top \stackrel{\text{def}}{=} \left(m^{-1} \sum_{t=i}^{m+i-1} x_t \right) \boldsymbol{J}_m^\top$, and, applying diagonal averaging $\mathcal{D}(\widehat{\boldsymbol{T}}_X)$ 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 5.

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

$$AR^s \stackrel{\text{def}}{=} \frac{1}{n} \sum_{t=m_1}^{m_n} R_t^s \tag{20}$$

2. The cumulative net profit

$$CNP^s \stackrel{\text{def}}{=} \left\{ \prod_{t=m_1}^{t=m_n} (1 + R_t^s) \right\} - 1 \tag{21}$$

3. The annualized volatility/standard deviation

$$SD^s \stackrel{\text{def}}{=} \sqrt{\frac{1}{n} \sum_{t=m_1}^{m_n} (R_t^s - AR^s)^2} \tag{22}$$

4. The gross Sharpe Ratio, annualized

$$SR^s \stackrel{\text{def}}{=} \frac{AR^s}{SD^s} \tag{23}$$

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:

$$MDD_t^s = \frac{\max_{T \in (0,t)} \{0, \max CNP_T^s - CNP_t^s\}}{\max_{T \in (0,t)} CNP_T^s} \tag{24}$$

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
XSM	0.077	0.173	0.445	0.163	-0.189	5.447	0.437
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, XSM, 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.