Risk-Adjusted Time Series Momentum*

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Abstract

We introduce a new class of momentum strategies, the risk-adjusted time series momentum (RAMOM) strategies, which are based on averages of past futures returns, normalized by their volatility. We test these strategies on a universe of 64 liquid futures contracts and show that RAMOM strategies outperform the time series momentum (TSMOM) strategies of Ooi, Moskowitz, and Pedersen (2012) for almost all combinations of holding and look-back periods. This outperformance is driven by the following new striking stylized fact that we document: For almost all of the 64 futures contracts, independent of the asset class, realized futures volatility is contemporaneously negatively related to the Fama and French (1987) market (MKT), value (HML), and momentum (UMD) factors. As a result, RAMOM returns have a natural, built-in exposure to the MKT, HML, and UMD factors and outperform TSMOM returns precisely in times when (some of) the factors deliver good returns. In particular, RAMOM allows investors to gain significant exposure to Fama and French factors without actually trading the very large stock universe. Furthermore, dollar turnover of RAMOM strategies is about 40% lower than that of TSMOM, implying a drastic reduction in trading costs.

We construct measures of momentum-specific volatility, both within and across asset classes, and show how these volatility measures can be used for risk management. We find that momentum risk management significantly increases Sharpe ratios, but at the same time may lead to more pronounced negative skewness and tail risk. Furthermore, momentum risk management leads to a much lower exposure to market, value, and momentum factors; as a result, risk-managed momentum returns offer much higher diversification benefits than those of standard momentum returns.

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1 Introduction

Momentum is the most actively used strategy class in the asset management industry. The idea of extrapolating past performance into the future, often-called "buying winners and selling losers," underlies many behavioral and rational asset pricing theories.[1] A typical momentum strategy uses trading signals that are based on averages of past realized returns and therefore completely ignores the noise that is introduced into these signals by the fluctuating stochastic volatility. This might be inefficient because averaging past realizations of highly heteroskedastic returns may produce a very noisy estimate of the true expected return. The goal of this paper is to study this inefficiency in the time series momentum (TSMOM) strategies introduced in an important paper by Ooi, Moscowitz, and Pedersen (2012) (henceforth OMP (2012)). We show that (partially) removing heteroskedasticity from the trading signals via a simple risk-adjustment procedure significantly improves the strategies' performance. This outperformance is driven by the following new striking stylized fact that we document: For almost all of the 64 futures returns, independent of the asset class, realized futures volatility is negatively related to the Fama and French (1987) market (MKT), value (HML), and momentum (UMD) factors. As a result, risk-adjusted time series momentum (RAMOM) returns have a natural, built-in exposure to the MKT, HML, and UMD factors and outperform TSMOM returns in times when (some of) the factors deliver good returns. In particular, RAMOM allows investors to gain significant exposure to Fama-French factors without actually trading the very large stock universe. Furthermore, dollar turnover of RAMOM strategies is about 40% lower than that of TSMOM, implying a drastic reduction in trading costs: Normalizing past returns by their realized volatility removes a part of their variation that is driven purely by changing volatility and not by changing fundamentals and as a result leads to much more stable trading signals.

While being a major driver of RAMOM abnormal performance, the negative relationship between futures volatility and factor returns is a puzzle by itself. If one interprets the value (HML) factor as a bet on value minus growth, commodity futures volatility could be linked to HML returns through time variations in the uncertainty about future growth opportunities. When growth is high (low HML returns), uncertainty about future growth is also high; this increases the sensitivity of commodity demand to news and thereby increases commodity futures volatility.[2] However, the link of bond futures and currency futures volatility to HML returns and the links of all asset class volatilities to factor returns are intriguing and present an interesting topic for future research. Furthermore, the links between volatility, momentum returns, and size (SMB) and momentum (UMD) factors are much less clear.

[1]See, e.g., Barberis, Shleifer, and Vishny (1998); Daniel, Hirshleifer, and Subrahmanyam (1998); Hong and Stein (1999); Berk, Green, and Naik (1999); Johnson (2002); Ahn, Conrad, and Dittmar (2003); Liu and Zhang (2008); Sagi and Seasholes (2007).

[2]We thank Leonid Kogan for suggesting this intuitive explanation.

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For SMB, there is no clear relationship between futures volatility and SMB returns, but RAMOM outperformance is positively related to SMB returns; for UMD, futures volatility is positively related to UMD returns, but the behavior of outperformance can be ambiguous.

Following the approach introduced by Jegadeesh and Titman (1993) for the cross-sectional momentum and extended by OMP (2012) to the time series momentum, we consider a two-parameter class of momentum strategies, each characterized by a pair of periods, a holding period and a look-back period. The look-back period determines the horizon of past returns that is used to form the trading signal; the holding period determines the time interval over which the realized past returns are used to determine future positions. The only difference between our strategy and the TSMOM strategy of OMP (2012) is that, instead of using averages of past realized returns as the trading signals, we construct trading signals from averages of past risk-adjusted returns (i.e., realized returns normalized by a measure of realized volatility). We call this class of strategies "risk-adjusted momentum." We find that for the past 30 years RAMOM has outperformed TSMOM for almost all combinations of look-back and holding periods (we consider look-back and holding periods of up to two years), with the difference in returns being statistically significant for most momentum strategies.

Our analysis emphasizes the importance of studying risk and return characteristics of both RAMOM and TSMOM strategies simultaneously for all pairs of look-back and holding periods. Selecting just one pair (e.g., one-year look-back period, one-month holding period) does not provide the full picture and may be misleading. For example, when we regress RAMOM and TSMOM returns on the four Fama and French factors, we find that the betas with respect to the market portfolio are significant and negative (positive) for short-term (long-term) momentum strategies. Furthermore, the alphas or RAMOM returns with respect to TSMOM returns have a positive exposure to the UMD factor when the sum of the look-back and holding periods is less than 12 months. However, for longer term strategies, it often happens that RAMOM outperforms TSMOM during times when UMD returns are low. In particular, the difference between RAMOM and TSMOM returns could potentially be used as a hedge against drops in the UMD returns.

In the second part of the paper, we follow the methodology of Barroso and Santa-Clara (2013) and Daniel and Moscowitz (2013) and investigate the dynamics of momentum-specific risk, defined as the realized volatility of momentum returns. More precisely, we study two types of momentum (i.e., RAMOM) volatilities: aggregate momentum volatility, defined as the realized volatility of momentum returns pooled across all 64 instruments, and class-specific momentum volatility, defined as the realized volatility of momentum returns pooled within a given asset class. First, we look at the behavior of momentum returns, normalized by the realized momentum volatility (aggregate or class-specific). Quite surprisingly, we find that using aggregate

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momentum volatility leads to a significantly higher realized Sharpe ratio than using class-specific momentum volatilities. To understand these effects, we regress RAMOM returns within each class on past momentum volatilities, both aggregate and class-specific. Except for equity index futures, we do not find any significant predictability of momentum returns by past momentum volatility. For equity index futures, the regression coefficient for the aggregate momentum (class-specific) volatility is negative (positive), which explains why aggregate momentum volatility is better than class-specific volatility in terms of managing the momentum risk-return profile. Finally, we compare the kurtosis of RAMOM returns adjusted by the two types of momentum volatilities and find that adjusting by the aggregate volatility increases negative kurtosis in most cases. In contrast, using class-specific momentum leads to a significant reduction in negative kurtosis. Finally, we find that RAMOM returns adjusted by the aggregate momentum volatility have a much lower exposure to market, value, and momentum factors. As a result, risk-managed momentum returns offer significantly better diversification benefits than standard momentum returns.

2 Related Literature

Until the important paper by OMP (2012), all existing studies of momentum had concentrated on so-called "cross-sectional" momentum, in which positions in different instruments are taken depending on their relative performance with respect to each other. The nature of this cross-sectional momentum anomaly has been documented and investigated for various asset classes. See Shleifer and Summers (1990); Cutler, Poterba, and Summers (1991); Jegadeesh and Titman (1993); Asness (1994); Asness, Liew, and Stevens (1997); Rouwenhorst (1998); Moskowitz and Grinblatt (1999); Bhojraj and Swaminathan (2006); Erb and Harvey (2006); Gorton, Hayashi, and Rouwenhorst (2008); and Asness, Moskowitz, and Pedersen (2010). None of these papers has investigated the role of stochastic volatility in the performance of momentum strategies.

OMP (2012) were the first to introduce TSMOM strategies, in which the position in any given instrument is based solely on the instruments' own past return in the look-back period. Using a universe of 58 liquid futures contracts, they show that TSMOM generates positive abnormal returns across most of the instruments. Furthermore, when aggregated across instruments, significant positive returns are achieved for all combinations of holding and look-back periods. That the performance is so pervasive across all instruments and asset classes is striking and has clear practical implications for the financial sector and, in particular, the so-called commodity trading advisors (CTAs), who to a large extent follow different forms of TSMOM strategies. OMP (2012) also use Commodity Futures Trading Commission (CFTC) data on traders positions to link momentum returns to the trading behavior of speculators and hedgers. In particular, OMP (2012) find that speculators profit from momentum at the expense of hedgers. This provides a direct link from the TSMOM anomaly to the theory of hedging pressure, introduced by Keynes (1923).[3] Baltas and Kosowski (2014) perform a more detailed investigation of TSMOM returns and study the different choices of momentum signals and volatility estimators.

Many theoretical explanations of time series momentum have been proposed in the literature, for example, slow diffusion of news (Hong and Stein, 1999), behavioral biases (Barberis, Shleifer, and Vishny, 1998), equilibrium over-reaction due to positive feedback strategies (De Long, Shleifer, Summers, and Waldmann, 1990), overconfidence (Daniel, Hirshleifer, and Subrahmanyam, (1998), herding (Bikhchandani, Hirshleifer, and Welch, 1992), the disposition effect (Shefrin and Statman, 1985; Frazzini, 2006), risk factor exposure and growth (Berk, Green, and Naik, 1999; Johnson, 2002; Ahn, Conrad, and Dittmar, 2003; Sagi and Seasholes, 2007; Liu and Zhang, 2008; and fund flows (Vayanos and Woolley, 2013). Intuitively, our results are most closely related to the risk-based theory of momentum. Indeed, if risk premia are time varying and momentum signals allow investors to simply filter risk premia from realized average returns, then risk adjustment is a natural step because it facilitates better construction and less noisy measures of average realized risk premia.

Our paper also relates to the literature on managing and forecasting momentum-specific risk for cross-sectional momentum strategies and, in particular, so-called "momentum crashes." Daniel, Jagannathan, and Kim (2012) develop a hidden Markov model in which the market moves between latent turbulent and calm states that can explain a large fraction of momentum crashes. In particular, a conditional momentum strategy that moves to the risk-free asset when the estimated probability of the turbulent state is high performs significantly better than the "plain" cross-sectional momentum strategy.

Barroso and Santa-Clara (2013) investigate momentum-specific risk, measured as the realized volatility of cross-sectional momentum returns. They show that managing this risk by simply normalizing trading positions by the realized momentum volatility nearly doubles the Sharpe ratio of the momentum strategy. This risk management strategy is effective because high risk forecasts both high risk and low returns. Our results for the systemic risk of RAMOM returns are to some extent parallel to the findings of Barroso and Santa-Clara (2013). We find that, over very short horizons (several days), the volatility of momentum returns is negatively correlated with RAMOM returns, both contemporaneously and with lags. The latter circumstance implies that investors can use the current levels of momentum volatility to manage momentum risk. We find that adjusting the size of the position by momentum volatility significantly improves the risk-return profile of momentum returns, but the impact on Sharpe ratios is not as large as in Barroso and Santa-Clara

[3]See also Fama and French (1987), Hirshleifer (1990), Bessembinder (1992), de Roon, Nijman, and Veld (2000), and Baltas and Kosowski (2011).

(2013) (typically, Sharpe ratios go up by about 20%). Interestingly, this negative relationship only exists in the aggregate (pooled across all instruments) momentum returns and equity futures asset class; in contrast, in other asset classes, this relationship is unstable and non-significant.

Barroso (2013) investigates the bottom-up beta of cross-sectional momentum, estimated from the betas of individual stocks, and shows that it exhibits significant variations over time, increasing in bull markets and decreasing in bear markets. He shows that the conditional betas can explain a large part of variations in momentum-specific risk. We do not look at the dynamics of betas, but at momentum betas with respect to the four Fama-French factors (market, size, value, and cross-sectional momentum). We find that all of these betas are significant and positive, with the exception only of short-term RAMOM and TSMOM returns that have a negative market beta. Furthermore, betas are larger for RAMOM returns because of a significant negative relationship between futures volatilities and Fama-French risk factors.

Daniel and Moscowitz (2013) show that returns to cross-sectional momentum are highly negatively skewed and subject to "crashes" (sequences of large, negative returns). They show that these crashes occur after market declines, when market volatility is high, and can therefore be (partially) forecast. They construct a regression model for predicting expected momentum returns and show that a dynamic choice of momentum exposure based on this forecast and combined with the predictability of momentum-specific risk (as in Barroso and Santa-Clara (2013)) significantly improves momentum performance and doubles the strategy's Sharpe ratio. Our results indicate that both RAMOM and TSMOM returns exhibit behavior that differs quite a bit from that of cross-sectional momentum. We do not find any significant predictive relationship between past market (and other factor) returns and future RAMOM returns. Similarly, there is no significant relationship between past market volatility and future RAMOM returns. In contrast, the contemporaneous relationships between RAMOM returns and the four factors are strong and significant. Therefore, one can exploit these relationships for diversification purposes but not to predict returns.

The paper is organized as follows. Section 3 describes RAMOM and TSMOM strategies and examines their returns. Section 4 studies the abnormal performance of RAMOM returns versus TSMOM returns. Section 5 studies momentum-specific risk and momentum risk management. Section 6 concludes.

3 Momentum Strategies and Performance

Data. Our data consist of the 64 liquid futures contracts (15 stock index futures, 25 commodity futures, 13 bond futures, 5 interest rate futures, and 6 currency futures) listed in the appendix.

For any instrument i, let $r_{i,t}$ be its daily return for day t, calculated via

$$r_{i,t} \;=\; \log \frac{p_{i,t}}{p_{i,t-1}}, \tag{3.1}$$

where $p_{i,t}$ is the closing price on day t. The h-day returns are defined similarly:

$$r_{i,t,h} \;\equiv\; \log \frac{p_{i,t}}{p_{i,t-h}} \;=\; \sum_{s=0}^{h-1} r_{i,t-s}\,.$$

We also define the exponentially weighted moving average (EWMA) volatility of *log returns* via[4]

$$(\sigma_{i,t}(\lambda))^2 \;=\; \lambda\,(\sigma_{i,t-1}(\lambda))^2 \;+\; (1-\lambda)\,r_{i,t}^2\,. \tag{3.2}$$

In the sequel, we will use EWMA(λ) to denote this volatility measure. Typically, we will use the values of $\lambda_1 = 0.94$, $\lambda_2 = 0.87$, and $\lambda_3 = 0.5$, corresponding to approximately 30-day, 15-day, and 5-day realized volatility, respectively.

The instruments and their basic characteristics are listed in Table 2. Since different futures contracts were introduced in different time periods, the number of instruments available for trading at time t is monotone increasing over time and denoted by N_t.

The original TSMOM strategy of OMP (2012) operates at a monthly frequency and therefore fails to incorporate the most up-to-date information into trading positions.[5] Furthermore, position size for TSMOM strategies with a long holding period is influenced by a potentially outdated volatility estimate. In this paper, we introduce a simple modification of TSMOM strategies that uses daily updating and always incorporates the most recent information into trading positions.

As in OMP (2012), we define a two-parameter family of momentum strategies characterized by the look-back and holding periods. However, we distinguish between the two momentum signals: TSMOM strategy uses the sign of past realized returns as the trading signal, whereas RAMOM uses averages of risk-adjusted daily returns. Specifically, the RAMOM signal is constructed as follows: First, we compute the realized 12-day returns. Then we normalize them by the EWMA(0.5) realized volatility,[6] and taken averages of these

[4]The existence of volatility clustering in daily, weekly, or monthly speculative returns has been extensively documented in the literature. This evidence is confirmed by the Ljung and Box (1978) portmanteau tests for up to the 30th-order serial correlation in the squared returns. For all instruments, the test statistics are above 200, which is highly significant in the asymptotic chi-squared distribution with 30 degrees of freedom. Given this evidence of autocorrelation, it is natural to expect that past volatility measures can be used to forecast future volatility. See Gmür and Malamud (2014) for details.

[5]A positive side of this approach is that the trading costs for such a low-frequency strategy are also quite low.

[6]Note that we are normalizing 12-day realized returns by a relatively short-term volatility measure, corresponding to roughly 5 a day in realized volatility. We have also constructed RAMOM trading signals using longer term volatility (e.g., EWMA(λ) with $\lambda \in [0.5, 0.94]$). The results are similar and are available from the authors upon request.

returns. Precisely, for any $t > h > 0$, we define

$$\mathcal{R}^{RA}_{i,t,h} \equiv \sum_{l=t-h}^{t} \frac{r_{i,l,12}}{\sigma_{i,l-1}(0.5)}, \tag{3.3}$$

We use the sign of (3.3) as the trading signal defining the direction of the trade;[7] Following the risk parity approach of OMP (2012), we normalize the size of the position by the EWMA(0.94) volatility measure. Formally, for any pair $(k_1, k_2)\cdot 25$ of look-back and holding periods (in days), we define momentum returns $r^{\text{TSMOM}}_{i,t}(k_1, k_2)$ and risk-adjusted momentum returns $r^{\text{RAMOM}}_{i,t}(k_1, k_2, \lambda)$ for an instrument i via

$$r^{\text{TSMOM}}_{i,t}(k_1, k_2) = \left(\sum_{l=0}^{k_2-1} \text{sign}\left(r_{i,t-1-25\cdot l, 25\cdot k_1}\right)\right) \frac{e^{r_{i,t}} - 1}{\sigma_{i,t-1}(0.94)}. \tag{3.4}$$

and

$$r^{\text{RAMOM}}_{i,t}(k_1, k_2) = \left(\sum_{l=0}^{k_2-1} \text{sign}\left(\mathcal{R}^{RA}_{i,t-1-25\cdot l, 25\cdot k_1 - 11}\right)\right) \frac{e^{r_{i,t}} - 1}{\sigma_{i,t-1}(0.94)} \tag{3.5}$$

respectively.[8] Here, a 25-day period is chosen to match the approximate duration of a business month, and the adjustment $25\cdot k_1 - 11$ is made to match the look-back periods on RAMOM and TSMOM strategies, as discussed in footnote 7.

[7]The bite of the RAMOM trading signals comes from the fluctuations in the realized volatility $\sigma_{i,l-1}(0.5)$. Intuitively, if $\sigma_{i,l-1}(0.5)$ were constant, we would expect the RAMOM and TSMOM to behave identically. However, there is a slight difference in the two signals that comes from "counting" of the returns. Namely, while a TSMOM trading signal is given by $\text{sign}\left(\sum_{l=t-h}^{t} r_{i,l}\right)$, the constant volatility RAMOM trading signal is given by $\text{sign}\left(\sum_{l=t-h}^{t} r_{i,l,12}\right) = \text{sign}\left(\sum_{\tau=t-h-11}^{t} v(\tau - t) r_{i,\tau}\right)$ where

$$v(\tau - t) = \begin{cases} t - \tau + 1, & \tau \geq t - 10, \\ 12, & t - 11 \geq \tau \geq t - h + 11 \\ \tau - t + h + 1\,, & \tau \leq t - h + 10\,. \end{cases}$$

Thus, the two signs are "almost" the same, except that the returns over the very first and the very last 12 days are "under-counted." Furthermore, the true look-back period of the RAMOM signal is $h + 11$. Therefore, everywhere in the sequel we properly adjust the look-back periods to make sure we are comparing trading strategies with identical look-back periods.

[8]In the choice of $\lambda = 0.94$ for the volatility used for adjusting position size, we follow the RiskMetrics approach of J. P. Morgan (1997). The choice of $\lambda = 0.5$ within the risk-adjusted momentum signal construction might look a bit too "extreme" at first glance. The reason for the choice of such a small λ is that, as $\lambda \uparrow 1$, RAMOM and TSMOM signals become barely distinguishable and the effects of risk adjustments become negligible. In contrast, a small λ makes the volatility estimate much more sensitive to news and, as a result, it has a strong effect on the signal behavior.

That is, at date $t-1$, we compute the sign of instrument i's returns (for the TSMOM) or the sign of instrument i's risk-adjusted returns (for the RAMOM) over the $25 \cdot k_1$-day period, as they are at the current date, 25 days ago, etc., up to $25 \cdot k_2$ days ago, then we add up those signs and normalize the total size of the position by the current realized volatility measure $\sigma_{i,t-1}(0.94)$. We let the parameters k_1 and k_2 defining the look-back and holding periods take integer values between 1 and 24. Then, we hold this position for one day until the returns $r_{i,t}$ are realized and repeat the procedure. Aggregate momentum returns are defined as the equally weighted portfolio of individual returns,[9]

$$\begin{aligned} R_t^{\mathrm{TSMOM}}(k_1,k_2) &\equiv \frac{1}{k_2 N_{t-1}} \sum_{i=1}^{N_{t-1}} r_{i,t}^{\mathrm{TSMOM}}(k_1,k_2) \\ R_t^{\mathrm{RAMOM}}(k_1,k_2,\lambda) &\equiv \frac{1}{k_2 N_{t-1}} \sum_{i=1}^{N_{t-1}} r_{i,t}^{\mathrm{RAMOM}}(k_1,k_2,\lambda)\,. \end{aligned} \tag{3.6}$$

Throughout this paper, we report results for the 30-year period of January 1984-January 2014. While data on some futures contracts are available for earlier periods, we use this period because it roughly corresponds to the time when at least half of our instrument sample was actively traded. In several tests, we split this time period into two equal 15-year periods (January 1984-December 1998 and January 1999-January 2014) and compare the results for both sub-periods to study the robustness of our results to the choice of a sub-sample.

As is common in the literature, we start our analysis by investigating the relationship of momentum returns to standard, equity market-based risk factors. To this end, we regress momentum returns using the Fama-French-Carhart four-factor model:

$$\begin{aligned} R_t^{\mathrm{TSMOM}}(k_1,k_2) &= \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \varepsilon_t \\ R_t^{\mathrm{RAMOM}}(k_1,k_2,\lambda) &= \hat{\alpha} + \hat{\beta}_1 R_t^{MKT} + \hat{\beta}_2 R_t^{SMB} + \hat{\beta}_3 R_t^{HML} + \hat{\beta}_4 R_t^{UMD} + \hat{\varepsilon}_t\,. \end{aligned} \tag{3.7}$$

That is, we control for exposures to four major risk factors: the stock market return R_t^{MKT}, as well as the returns on the three Fama and French factors R_t^{SMB} (Small Minus Big, the size factor), R_t^{HML} (High Minus Low, the value factor), and the cross-sectional momentum factor, R_t^{UMD}. The MKT, HML, SMB, and UMD Fama and French factors are all obtained from the website of Professor Kenneth French.

Table 3 reports t-statistics for α and β coefficients for these regressions.[10]

[9] We always normalize the position size by the holding period k_2 because longer holding period strategies naturally have a higher leverage.

[10] In this paper, we compute the t-statistics using Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors with the number of lags based on the Newey and West (1994) plug-in procedure.

Consistent with OMP (2012), the abnormal performance of TSMOM (measured by the α from regression and the corresponding t-statistic) is large and significant for all combinations of look-back and holding periods. Furthermore, the behavior of α for both RAMOM and TSMOM strategies is similar.

While we do not report the values of the regression coefficients, the behavior of the corresponding t-statistics is quite similar to that of the coefficients in terms of both the sign[11] and the magnitude.[12] As can be seen, for most combinations of (k_1, k_2), both TSMOM and RAMOM have a significant positive exposure to all four factors, with the exposures of RAMOM almost always being of higher significance than those for TSMOM. This already indicates that RAMOM has a larger positive exposure to Fama and French factors, a conjecture that we test in the next section. Several interesting patterns emerge for very short-term (small k_1, k_2) and very long-term (large k_1, k_2) momentum. First, short-term momentum returns have a negative market beta and can therefore potentially be used as a hedge against market downturns. Second, very long-term (two years) momentum returns have a negative beta with respect to the SMB and HML factors. This negative relationship with the value factor is intuitive: Value is often defined as a bet against past very long-term returns (see, e.g., Asness, Moscowitz, and Pedersen, 2010). The relationship with the size factor is similar.

Tables 4-8 report the same t-statistics for each of the asset classes. Not surprisingly, Table 4 shows that, for equity index futures, there is little (or no) significance in abnormal performance for time series momentum; most of it is captured by the four factors. The only exception is the very short-term momentum for which the market beta is significantly negative. For the other four asset classes, alpha is highly significant for all possible combinations of look-back and holding periods. The behavior of exposures of the time series momentum on commodities is very similar to that of the equity class; except for the very short-term momentum market betas and very long-term momentum HML betas, both TSMOM and RAMOM on commodities have a significant positive exposure to all four risk factors, typically with RAMOM exposures being higher.

The behavior of bond and interest rate futures' exposures differs drastically from that of equity and commodity asset classes. First, momentum for bond and interest rate futures has a large, negative, and highly significant beta with respect to the market. This is not surprising given that bond returns are negatively correlated with the market and that bond momentum has mostly been long in the past few decades. Second, longer term momentum for bond and interest rate futures has a large and significant negative exposure to the size (SMB) factor; at the same time, no significant exposure to the value (HML) factor is apparent. Finally, bond and interest rate momentum is strongly positively related to the cross-sectional momentum (UMD) factor. In general, the behavior of RAMOM and TSMOM returns for the first four

[11]The signs of a t-statistic and the corresponding coefficient always coincide.

[12]If we properly normalize returns by some measure of realized volatility.

asset classes is very similar, with the key difference being that RAMOM typically has a higher exposure to most of the factors. The evidence for currency momentum returns is similar, with the only important difference arising for market exposure: While for TSMOM on currencies, market beta can take both signs and is typically insignificant, RAMOM on currencies has a significant positive exposure to the market. Exposures to the other three risk factors are large and positive for both TSMOM and RAMOM.

4 RAMOM versus TSMOM

4.1 Abnormal Performance and Fama-French Factors

We now turn to comparing the performance of RAMOM and TSMOM strategies. Table 9 reports the Sharpe ratios for the entire 30-year sample period as well as the two sub-periods. As shown, RAMOM systematically outperforms TSMOM for almost all combinations of look-back and holding periods. The value of using RAMOM is often quite high; the Sharpe ratio of RAMOM is about 10%-15% higher on average than the corresponding Sharpe ratio of the TSMOM strategy. The effect is particularly strong for very long-term momentum.

Figure 1 illustrates the differences in performance between RAMOM and TSMOM for a one-year look-back period and both short (one-month) and long (one-year) holding periods. For the long holding period momentum, the outperformance of RAMOM returns is very large over the entire sample time period. Both for the one-month holding period momentum (which is precisely the strategy studied in OMP, 2012) and the one-year holding period, TSMOM fails to produce positive returns over the past five years (2009-2014). In contrast, RAMOM still generates significantly positive returns. The dramatic drop in momentum returns in the post-crisis period might be associated with the "evaporating liquidity" phenomenon, as documented by Nagel (2012): In times of low funding liquidity, agents trading reversal strategies effectively provide liquidity to other market participants and earn a high rate of return as compensation for this liquidity provision. Ideally, one finds a way to connect such liquidity regimes to time momentum performance. Simple tests suggest that standard liquidity measures such as the VIX cannot be used for timing momentum returns. However, momentum returns themselves contain important information about the risk and risk-taking capacity of speculators. As we show in Section 5, measures of momentum-specific risk (realized volatility of momentum returns) can be efficiently used to reduce momentum losses.

To test for the significance of RAMOM's abnormal performance in relation to TSMOM, we run the regressions

$$R_t^{\text{RAMOM}}(k_1, k_2, \lambda) \;=\; \alpha + \beta R_t^{\text{TSMOM}}(k_1, k_2) + \varepsilon_t \tag{4.1}$$

for each combination of (k_1, k_2) and $\lambda = 0.5,\ 0.87$. Table 10 reports t-statistics for the α coefficient for all combinations (k_1, k_2). As can be seen, RAMOM significantly outperforms TSMOM for almost all combinations of look-back and holding periods. The values corresponding to $\lambda = 0.5$ and $\lambda = 0.87$ are comparable, but the outperformance is largely concentrated in the first half of the sample period; the outperformance in the second half of the period is insignificant.

We now discuss the contribution of different asset classes to RAMOM performance. Tables 11-15 report t-statistics for α from regressions (4.1) run for equally weighted returns per asset class for each of the five asset classes (equities, commodities, bonds, interest rates, and currencies). As we can see from Table 11, the outperformance of RAMOM versus TSMOM within the equity index futures is not highly significant, but is quite uniform across different look-back and holding periods. In contrast, Table 12 shows that RAMOM significantly outperforms TSMOM within the commodity asset class. Interestingly enough, there is a large drop in the outperformance in the second half of the sample. The results for bond, interest rate, and currency momentum (Tables 13 and 14) are similar to those for equity index futures: Outperformance is present for most combinations of (k_1, k_2), but is not uniform. The only exception is the very long-term (two-year look-back period) currency momentum, for which RAMOM significantly underperforms relative to TSMOM. We conclude that, while the outperformance of RAMOM with respect to TSMOM is not very large for any given class, the results are quite uniform across classes and generate a significant alpha when all 64 momentum returns are pooled together.

Everywhere in the sequel, unless stated otherwise, we use EWMA(0.5) to construct the RAMOM trading signals.[13]

To understand the sources of differences in performance between RAMOM and TSMOM, we run the following regression:

$$\begin{aligned} & R_t^{\mathrm{RAMOM}}(k_1, k_2) \\ = \ & \hat{\alpha} + \hat{\beta}_1 R_t^{MKT} + \hat{\beta}_2 R_t^{SMB} + \hat{\beta}_3 R_t^{HML} + \hat{\beta}_4 R_t^{UMD} + \hat{\beta}_5 R_t^{\mathrm{TSMOM}}(k_1, k_2) + \hat{\varepsilon}_t \end{aligned} \tag{4.2}$$

Adding $R_t^{\mathrm{TSMOM}}(k_1, k_2)$ to the set of regression variables allows us to identify whether the abnormal performance of RAMOM is due to additional exposure to basic risk factors. Table 18 reports t-statistics for this regression. As we can see, a large part of RAMOM alpha relative to TSMOM can be explained by a large and highly significant exposure to all four Fama and French factors. This is consistent with our finding in Table 3, which shows that RAMOM has a larger systemic exposure to those risk factors. The only (surprising) exception is the behavior of long holding periods' RAMOM relative to the cross-sectional momentum (UMD) factor. Specifically, the UMD betas of RAMOM with long holding periods are significant and negative after controlling for exposure to TSMOM. Tables 19-23 confirm these findings across asset classes: A large

[13] And we always use EWMA(0.94) to adjust the position size.

part of the abnormal performance vanishes if we control for exposure to Fama and French factors. More precisely, beta coefficients of the equity index and commodity momentum returns behave very similarly to those of the pooled returns; beta coefficients of bond and interest rate futures momentum returns are different. First, the market and HML betas for short-term look-back periods are either negative or insignificant, but they become positive and significant for longer term momentum returns; second, their SMB betas are significant and negative; third their UMD betas are positive for shorter term momentum and negative for longer term momentum.

The general conclusion is that RAMOM has a built-in significant exposure to systemic risk factors driving the equity market. While for equities increased systemic risk of RAMOM can be attributed to the leverage effect, it is not at all clear why this is the case for other asset classes. Intricate links seem to exist among Fama and French factors, futures volatility, and momentum returns within and across all asset classes. To test these relationships, we compute the 12-day realized standard deviation of futures returns $\sigma_{i,t-11,t}$ for every instrument i in our sample and regress it on the 12-day returns on the Fama-French factors,

$$\begin{aligned}&\sigma_{i,t-11,t}\\ &= \alpha_i^v + \beta_{1i}^v R_{t-11,t}^{MKT} + \beta_{2i}^v R_{t-11,t}^{SMB} + \beta_{3i}^v R_{t-11,t}^{HML} + \beta_{4i}^v R_{t-11,t}^{UMD} + \varepsilon_{it}^v\,.\end{aligned} \tag{4.3}$$

Figures 2 and 3 report the t-statistics for the β_{it}^v coefficients for this regression. While not all t-statistics are highly significant, all coefficients having the same negative sign is remarkable. To test this negative relationship further, we run a pooled regression of realized volatilities, normalized by their in-sample mean on the four Fama-French factors. This gives[14]

$$\begin{aligned}&\sigma_{t-11,t}\\ &= 1.02 \underset{(-14)}{-0.23}\, R_{t-11,t}^{MKT} \underset{(-8)}{-0.14}\, R_{t-11,t}^{SMB} \underset{(-17)}{-0.29}\, R_{t-11,t}^{HML} \underset{(-14)}{-0.17}\, R_{t-11,t}^{UMD} + \varepsilon_t^v\,.\end{aligned} \tag{4.4}$$

Completely consistent with Figures 2 and 3, we see that the negative relationship is highly significant and uniform for the MKT, HML, and UMD factors, with the t-statistic for the SMB factor about two times lower.

The economic intuition underlying this striking phenomenon is not trivial. Even the negative relationship with market returns is surprising: While for stocks this is simply the known leverage effect, there is no such relationship for other asset classes. In fact, for commodities, there is often a positive relationship between returns and volatility. The negative relationship between volatility and value and momentum factors is even more striking. It suggests some important links between the behavior of the Fama-French factors and macroeconomic uncertainty.

One might think that this phenomenon could also be partially driven by the trading activities of investors (e.g., in mutual funds) who hold exposure to

[14] Numbers in parentheses are the t-statistics computed with the Newey-West standard errors.

Fama-French factors and also participate in the futures market. However, in this case, we would expect a similar significant relationship between futures returns and the Fama-French factors. Indeed, if, for example, $r_{i,t} \approx \beta R_t^{MKT}$, simple heuristics suggests that volatility (returns squared) satisfies

$$\sigma_{i,t}^2 \approx \beta^2 (R_t^{MKT})^2, \tag{4.5}$$

and the required relationship would follow from the negative correlation between factor returns and factor volatility. To test this hypothesis, we run the same regression as in (4.3), but with 12-day futures returns on the left-hand side. Figures 4 and 5 report t-statistics for the corresponding beta coefficients. As shown, the relationship is often not significant, with both the sign and the magnitude of the t-statistics exhibiting large heterogeneity across instruments. Simply comparing the coefficients in (4.4) with those implied by the heuristics (4.5) suggests that we cannot capture even a small part of the relationship (4.4).

While we do not take a stand on the economic mechanism underlying (4.4), this relationship has major implications for the behavior of RAMOM returns. Specifically, by dividing the trading signal by volatilities, we effectively create an extra positive exposure to Fama-French risk factors, which gives rise to the abnormal performance of the strategy relative to TSMOM returns. While one could formally view this as an "explanation" of the RAMOM alpha relative to TSMOM, it is important to note that Fama-French factors are not tradable securities. Replicating them on a daily basis would be costly and inefficient and would require trading an enormous amount of stocks. In contrast, RAMOM strategies can easily be replicated using a relatively small number of highly liquid securities. Thus, RAMOM allows investors to gain significant exposure to Fama-French factors without actually trading the (very large) stock universe.

4.2 Turnover and Transaction Costs

In contrast to OMP (2012), who only consider strategies with a monthly trading frequency, in this paper all momentum strategies are implemented daily. Daily position adjustment has the clear advantage of giving an investor the ability to react quickly to new information and a changing market environment. However, at the same time, daily adjustment significantly increases turnover, which may be quite inefficient in the presence of transaction costs. To get an idea of these transaction costs, we compute a measure of turnover for a strategy using the following formula: If a strategy's returns are given by $I_{i,t-1} r_{i,t+1}$, then $I_{i,t}$ is the dollar exposure to security i, and therefore the absolute variation.

$$\text{Turnover}_i = \sum_t |I_{i,t} - I_{i,t-1}| \tag{4.6}$$

represents a measure of dollar turnover for security i. For a diversified strategy, we compute the total turnover by summing Turnover_i over all i. Following this procedure, we compute total turnover for both RAMOM and TSMOM strategies and report the quotient of these turnovers and the normalized turnover of RAMOM in Table 16. As shown, using RAMOM instead of TSMOM reduces turnover by about 50%. This is a very large effect with important implications for both the efficiency of the strategy and the cost to implement it. The intuition behind such a large reduction in turnover is clear: A large part of the variation in TSMOM trading signals is driven by fluctuations in returns volatility that have nothing to do with the directional signal and lead to excessive trading.

In the presence of transaction costs, the effect of such a large reduction in turnover on the strategy's performance may also be large. To test the magnitude of this effect, for each of the 64 instruments, we compute realized Sharpe ratios of RAMOM and TSMOM strategies assuming a proportional transaction cost of 5 basis points (0.0005) per dollar traded. These Sharpe ratios are reported in Table 17. The difference between RAMOM and TSMOM performance is very large. In fact, for short- and mid-term momentum strategies, TSMOM delivers Sharpe ratios close to zero, while RAMOM performance is still reasonable. In the second half of the sample (January 1999-January 2013), all TSMOM Sharpe ratios are negative after transaction costs, while most of the RAMOM Sharpe ratios are still positive. We conclude that, even ignoring the alpha of RAMOM in relation to TSMOM, the reduced transaction costs for RAMOM strategies are highly attractive for investors.

5 Momentum-Specific Risk

Barroso and Santa-Clara (2012) show a surprising and important property of the cross-sectional momentum strategy: Momentum-specific risk (measured as the realized volatility of momentum returns) is highly predictable and also forecasts momentum returns. Specifically, high momentum volatility indicates both high expected future volatility and low expected returns. As a consequence, normalizing momentum position by momentum volatility significantly improves the performance of the cross-sectional momentum strategy. In this section, we test and further develop Barroso and Santa-Clara's (2012) idea on our RAMOM strategy.[15]

In contrast to the Barroso and Santa-Clara (2012) cross-sectional momentum strategy, our TSMOM and RAMOM strategies involve five different asset classes. One might expect momentum volatilities to behave differently across asset classes and aggregating them into a single volatility index to be sub-optimal. For this reason, we will consider two different ways of defining momentum-specific risk: The first uses the realized (EWMA) volatility measure of pooled momentum returns across all 64 instruments; the second uses

[15]Daniel and Moscowitz (2013) show that predictability of momentum returns by momentum volatility and other factors can be further exploited to construct an optimal strategy exploiting this predictability.

the realized (EWMA) volatility of momentum returns for every asset class for managing momentum risk within a given class.

For every pair (k_1, k_2) of look-back and holding periods, we compute the EWMA(0.94) volatility for the pooled momentum returns $R_t^{\text{RAMOM}}(k_1, k_2)$, as well as the EWMA(0.94) volatility for $R_{t,c}^{\text{RAMOM}}(k_1, k_2)$ where class c may denote equities, commodities, bonds, interest rates, or currencies. We denote the corresponding realized volatilities by $\sigma_t^{\text{RAMOM}}(k_1, k_2)$ and $\sigma_{t,c}^{\text{RAMOM}}(k_1, k_2)$, respectively. Then, we consider two types of adjusted momentum returns: The first is simply

$$\hat{R}_t^{\text{RAMOM}}(k_1, k_2) \equiv R_t^{\text{RAMOM}}(k_1, k_2)/\sigma_{t-2}^{\text{RAMOM}}(k_1, k_2). \tag{5.1}$$

The second is

$$\widetilde{R}_t^{\text{RAMOM}}(k_1, k_2) \equiv \frac{1}{k_2 N_{t-1}} \sum_{i=1}^{64} r_{i,t}^{\text{RAMOM}}(k_1, k_2)/\sigma_{t-2,c(i)}^{\text{RAMOM}}(k_1, k_2), \tag{5.2}$$

where $c(i)$ is the class to which instrument i corresponds.[16]

Tables 24-29 show the quotients of the Sharpe ratios of the adjusted RAMOM returns and those of the simple RAMOM returns. Significant gains come from using both momentum-specific risk and class-specific momentum risk to size risk exposure. Quite surprisingly, using aggregate momentum risk significantly dominates the use of class-specific risk. As Table 24 shows, managing momentum risk with aggregate momentum volatility (i.e., with $\sigma_{t-2}^{\text{RAMOM}}$) increases the Sharpe ratio by about 20% over the 30-year sample period, while using class-specific volatilities $\sigma_{t,c}^{\text{RAMOM}}$ only increases Sharpe ratios by about 10%. The differences in performance are particularly strong for long-term momentum (in which case class-specific volatilities reduce Sharpe ratios) and in the second half of the sample period. This surprising finding might be related to the increasing financialization and integration of futures markets (see, e.g., Singleton (2012) and Tang and Xiong (2012)) and increasing arbitrage activity (see Dou and Polk, 2013), as well as increased correlations across asset classes.[17] To look deeper into these effects, we compare performance of these two risk management strategies for each of the five asset classes. As Table 25 shows, class-specific volatility clearly dominates aggregate volatility for equities if we look over the whole 30-year period. However, in the second half of the period, class-specific volatility does not work at all, whereas aggregate volatility works efficiently and uniformly across different look-back and

[16] Note that we always lag volatility by two days. Lagging is important because of the differences in time zones; otherwise, we may be using information from one day ahead that is unavailable when the trading position is chosen.

[17] To look further into joint dynamics of momentum-specific risk across asset classes, we also compute the correlations between σ_t^{RAMOM} and $\sigma_{t,c}^{\text{RAMOM}}$ over the different sub-periods. We find that joint behavior of momentum volatilities across classes is highly non-trivial. Not surprisingly, the aggregate volatility measure σ_t^{RAMOM} is positively correlated with all class-specific volatility measures. However, the cross-correlations between different class-specific momentum volatilities are often close to zero and may even change signs over time. Understanding their joint dynamics is an interesting endeavor for future research.

holding periods. For the other asset classes (commodities, bonds, and interest rates, Tables 26-29), the effects of class-specific and aggregate volatilities are similar; both lead to a similar improvement in performance for both parts of the sample period.

Figure 6 compares the cumulative performance of "plain" RAMOM returns with that of RAMOM returns adjusted by aggregate or class-specific volatilities. As shown, aggregate volatility adjustment clearly dominates the adjustment by class-specific volatilities, and the effect is not concentrated in any particular sub-period.

So, why does using momentum-specific risk have such a strong effect on momentum performance? Barroso and Santa-Clara (2012) show that the strong effect of adjusting position size by momentum-specific risk can be largely attributed to the predictability of both risk and return of cross-sectional momentum by the momentum volatility: High volatility predicts both low returns and high future volatility. For RAMOM, these effects are only partially present. As Table 30 shows, heterogeneity in behavior exists across classes. First, for equity index futures, class-specific volatility is *positively* related to future momentum returns. This is surprising given the opposite relationship for cross-sectional momentum. In contrast, aggregate momentum volatility is indeed negatively related to future momentum returns, which explains why it works for the position size adjustment but leaves open the question of why class-specific volatility also works. In none of the other four asset classes can we see any significant relationship between past momentum volatility (both aggregate and class-specific) and future momentum returns. In contrast, Table 31 shows that momentum volatility is highly persistent and (not surprisingly) can be better predicted by its own lags than by aggregate momentum volatility. Given these findings, it remains a puzzle why aggregate momentum volatility works as well as (and is often even superior to) class-specific volatility for all five asset classes.

Clearly, adjusting momentum positions by their own volatility introduces even more non-linearity into momentum returns and may lead to more pronounced non-Gaussian behavior of returns. To investigate these effects, we compute the realized *negative kurtosis* of momentum returns.[18] Table 32 shows the relationship between the negative kurtosis for TSMOM and RAMOM returns. As shown, the negative kurtosis is very large, indicating a highly non-Gaussian structure in momentum returns. Second, there seems to be a dichotomy in the kurtosis behavior for short-term and longer term momentum. Specifically, over the whole 30-year period, shorter term RAMOM returns have a slightly higher kurtosis than the corresponding TSMOM returns; however, this relationship reverses for longer term momentum. The effect is particularly strong in the first half of the sample period.

Table 33 compares the negative kurtosis of RAMOM returns before and after adjustment by the two volatilities (aggregate and class-specific). As

[18] That is, the kurtosis of negative returns.

shown, adjusting position size by the aggregate momentum volatility leads to a huge increase in the negative kurtosis. In contrast, adjusting position size by the class-specific volatility leads to a significant (about 30% on average) reduction in the negative kurtosis. Thus, while aggregate volatility risk management leads to a significant improvement in the risk-return profile, it comes with the cost of significantly increasing tail risk. A kurtosis-averse investor [19] may therefore prefer to use the class-specific momentum volatility instead of the aggregate momentum volatility. The increase in kurtosis from using aggregate momentum volatility might indicate additional systemic risk exposure that this position size normalization generates.

We now take a more thorough look at the nature and sources of alpha generated by RAMOM risk management versus plain RAMOM returns. To this end, we first regress the adjusted RAMOM returns on the four Fama and French factors plus plain RAMOM returns. Tables 34 and 35 report the t-statistics for this regression for the case of RAMOM adjusted by $\sigma_{t-2}^{\mathrm{RAMOM}}$ and $\sigma_{c,t-2}^{\mathrm{RAMOM}}$, respectively. As can be seen, in both cases, the alpha generated by the risk management is highly significant. Furthermore, quite surprisingly, both adjustment procedures lead to a *negative* exposure to the UMD factor. Since RAMOM returns themselves have a high positive exposure to UMD, this means that, effectively, momentum risk management significantly reduces RAMOM exposure to UMD. This has clear implications for investors who already have positive exposure to the UMD factor: Risk management not only improves the risk-return profile, but also significantly increases diversification benefits. The behavior of momentum exposures to market returns (MKT factor) are even more intriguing: As seen in Table 34, RAMOM adjusted by the aggregate volatility has a significant positive exposure to the market even though a large part of this exposure already exists through the RAMOM returns themselves. In contrast, Table 35 shows that longer term momentum returns, adjusted by class-specific volatilities, have negative exposure to MKT. Since plain RAMOM returns have a high positive exposure to MKT, this means that adjusting momentum returns by class-specific volatilities reduces market exposure and, as a result, significantly increases diversification benefits for investors that are long the market.

To understand the origins of these effects, we investigate the relationship between the aggregate momentum volatility and the four Fama and French factors. As seen in Table 36, aggregate momentum volatility has a significant and negative exposure to MKT, HML, and UMD factors. Thus, intuitively, dividing position size by this volatility should create a larger positive exposure to all three of these factors. While we do see some of these effects for the MKT factor (Table 34), none of it is present for HML and UMD factors. In fact, momentum risk management reduces exposure to HML and UMD factors. The effect for the UMD factor is the strongest, with a highly significant exposure reduction. This strong negative relationship between momentum volatility

[19] Which is the case for all standard preferences, including CARA and CRRA.

and MKT, HML, and UMD factors is closely linked to the analogous relationship for the realized futures volatility (Figures 2 and 3). However, in contrast to signal adjusting, position size adjusting has an opposite effect on the relationship between returns and risk factors. The reason is that RAMOM returns gain additional factor exposure though volatility effects on the *direction (sign) of the position*, whereas adjusted RAMOM returns' exposure to factors is reduced through the effect of volatility on the *size of the position*.

6 Conclusion

We introduce a new class of momentum strategies that we call the risk-adjusted time series momentum. The trading signals for these strategies are based on averages of past realized returns, normalized by their volatility. We show that RAMOM strategies outperform standard TSMOM strategies for all combinations of look-back and holding periods and all asset classes. We find that this outperformance is to a large extent driven by RAMOM having higher exposure to the Fama and French equity risk factors (market, size, value, and momentum). This built-in exposure to Fama and French factors is closely related to a new and surprising stylized fact that we document: For almost all of the 64 futures contracts that we analyze, the realized futures volatility is negatively related to market, value, and momentum factor returns. Another important advantage of our RAMOM trading signals is that they oscillate much less versus their TSMOM counterparts and, as result, dollar turnover of RAMOM strategies is about 40% lower than that of TSMOM, implying a large reduction in trading costs.

Similar to the volatility of futures returns, we find that momentum-specific risk (i.e., volatility of momentum returns) is also significantly and negatively related to the Fama and French factors. However, quite surprisingly, normalizing momentum returns by their own volatility reduces exposure of momentum returns to the Fama and French factors and, at the same time, significantly improves the momentum of the Sharpe ratio. We show, however, that this momentum risk management may come at a cost of increased tail risk that depends on whether aggregated (across all instruments) or asset class-specific volatility is used for risk management.

Summarizing, the new relationships between momentum returns and their momentum discovered in our paper can be used to significantly improve the performance of momentum strategies. Developing new asset pricing models that explain these findings is an important challenge for future research.

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A Data

Our dataset comprises 64 instruments, 61 thereof are obtained by CSI, a commercial market data provider. The prices for aluminium, nickel, and zinc, which trade at the London Metal Exchange (LME), are sourced via Bloomberg.

For the CSI data, historical time series are constructed by concatenating daily excess returns of the nearest futures contracts, excepting interest rates futures for which we choose the fifth expiry month to avoid almost stale prices.

The roll-trigger is a simultaneous shift in the size of both open interest and volume; the roll-timing reflects a market spread order at close. For the LME contracts, we directly retrieve 3 months constant maturity time series due to the distinct market structure. Table 2 presents the instrument universe. Summarized, we include 13 bond, 25 commodity, 6 currency, 15 equity, and 5 interest rate contracts. The choice contains the most liquid futures contracts and is similar to the dataset used by Ooi, Moskowitz, and Pedersen (2012). We use the JP Morgan Government Bond Index prior to the availability of bond futures.

	Bond futures	Commodity futures	Currency futures	Equity Index futures	Interest Rate futures
CBT	2/5/10/30-year US	Corn, Oats, Soybeans, Soybean Meal, Wheat			
CME		Lean Hogs, Live Cattle	AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD, JPY/USD	Dow Jones, Nasdaq, Nikkei, S&P 500	Eurodollar
COMEX		Copper, Gold, Silver			
CSCE		Cocoa, Coffee, Sugar			
EOE				AEX	
EUREX	2/5/10/30-year EURO			DAX, SMI, Euro Stoxx 50	
EURONEXT	10-year UK			CAC 40, FTSE 100	Euribor, Euroswiss, Shortsterling
ICE		Brent			
LME		Aluminium, Nickel, Zinc			
MSE	10-year CAN				
MEFF				IBEX 35	
MIF				MIB FTSE	
NYCE		Cotton, Orange Juice			
NYMEX		Crude, Gasoline, Heating, Natgas, Palladium, Platinum			
OMX				OMXS 30	
SFE	3/10-year AUS			SPI 200	
TFX					Euroyen
TSE	10-year JPY			Topix	

Table 1: Instruments organised by asset class and exchange

Instruments	Data Availability	Backfilled Range	Annualized Volatility
AEX	Oct-92	-	23%
CAC 40	Aug-88	-	22%
DAX	Nov-90	-	23%
Dow Jones	Oct-97	-	20%
Euro Stoxx 50	Jun-98	-	26%
FTSE 100	May-84	-	19%
IBEX 35	Apr-92	-	24%
MIB FTSE	Nov-94	-	24%
Nasdaq	Jun-99	-	30%
Nikkei	Sep-90	-	25%
OMXS 30	Oct-92	-	25%
S&P 500	Apr-82	-	20%
SMI	Nov-90	-	19%
SPI 200	Feb-83	-	20%
TOPIX	Apr-90	-	23%
Aluminium	Jun-87	-	21%
Brent	Jun-88	-	33%
Cocoa	Dec-65	-	29%
Coffee	Aug-72	-	33%
Copper	Jan-66	-	27%
Corn	Jan-47	-	20%
Cotton	Mar-67	-	23%
Crude Oil	Mar-83	-	34%
Gasoline	Dec-84	-	34%
Gold	Jan-75	-	19%
Heating Oil	Nov-78	-	32%
Lean Hogs	Feb-66	-	23%
Live Cattle	Nov-64	-	16%
Natgas	Apr-90	-	48%
Nickel	Jan-87	-	36%
Oats	Jan-47	-	25%
Orange Juice	Oct-66	-	28%
Palladium	Jan-77	-	32%
Platinum	Jan-64	-	26%
Silver	Jun-63	-	29%
Soybean Meal	Aug-51	-	25%
Soybeans	Jul-47	-	21%
Sugar	Dec-65	-	38%
Wheat	Jan-47	-	22%
Zinc	Jan-89	-	26%
Australian 10yr	Dec-87	Dec-87 - Nov-89	2%
Australian 3yr	Dec-87	Dec-87 - Feb-90	2%
Canada 10yr	Dec-87	Dec-87 - Sep-89	6%
Euro Buxl	Dec-87	Dec-87 - Oct-98	9%
Euro Bobl	Dec-87	Dec-87 - Nov-90	3%
Euro Bund	Dec-87	Dec-87 - Oct-91	5%
Euro Schatz	Dec-87	Dec-87 - Mar-97	1%
Gilt Long	Nov-82	-	8%
Japan 10yr	Dec-87	Dec-87 - Apr-90	4%
T-Bond US	Aug-77	-	11%
T-Note US 10yr	May-82	-	7%
T-Note US 2yr	Dec-87	Dec-87 - Jun-90	2%
T-Note US 5yr	Dec-87	Dec-87 - May-88	4%
Euribor 3 Month	Apr-89	-	1%
Euro Swiss Franc	Feb-91	-	1%
Eurodollar 3 Month	Feb-82	-	1%
Euroyen 3 Month	Jul-89	-	1%
Sterling Rate 3 Month	Jan-83	-	1%
AUD/USD	Jan-87	-	12%
CAD/USD	May-72	-	6%
CHF/USD	May-72	-	12%
EUR/USD	May-72	-	10%
GBP/USD	May-72	-	10%
JPY/USD	May-72	-	11%

Table 2: Overview of the data sample

B Tables

1984-2013	RAMOM(0.5)						TSMOM					
t-stat for α												
look-back \ holding (months)	1	3	6	9	12	24	1	3	6	9	12	24
1	5.9	6.9	6.3	7.6	7.3	6.0	6.3	6.2	5.6	6.9	6.8	5.6
3	6.5	5.6	5.6	6.6	5.6	4.5	6.7	5.2	5.0	6.3	5.5	4.8
6	5.5	5.6	6.0	5.8	4.7	3.7	5.5	5.3	5.9	5.8	4.9	3.8
9	6.6	6.8	6.0	5.3	4.5	3.5	6.8	6.9	5.9	5.2	4.6	3.5
12	6.2	5.6	4.9	4.5	4.0	3.2	6.2	5.2	4.5	4.2	3.6	2.9
24	4.3	4.1	3.8	3.6	3.3	3.0	4.6	4.1	3.5	3.5	3.2	2.9
t-stat for Market β												
1	-3.2	-1.3	2.4	4.6	5.7	9.1	-5.0	-2.6	1.0	3.2	4.1	6.6
3	0.3	2.8	7.6	8.3	8.9	11.1	-3.8	-0.5	2.8	4.0	4.0	6.0
6	4.0	6.2	7.4	7.3	8.2	10.3	-1.5	1.5	3.2	3.3	3.4	5.5
9	5.1	6.2	6.8	7.0	7.3	9.5	-0.6	1.5	2.1	2.1	2.3	4.5
12	6.0	6.7	7.7	7.8	7.9	10.9	-0.7	0.7	1.5	1.3	1.6	3.9
24	12.4	12.7	12.8	13.3	13.9	16.2	-0.5	0.3	0.9	1.1	1.4	3.2
t-stat for SMB β												
1	1.2	2.6	2.9	2.6	2.7	0.8	1.9	2.5	3.0	2.7	2.7	0.6
3	3.9	4.2	3.6	3.3	3.3	1.3	2.2	2.5	2.6	2.2	2.3	0.1
6	4.5	4.2	3.4	3.1	2.7	0.7	2.1	2.4	2.3	2.3	2.0	-0.2
9	3.6	3.2	3.0	2.6	1.9	-0.3	2.3	2.2	2.2	1.9	1.1	-1.5
12	3.4	3.2	2.6	1.8	1.2	-0.8	2.1	2.0	1.6	0.8	0.0	-2.6
24	1.1	0.7	0.4	-0.1	-0.5	-2.0	-1.6	-2.3	-2.8	-3.8	-4.8	-7.8
t-stat for HML β												
1	1.4	3.2	5.6	5.8	4.0	3.8	1.3	3.5	6.1	6.5	4.3	2.8
3	5.1	5.9	7.4	5.9	3.5	3.1	3.2	4.8	6.2	5.3	2.7	1.1
6	6.7	6.8	5.4	3.2	2.2	2.3	4.5	6.0	4.9	2.7	0.9	0.5
9	6.0	5.1	2.9	1.5	0.6	1.5	4.8	4.0	1.8	0.0	-1.5	-1.3
12	4.1	2.7	1.4	0.3	-0.3	1.6	2.2	1.0	-0.8	-2.5	-3.3	-2.5
24	4.3	4.1	3.7	3.6	4.0	6.5	-4.0	-4.3	-4.4	-4.5	-4.3	-2.7
t-stat for UMD β												
1	1.8	7.4	13.6	16.4	15.6	9.1	1.0	7.9	14.3	18.1	17.4	10.4
3	9.9	14.0	17.0	17.8	16.4	8.5	7.1	12.5	17.0	18.8	17.8	9.9
6	16.0	17.9	17.8	16.4	13.9	7.1	13.7	18.0	18.7	17.6	15.6	8.2
9	18.3	18.1	16.1	13.4	10.5	5.1	18.3	19.1	17.6	15.2	12.3	5.8
12	18.5	16.7	13.3	10.2	7.6	3.5	18.1	17.3	14.8	11.6	8.5	3.3
24	9.0	8.2	6.2	4.4	3.2	3.1	9.0	8.1	6.3	4.4	2.7	1.0

Table 3: t-statistics of the alpha and beta coefficients of the realized daily RAMOM and TSMOM returns, pooled across all 64 instruments. Reported are the t-statistics of the alpha and beta coefficients from the time series regressions of the realized daily RAMOM and TSMOM returns, pooled across all 64 instruments on daily returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

1984-2013

	RAMOM(0.5)						TSMOM					
t-stat for α												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	2.2	1.9	1.4	1.6	1.5	1.0	1.7	1.3	1.3	1.3	1.2	1.4
3	1.1	1.2	0.6	0.7	0.5	0.7	2.8	1.3	0.5	0.8	1.1	1.2
6	1.2	1.3	1.3	1.2	0.7	0.6	2.0	1.2	1.2	1.2	1.1	0.7
9	1.8	1.8	1.3	1.0	0.8	0.7	1.8	1.5	1.2	1.0	0.7	0.6
12	1.2	1.0	0.7	0.5	0.6	0.6	1.4	0.8	0.6	0.6	0.3	0.4
24	0.8	0.7	0.6	0.8	0.8	0.9	1.2	1.2	1.0	1.3	1.2	1.0
t-stat for Market β												
1	-1.1	2.5	6.2	7.9	8.7	9.8	-2.6	1.4	5.6	5.3	6.3	10.6
3	4.6	6.8	8.9	8.3	8.2	11.0	-0.6	3.3	4.9	4.8	6.2	7.7
6	6.7	7.7	7.9	7.8	8.3	9.4	2.4	4.5	4.8	4.6	5.3	5.6
9	7.6	8.0	8.5	8.8	9.2	9.6	3.7	4.6	4.7	4.6	4.7	5.1
12	8.4	8.7	9.6	10.0	10.2	10.8	3.8	4.3	4.4	4.2	4.4	4.9
24	15.5	16.0	16.0	16.0	16.0	18.5	3.4	3.7	4.1	4.2	4.4	5.6
t-stat for SMB β												
1	0.8	2.8	3.4	3.7	4.4	2.5	0.6	2.8	3.9	3.4	3.1	2.2
3	4.3	5.1	4.7	4.2	3.8	2.4	1.9	3.4	3.6	3.2	3.0	1.4
6	4.8	4.8	4.4	3.9	3.3	1.8	2.5	3.7	4.0	3.7	3.1	1.2
9	5.0	4.9	4.3	3.7	3.1	1.6	4.0	4.2	3.9	3.4	2.5	0.7
12	5.1	4.7	3.9	3.3	2.8	1.6	3.5	3.7	3.1	2.4	1.7	0.0
24	3.1	3.0	2.8	2.5	2.2	1.5	-0.7	-0.8	-1.0	-1.5	-2.0	-2.5
t-stat for HML β												
1	0.8	2.6	4.2	4.2	2.9	1.6	0.5	2.9	4.9	4.2	2.6	-0.2
3	3.6	4.4	4.7	3.4	1.6	0.1	2.2	4.3	4.9	3.8	1.2	-1.8
6	4.4	4.1	2.7	1.1	0.0	-1.3	3.2	4.4	3.2	1.2	-0.7	-2.5
9	3.4	2.7	1.2	0.1	-1.0	-1.8	3.8	3.0	0.9	-0.8	-2.6	-3.6
12	2.2	1.1	0.0	-0.9	-1.8	-1.8	1.6	0.4	-1.7	-3.6	-4.6	-4.7
24	1.3	1.1	0.3	-0.1	-0.2	0.8	-6.2	-6.4	-6.6	-6.6	-6.7	-6.7
t-stat for UMD β												
1	1.1	6.9	11.0	14.2	12.8	6.7	0.5	8.0	13.7	12.5	12.7	9.3
3	10.1	14.5	13.9	12.4	10.5	6.7	4.9	14.3	13.7	12.2	14.3	8.7
6	13.4	14.5	14.0	12.3	10.6	5.4	12.4	15.9	14.6	12.7	12.3	5.7
9	14.8	14.5	13.0	11.0	9.2	4.1	13.7	14.4	13.0	11.2	9.2	3.8
12	14.0	12.8	10.8	9.0	7.2	3.0	13.2	12.7	11.2	9.0	7.1	2.4
24	6.7	6.1	4.6	3.1	2.2	0.8	7.0	6.1	4.7	3.4	2.2	-0.6

Table 4: t-statistics of the alpha and beta coefficients of the realized daily RAMOM and TSMOM returns, pooled across all 15 equity index futures. Reported are the t-statistics of the alpha and beta coefficients from the time series regressions of the realized daily RAMOM and TSMOM returns, pooled across 15 equity index futures on daily returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

1984-2013

		RAMOM(0.5)						TSMOM					
		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
t-stat for α													
look-back	1	2.0	4.5	4.6	4.6	4.6	1.7	2.4	2.9	3.0	3.0	3.1	0.8
	3	3.3	3.5	3.5	4.0	2.9	0.4	4.0	3.4	3.3	3.8	2.8	0.6
	6	2.8	3.3	3.5	3.2	2.2	0.2	3.2	3.1	3.4	3.1	2.3	0.3
	9	3.5	4.0	3.3	2.6	1.8	-0.1	3.8	3.9	2.9	2.1	1.6	-0.1
	12	3.6	3.1	2.4	2.0	1.3	-0.3	3.1	2.2	1.5	1.3	0.7	-0.8
	24	1.1	0.6	0.0	-0.5	-0.8	-0.6	1.1	0.4	-0.2	-0.6	-0.9	-0.8
t-stat for Market β													
look-back	1	-0.4	-0.2	1.3	3.1	3.6	5.1	-1.4	-0.9	0.7	2.8	3.3	5.0
	3	0.9	2.0	4.5	6.1	6.4	6.6	-1.2	0.2	2.3	4.3	4.5	5.7
	6	2.6	4.0	5.6	5.8	5.9	6.6	-0.7	1.3	3.3	3.5	3.5	4.9
	9	4.0	4.9	4.9	4.8	4.7	5.5	0.8	2.2	2.6	2.7	2.5	3.8
	12	4.3	4.5	4.6	4.4	4.5	5.4	0.7	1.4	1.9	1.8	1.8	2.9
	24	5.7	6.2	6.2	6.4	6.6	6.4	-1.2	-0.6	-0.2	-0.2	-0.4	0.0
t-stat for SMB β													
look-back	1	1.6	3.0	3.4	3.0	2.6	2.2	2.7	3.4	2.8	2.9	2.8	2.3
	3	3.5	4.3	3.8	3.2	3.1	2.9	3.1	2.3	2.6	2.2	2.4	2.0
	6	3.0	3.3	2.7	2.3	2.5	2.5	2.1	2.1	1.7	1.6	1.7	1.6
	9	3.1	2.5	2.3	2.4	2.3	2.2	2.4	1.5	1.5	1.5	1.3	1.0
	12	2.4	2.4	2.5	2.4	2.3	2.1	2.1	1.8	1.5	1.1	1.1	0.3
	24	2.7	2.3	2.0	1.9	1.8	1.5	0.6	0.1	-0.3	-0.9	-1.5	-2.6
t-stat for HML β													
look-back	1	2.5	3.4	3.3	3.8	3.1	3.9	2.4	3.7	3.8	4.4	3.9	4.1
	3	4.7	4.5	5.0	5.1	4.9	5.5	3.1	3.5	4.2	4.3	4.1	4.9
	6	5.0	5.0	5.1	4.5	4.6	5.5	3.4	4.0	3.8	3.5	3.4	4.4
	9	5.3	4.9	4.0	3.6	3.3	4.4	4.3	3.3	2.6	2.1	1.4	2.4
	12	4.2	3.6	3.2	2.7	2.6	4.0	2.5	2.0	1.3	0.4	0.0	0.8
	24	4.6	4.7	4.7	4.5	4.7	5.6	-1.5	-1.9	-2.1	-2.5	-2.5	-0.5
t-stat for UMD β													
look-back	1	1.7	5.3	8.1	9.7	9.4	5.8	0.9	5.2	8.4	10.2	10.1	6.9
	3	5.7	7.4	9.9	10.2	9.4	5.9	4.0	6.7	9.9	10.4	9.8	6.8
	6	8.9	9.9	10.3	9.4	8.0	5.6	8.2	10.3	10.6	10.1	9.0	6.3
	9	10.2	10.4	9.5	8.0	6.0	4.1	10.6	11.2	10.6	9.0	6.9	4.8
	12	10.7	9.9	8.0	5.8	4.2	3.2	11.0	10.5	8.9	6.5	4.2	3.1
	24	6.0	5.9	4.8	3.8	3.0	3.6	6.0	5.7	3.9	2.3	1.0	1.6

Table 5: t-statistics of the alpha and beta coefficients of the realized daily RAMOM and TSMOM returns, pooled across all 25 commodity futures. Reported are the t-statistics of the alpha and beta coefficients from the time series regressions of the realized daily RAMOM and TSMOM returns, pooled across 25 commodity futures on daily returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

1984-2013

	RAMOM(0.5)						TSMOM					
t-stat for α												
look-back	holding (months)						holding (months)					
	1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
1	5.5	5.5	4.8	5.7	5.5	5.9	5.4	5.4	4.4	5.5	5.4	5.6
3	5.3	4.3	4.3	5.1	4.4	4.9	4.5	3.8	3.9	5.0	4.2	4.9
6	4.1	3.9	4.3	4.4	4.0	4.5	3.5	3.4	4.0	4.3	3.9	4.3
9	4.1	4.3	4.3	4.2	4.1	4.3	4.7	4.8	4.5	4.4	4.3	4.4
12	4.1	3.9	3.9	4.0	4.0	4.4	4.6	4.2	4.1	4.1	4.0	4.4
24	4.2	4.2	4.5	4.7	4.6	4.8	4.3	4.1	4.4	4.6	4.6	4.7
t-stat for Market β												
look-back												
1	-6.8	-6.0	-5.2	-4.5	-4.2	-2.6	-7.1	-6.4	-4.8	-4.2	-4.1	-2.6
3	-6.6	-5.1	-3.9	-3.4	-3.3	-1.8	-6.6	-4.7	-3.7	-3.5	-3.3	-1.7
6	-5.0	-4.0	-3.1	-3.0	-2.5	-1.3	-5.2	-3.9	-3.2	-3.1	-2.8	-1.3
9	-5.2	-4.2	-3.6	-3.3	-2.7	-2.0	-6.4	-5.5	-4.8	-4.5	-3.9	-2.3
12	-4.9	-4.2	-3.1	-2.6	-2.1	-1.3	-6.6	-5.5	-4.5	-3.9	-3.3	-1.9
24	-1.2	-1.0	-0.8	-0.7	-0.4	-0.1	-2.3	-1.6	-1.3	-1.1	-0.8	0.1
t-stat for SMB β												
look-back												
1	-0.3	-0.1	-0.4	-2.1	-1.9	-6.6	-0.5	-0.2	-1.2	-3.2	-3.7	-7.1
3	-0.5	-0.6	-1.2	-3.9	-4.9	-8.3	-0.4	-1.1	-1.4	-4.2	-4.6	-8.2
6	-1.1	-1.6	-3.2	-5.3	-5.9	-7.9	-1.1	-1.2	-2.0	-3.7	-4.6	-8.5
9	-3.8	-4.0	-6.0	-6.5	-7.1	-7.6	-3.7	-3.6	-3.8	-4.9	-6.0	-9.1
12	-1.9	-5.1	-7.0	-7.2	-7.5	-7.6	-1.6	-2.7	-3.4	-6.4	-7.2	-9.3
24	-8.0	-8.1	-8.4	-8.5	-8.9	-9.8	-9.6	-9.4	-9.3	-9.3	-9.6	-9.9
t-stat for HML β												
look-back												
1	-0.9	-0.7	0.9	1.0	0.1	0.0	-0.7	-0.2	1.7	1.8	1.0	0.1
3	-0.3	0.7	1.3	0.8	-0.4	-0.5	-0.5	0.6	1.5	1.0	-0.3	-0.9
6	1.1	1.5	1.0	0.0	-0.6	-0.1	1.1	1.7	1.3	0.4	-0.6	-0.5
9	0.9	0.7	0.0	-0.9	-1.2	-0.3	0.5	1.1	0.4	-0.9	-1.7	-1.2
12	-0.1	-0.2	-1.0	-1.6	-1.8	-0.4	-0.1	-0.2	-1.3	-2.3	-2.9	-1.7
24	-1.1	-1.1	-1.1	-0.8	-0.4	1.2	-2.5	-2.4	-2.4	-2.4	-2.1	-0.6
t-stat for UMD β												
look-back												
1	0.4	2.7	5.4	7.1	7.1	5.7	-0.2	2.8	6.2	7.9	8.3	6.2
3	4.1	5.9	7.6	8.5	8.3	5.2	2.9	5.3	7.3	8.5	8.3	5.6
6	7.6	8.1	8.6	8.3	7.2	4.7	6.4	7.9	8.5	8.7	7.7	5.5
9	9.1	9.2	9.0	7.7	6.4	3.9	8.1	9.4	9.5	8.2	7.0	4.5
12	8.4	9.0	7.9	6.4	5.1	3.3	8.3	8.8	8.0	6.8	5.6	3.4
24	6.1	5.8	5.0	4.3	4.0	4.6	5.4	5.6	5.2	4.4	4.0	4.4

Table 6: t-statistics of the alpha and beta coefficients of the realized daily RAMOM and TSMOM returns, pooled across all 13 bond futures. Reported are the t-statistics of the alpha and beta coefficients from the time series regressions of the realized daily RAMOM and TSMOM returns, pooled across 13 bond futures on daily returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

1984-2013

		RAMOM(0.5)						TSMOM					
		t-stat for α											
		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
look-back	1	5.7	5.0	3.8	4.4	4.0	4.0	7.0	5.0	3.5	4.8	4.6	4.2
	3	5.8	4.3	3.8	4.7	3.9	3.4	5.2	3.9	3.1	4.1	3.5	3.1
	6	3.7	3.5	3.6	3.6	2.9	2.4	3.9	3.1	3.3	3.4	2.7	2.4
	9	4.1	4.3	3.8	3.5	2.7	2.2	3.7	4.4	3.7	3.5	2.9	2.4
	12	4.4	3.5	3.2	2.9	2.4	2.1	3.9	3.3	3.0	3.0	2.7	2.6
	24	3.3	3.0	2.7	2.5	2.3	1.8	4.4	4.0	3.6	3.5	3.2	2.5
		t-stat for Market β											
look-back	1	-4.9	-5.5	-4.1	-3.6	-3.3	-2.4	-6.6	-6.1	-4.8	-4.8	-4.6	-3.0
	3	-6.0	-4.1	-3.1	-3.3	-3.2	-2.1	-6.5	-4.5	-3.5	-3.8	-3.6	-2.3
	6	-4.2	-3.3	-2.5	-2.7	-2.2	-1.3	-4.7	-3.2	-2.6	-2.8	-2.6	-1.8
	9	-3.6	-3.0	-2.4	-2.1	-1.5	-0.6	-4.8	-3.8	-3.2	-3.2	-2.7	-1.5
	12	-3.3	-2.7	-1.9	-1.5	-1.2	-0.5	-4.8	-3.5	-2.6	-2.6	-2.1	-1.1
	24	-0.4	-0.2	0.0	0.3	0.5	1.1	-2.2	-1.5	-1.1	-0.7	-0.3	0.5
		t-stat for SMB β											
look-back	1	0.1	0.3	0.0	-0.9	-1.2	-5.1	-0.7	0.2	-0.1	-2.1	-2.5	-6.9
	3	0.2	-0.4	-1.1	-4.1	-4.5	-5.3	0.3	-0.3	-0.7	-2.6	-3.6	-5.8
	6	0.4	-0.7	-2.2	-3.8	-4.3	-5.0	-0.2	-1.1	-1.6	-3.3	-4.1	-5.8
	9	-1.7	-3.8	-3.8	-3.6	-3.8	-4.6	-2.1	-2.4	-3.6	-4.6	-4.7	-5.7
	12	-2.0	-3.5	-3.6	-3.7	-4.0	-4.8	-0.4	-1.4	-3.7	-5.3	-5.7	-6.3
	24	-5.2	-5.6	-5.8	-6.1	-6.2	-6.3	-4.9	-5.3	-5.7	-5.9	-6.0	-6.5
		t-stat for HML β											
look-back	1	0.2	0.3	1.4	1.2	0.1	0.5	0.0	0.4	2.0	1.3	0.0	0.5
	3	1.0	1.9	1.9	0.7	-0.6	0.2	0.4	1.3	1.4	0.1	-1.1	-0.5
	6	1.8	2.1	1.4	0.2	-0.3	1.0	1.3	1.8	0.9	-0.3	-0.9	0.5
	9	1.6	1.3	0.0	-0.5	-0.6	1.1	0.6	0.5	-0.5	-1.3	-1.6	0.0
	12	1.4	0.7	-0.1	-0.6	-0.5	1.6	0.4	-0.1	-0.8	-1.5	-1.8	0.5
	24	0.7	0.8	0.8	1.0	1.3	2.7	0.5	0.7	0.7	0.6	0.9	2.2
		t-stat for UMD β											
look-back	1	1.9	4.6	5.1	6.4	5.7	4.0	1.3	4.1	4.9	6.0	5.6	4.0
	3	4.6	5.6	5.4	6.0	5.4	3.1	3.9	5.3	5.2	6.1	5.5	3.1
	6	5.6	5.9	5.9	5.3	4.2	1.9	4.3	5.2	5.4	5.3	4.5	2.4
	9	6.8	6.8	5.9	4.7	3.5	1.6	5.2	6.2	6.1	5.4	4.4	2.1
	12	6.7	6.4	4.9	3.7	2.7	1.3	6.0	6.4	5.9	5.0	3.8	2.0
	24	4.0	3.8	3.0	2.6	2.4	2.8	5.1	4.9	4.3	3.9	3.4	3.3

Table 7: t-statistics of the alpha and beta coefficients of the realized daily RAMOM and TSMOM returns, pooled across all 5 interest rate futures. Reported are the t-statistics of the alpha and beta coefficients from the time series regressions of the realized daily RAMOM and TSMOM returns, pooled across 5 interest rate futures on daily returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

1984-2013

		RAMOM(0.5)						TSMOM					
		t-stat for α											
		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
look-back	1	1.8	2.5	1.9	3.1	3.2	2.1	3.1	3.0	2.2	3.0	3.1	1.9
	3	3.0	2.6	2.7	3.6	2.8	1.5	2.6	2.5	2.0	2.9	2.4	1.3
	6	2.6	2.3	2.9	2.9	2.0	0.6	2.7	2.8	3.3	3.1	2.3	0.7
	9	3.1	3.6	3.1	2.6	2.1	0.5	3.0	3.3	2.9	2.5	2.2	0.7
	12	3.0	3.0	2.3	2.0	1.6	0.2	2.7	2.7	2.1	1.8	1.4	0.0
	24	1.7	1.8	1.4	1.1	0.7	-0.6	1.8	1.7	1.0	0.7	0.4	-0.6
		t-stat for Market β											
look-back	1	-0.5	-0.3	2.8	3.1	3.6	4.0	-2.3	-1.4	0.9	1.0	1.7	3.0
	3	0.2	1.7	3.5	3.0	3.5	4.7	-1.9	-0.1	1.0	0.4	1.2	2.6
	6	2.6	3.0	2.3	2.4	3.0	4.5	-0.3	0.0	-0.3	0.0	0.5	2.1
	9	1.2	1.4	1.6	2.1	2.5	4.4	-1.5	-1.3	-0.9	-0.6	-0.3	1.7
	12	1.4	1.8	2.2	2.5	2.8	5.3	-1.8	-1.2	-0.6	-0.6	-0.3	2.1
	24	4.7	4.5	4.8	5.3	5.8	8.6	-0.8	0.2	0.8	1.3	1.8	4.1
		t-stat for SMB β											
look-back	1	0.7	0.8	1.3	1.7	2.8	2.7	1.7	2.0	2.2	2.1	2.7	2.7
	3	2.8	2.8	2.7	2.6	3.5	2.7	1.9	2.2	2.3	2.1	3.1	2.3
	6	3.2	3.2	2.6	3.0	3.3	2.6	2.3	2.4	2.3	2.8	3.1	2.4
	9	2.6	2.5	2.7	3.0	2.9	2.7	2.5	2.4	2.7	2.9	2.8	2.3
	12	2.5	2.6	2.8	2.7	2.6	2.8	2.7	2.9	2.9	2.7	2.5	2.2
	24	2.6	2.6	2.6	2.8	2.9	3.1	2.4	2.0	1.8	1.9	1.9	1.6
		t-stat for HML β											
look-back	1	2.2	3.5	3.2	3.4	3.3	3.7	2.6	3.0	2.5	2.7	2.5	3.6
	3	4.6	3.9	3.8	3.4	2.7	3.6	4.1	3.2	2.3	1.7	1.1	2.1
	6	4.1	3.3	2.7	2.4	2.2	3.6	2.7	2.1	1.6	1.4	0.7	1.8
	9	2.8	2.4	1.8	1.7	1.6	3.7	2.1	1.3	0.5	0.2	-0.4	1.5
	12	1.7	1.5	1.3	1.2	1.5	3.9	0.9	0.0	-0.6	-1.2	-1.3	1.3
	24	5.0	4.6	4.5	4.7	5.0	6.0	0.8	0.9	0.7	0.8	1.2	3.3
		t-stat for UMD β											
look-back	1	1.7	4.5	6.9	6.8	6.0	1.6	1.1	3.9	6.1	6.4	5.2	1.0
	3	4.9	6.7	7.0	6.7	5.5	0.9	3.2	6.5	7.3	7.0	5.8	1.3
	6	6.8	6.7	6.3	5.6	4.3	0.3	6.5	6.8	6.6	5.8	4.5	0.4
	9	5.9	6.3	5.4	4.0	2.2	-0.9	7.2	7.3	6.3	5.0	3.1	-0.5
	12	5.9	5.3	4.0	2.1	0.5	-1.9	7.4	6.5	5.1	3.1	1.3	-1.8
	24	0.6	0.2	-0.4	-1.0	-1.4	-0.9	3.4	3.0	2.0	0.4	-0.9	-1.7

Table 8: t-statistics of the alpha and beta coefficients of the realized daily RAMOM and TSMOM returns, pooled across all 6 currency futures Reported are the t-statistics of the alpha and beta coefficients from the time series regressions of the realized daily RAMOM and TSMOM returns, pooled across 6 currency futures on daily returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

		TSMOM Sharpe Ratio						RAMOM Sharpe Ratio/TSMOM Sharpe Ratio					
1984-2013 (whole period)													
		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
look-back	1	1.1	1.3	1.3	1.6	1.6	1.3	1.0	1.2	1.1	1.1	1.1	1.1
look-back	3	1.3	1.2	1.2	1.5	1.3	1.1	1.1	1.1	1.1	1.1	1.0	1.0
look-back	6	1.3	1.3	1.4	1.3	1.2	0.9	1.1	1.1	1.0	1.0	1.0	1.0
look-back	9	1.5	1.5	1.3	1.2	1.0	0.8	1.0	1.0	1.0	1.1	1.0	1.1
look-back	12	1.4	1.2	1.0	0.9	0.8	0.7	1.1	1.1	1.1	1.1	1.2	1.2
look-back	24	1.0	0.9	0.8	0.7	0.7	0.6	1.1	1.2	1.2	1.2	1.2	1.3
1984-1998 (first half)													
look-back	1	2.0	2.0	2.0	2.4	2.4	2.0	1.0	1.1	1.1	1.1	1.1	1.1
look-back	3	2.1	1.8	1.9	2.3	1.9	1.8	1.0	1.1	1.1	1.0	1.1	1.1
look-back	6	1.9	1.9	2.1	2.0	1.6	1.5	1.0	1.0	1.0	1.1	1.1	1.1
look-back	9	2.1	2.2	2.0	1.7	1.5	1.4	1.0	1.0	1.1	1.1	1.1	1.0
look-back	12	2.0	1.7	1.6	1.4	1.3	1.3	1.1	1.1	1.1	1.2	1.2	1.1
look-back	24	1.7	1.6	1.5	1.5	1.4	1.2	1.0	1.0	1.0	1.0	1.0	1.0
1999-2013 (second half)													
look-back	1	0.4	0.7	0.7	0.8	0.9	0.7	1.0	1.3	1.1	1.1	0.9	1.0
look-back	3	0.8	0.8	0.7	0.8	0.8	0.5	1.2	1.2	1.3	1.1	1.0	0.9
look-back	6	0.7	0.8	0.8	0.8	0.8	0.4	1.3	1.2	1.1	1.0	1.0	1.0
look-back	9	1.0	1.0	0.9	0.8	0.7	0.4	1.0	1.0	1.0	1.0	1.0	1.1
look-back	12	0.9	0.8	0.7	0.6	0.5	0.2	1.1	1.1	1.1	1.1	1.2	1.5
look-back	24	0.4	0.3	0.2	0.2	0.1	0.1	1.3	1.4	2.0	2.2	2.6	3.5

Table 9: Sharpe ratios for TSMOM returns and the quotients of the Sharpe Ratios of RAMOM returns and TSMOM returns, over different time intervals.

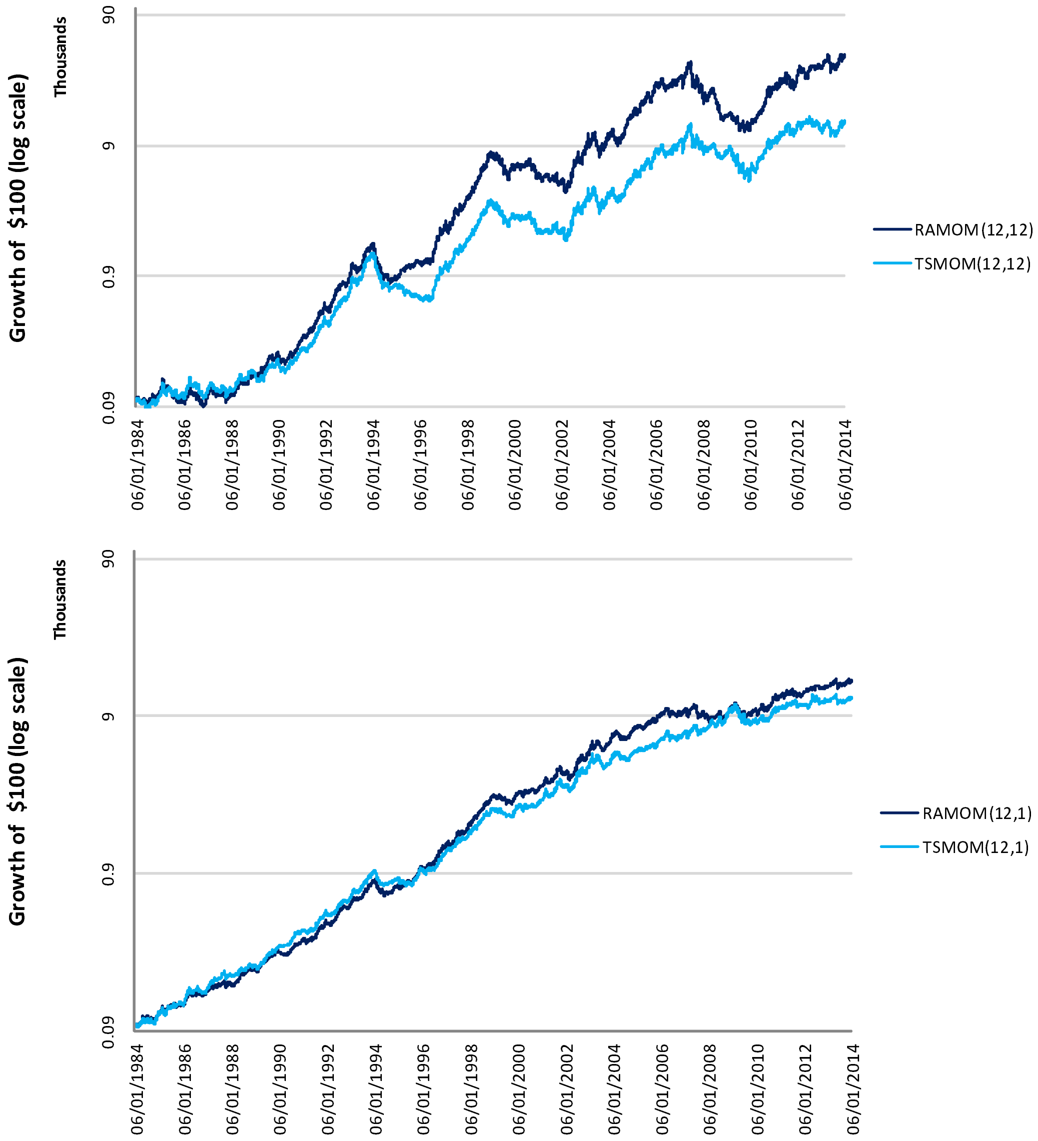


Figure 1: Cumulative excess return of RAMOM and TSMOM strategies, January 1984 to January 2014. Plotted are the cumulative excess returns of the diversified RAMOM and TSMOM portfolios. The RAMOM and TSMOM portfolios are defined in (3.6). Sample period is January 1984 to January 2014.

	λ=0.87						λ=0.5					
1984-2013 (whole period)												
	holding (months)						**holding (months)**					
look-back	**1**	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
1	1.8	3.8	3.3	3.6	3.1	2.6	1.7	4.2	3.6	3.5	3.0	2.4
3	3.3	3.7	3.0	2.2	1.5	0.5	2.9	3.2	3.8	2.5	1.8	0.6
6	1.2	1.3	1.5	1.1	0.2	0.0	2.5	2.7	2.2	1.6	0.9	1.0
9	1.5	1.5	1.2	1.5	1.0	1.0	2.3	2.2	2.2	2.2	1.6	1.4
12	2.2	2.3	2.1	1.9	2.1	1.8	2.8	3.1	3.1	2.8	2.8	2.5
24	2.3	2.5	2.7	2.4	2.2	2.5	2.7	2.8	2.8	2.6	2.4	2.6
1984-1998 (first half)												
look-back												
1	3.0	3.8	3.7	4.0	4.2	3.4	2.6	3.9	4.0	4.1	4.4	3.6
3	3.2	2.6	2.1	2.2	2.2	1.9	2.3	2.2	3.0	2.6	2.8	2.5
6	0.0	0.8	1.4	1.6	1.2	0.6	0.9	1.8	2.2	2.5	2.3	2.3
9	1.2	1.0	1.2	1.5	1.1	0.6	2.0	2.1	2.5	2.9	2.3	1.4
12	2.3	2.2	1.6	1.6	1.5	0.5	2.8	3.3	3.1	3.2	2.9	1.9
24	0.3	0.9	1.1	0.5	0.0	0.2	1.3	1.8	1.6	1.0	0.5	0.8
1999-2013 (second half)												
look-back												
1	0.1	2.0	1.3	1.4	0.7	0.8	0.3	2.3	1.3	1.2	0.4	0.3
3	1.6	2.6	2.3	1.6	0.6	0.2	1.7	2.2	2.4	1.6	0.6	-0.1
6	1.9	1.3	1.2	0.7	-0.1	0.5	2.5	2.1	1.4	0.7	0.1	0.4
9	1.0	1.1	0.7	0.9	0.6	1.0	1.1	1.1	0.9	0.7	0.4	0.8
12	0.9	1.2	1.4	1.1	1.4	1.8	1.3	1.3	1.3	1.0	1.2	1.4
24	1.8	1.7	2.0	1.9	2.0	2.2	1.4	1.4	1.5	1.5	1.6	1.8

Table 10: t-statistics of the alpha coefficient for the regression of momentum returns, pooled across all 64 instruments: $R_t^{\mathrm{RAMOM}}(k_1, k_2) = \alpha(k_1, k_2) + \beta(k_1, k_2) R_t^{\mathrm{TSMOM}}(k_1, k_2) + \varepsilon_t$. The momentum signals for RAMOM returns are constructed using the returns, adjusted by EWMA(0.87) and the EWMA(0.5) volatilities respectively.

		λ=0.87						λ=0.5					
1984-2013 (whole period)													
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	1.4	1.6	0.8	1.3	1.3	-0.1	1.7	1.9	0.9	1.2	1.2	0.0
	3	-0.7	1.8	1.2	0.3	-0.5	-0.3	-0.5	1.4	1.5	0.6	-0.4	-0.3
	6	0.8	1.4	1.2	0.7	-0.1	0.2	1.0	1.6	1.4	1.0	0.3	0.6
	9	1.3	1.5	1.2	1.0	1.3	0.9	1.5	1.8	1.3	1.0	1.3	1.3
	12	0.9	1.2	1.0	0.9	1.4	1.0	1.2	1.6	1.5	1.2	1.7	1.6
	24	1.0	0.7	0.8	0.7	0.8	1.5	1.6	1.3	1.2	1.1	1.2	1.8
1984-1998 (first half)													
look-back	**1**	1.1	1.1	1.0	1.4	2.3	-0.2	1.2	1.3	1.1	1.5	2.4	0.0
	3	-1.2	1.2	0.6	0.4	-0.3	-0.4	-1.5	1.6	1.3	0.9	-0.1	-0.3
	6	-0.8	0.4	0.5	0.5	0.2	-0.1	-0.3	1.0	1.1	1.3	0.8	0.5
	9	0.5	1.4	1.4	1.4	1.6	0.4	0.8	1.8	1.5	1.5	1.8	0.8
	12	0.8	1.4	1.1	1.2	1.6	0.3	1.1	1.9	1.8	1.8	2.0	0.8
	24	1.0	0.4	0.2	-0.7	-1.0	-1.3	1.6	0.7	0.3	-0.8	-1.3	-1.3
1999-2013 (second half)													
look-back	**1**	1.0	1.1	0.3	0.5	-0.1	0.2	1.3	1.4	0.3	0.3	-0.4	0.0
	3	0.5	1.2	1.1	0.0	-0.5	0.0	0.8	0.4	0.8	0.0	-0.5	-0.2
	6	2.8	1.8	1.3	0.5	-0.4	0.6	1.8	1.2	0.9	0.1	-0.3	0.5
	9	1.5	0.7	-0.1	-0.2	0.0	1.2	1.4	0.8	0.3	0.0	0.1	1.1
	12	0.4	0.2	0.1	-0.2	0.3	1.2	0.6	0.4	0.3	0.1	0.5	1.3
	24	0.2	0.3	0.5	0.8	1.1	1.6	0.6	0.6	0.6	0.8	1.0	1.4

Table 11: t-statistics of the alpha coefficient for the regression of momentum returns, pooled across 15 equity index futures: $R^{\mathrm{RAMOM}}_{t,\mathrm{equity}}(k_1,k_2) = \alpha(k_1,k_2) + \beta(k_1,k_2)R^{\mathrm{TSMOM}}_{t,\mathrm{equity}}(k_1,k_2) + \varepsilon_t$. The momentum signals for RAMOM returns are constructed using the returns, adjusted by EWMA(0.87) and the EWMA(0.5) volatilities respectively.

	λ=0.87						λ=0.5					
1984-2013 (whole period)												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	0.3	3.6	3.7	3.9	3.6	2.1	0.4	4.0	4.1	4.1	3.7	2.0
3	0.6	1.3	1.5	1.7	1.2	0.3	0.6	1.7	2.1	1.8	1.3	0.1
6	0.1	0.7	0.9	1.0	0.2	-0.4	0.7	1.7	1.5	1.4	0.8	0.3
9	0.6	1.5	1.4	2.3	1.6	0.7	1.1	1.5	1.9	2.4	1.4	0.6
12	1.5	2.4	2.6	2.3	2.1	1.8	2.4	3.1	3.2	2.7	2.3	2.1
24	1.4	1.6	1.7	1.3	1.2	1.5	1.3	1.5	1.3	1.2	1.1	1.3
1984-1998 (first half)												
1	1.4	3.4	3.2	3.9	3.8	2.7	1.6	3.8	3.5	4.2	4.2	3.2
3	2.7	2.0	1.3	1.5	1.6	0.4	2.7	2.0	1.8	1.6	2.0	1.2
6	0.5	1.8	1.8	1.5	1.0	-0.9	0.9	2.4	2.6	2.4	2.2	0.9
9	2.2	2.3	1.7	2.2	1.6	0.0	2.6	2.3	2.2	2.5	1.8	0.6
12	2.0	2.2	1.9	1.7	1.4	0.0	2.4	2.7	2.4	2.2	2.0	1.3
24	-0.2	0.5	0.4	0.3	0.0	0.1	0.4	0.8	0.5	0.6	0.4	0.7
1999-2013 (second half)												
1	-0.8	1.9	2.1	1.8	1.5	0.4	-0.9	1.9	2.4	1.8	1.3	-0.2
3	-1.5	0.0	1.0	1.3	0.4	0.1	-1.4	0.6	1.3	1.3	0.4	-0.8
6	-0.1	-0.5	0.0	0.4	-0.4	0.0	0.3	0.4	0.2	0.3	-0.4	-0.3
9	-0.9	0.0	0.3	1.2	0.8	0.9	-0.6	0.1	0.7	1.1	0.5	0.3
12	0.3	1.3	1.9	1.7	1.7	2.1	1.2	1.8	2.2	1.8	1.5	1.6
24	1.7	1.5	1.6	1.3	1.4	1.7	1.2	1.2	1.2	1.0	1.0	1.2

Table 12: t-statistics of the alpha coefficient for the regression of momentum returns, pooled across 25 commodity futures: $R^{\mathrm{RAMOM}}_{t,\mathrm{commodity}}(k_1, k_2) = \alpha(k_1, k_2) + \beta(k_1, k_2) R^{\mathrm{TSMOM}}_{t,\mathrm{commodity}}(k_1, k_2) + \varepsilon_t$. The momentum signals for RAMOM returns are constructed using the returns, adjusted by EWMA(0.87) and the EWMA(0.5) volatilities respectively.

	λ=0.87						λ=0.5					
1984-2013 (whole period)												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	1.8	2.0	2.0	2.3	1.9	2.3	1.9	2.2	2.1	1.9	1.6	1.9
3	3.6	3.0	1.6	1.8	2.0	1.1	2.9	2.2	2.1	1.1	1.6	0.5
6	1.3	1.3	1.5	0.7	0.6	0.5	2.6	2.3	1.6	0.9	1.0	1.2
9	0.1	0.0	0.1	0.0	-0.3	0.2	0.0	-0.1	0.1	0.0	-0.1	-0.1
12	0.6	0.4	0.4	0.6	0.5	0.7	0.3	0.1	0.4	0.7	0.6	0.6
24	1.2	1.4	1.8	1.6	1.2	1.6	1.2	1.7	1.8	1.4	1.1	1.4
1984-1998 (first half)												
1	2.1	1.7	1.8	2.2	1.8	2.1	1.7	1.6	2.0	2.1	1.7	1.8
3	2.2	1.6	0.7	2.1	2.4	2.6	1.4	1.1	1.3	1.2	1.8	1.5
6	0.8	0.7	1.5	0.9	0.3	1.5	1.5	1.1	1.3	1.0	0.8	2.4
9	-0.5	-0.4	-0.2	-0.3	-0.7	0.4	0.0	0.3	0.4	0.2	0.0	0.2
12	1.2	0.5	0.6	0.6	0.4	1.2	0.9	0.6	0.9	1.2	0.9	1.2
24	0.9	1.4	2.0	2.0	1.8	2.5	1.6	2.1	2.3	2.2	2.1	2.5
1999-2013 (second half)												
1	0.5	1.2	1.0	1.1	1.0	1.2	1.1	1.5	0.8	0.6	0.6	0.9
3	3.3	2.8	2.2	1.5	1.7	1.0	2.9	2.2	2.1	1.1	1.4	0.6
6	1.2	1.4	1.1	0.8	1.3	0.8	2.2	2.2	1.4	0.8	1.3	0.6
9	1.1	1.0	1.0	1.0	1.2	0.6	0.6	0.1	0.1	0.2	0.3	-0.1
12	-0.1	0.7	0.6	0.9	1.1	0.6	-0.4	-0.2	-0.2	-0.1	0.2	-0.6
24	1.4	1.3	1.3	1.0	0.6	0.6	0.5	0.8	1.0	0.3	-0.1	-0.1

Table 13: t-statistics of the alpha coefficient for the regression of momentum returns, pooled across 13 bond futures: $R^{\mathrm{RAMOM}}_{t,\mathrm{bond}}(k_1, k_2) = \alpha(k_1, k_2) + \beta(k_1, k_2) R^{\mathrm{TSMOM}}_{t,\mathrm{bond}}(k_1, k_2) + \varepsilon_t$. The momentum signals for RAMOM returns are constructed using the returns, adjusted by EWMA(0.87) and the EWMA(0.5) volatilities respectively.

		λ=0.87						λ=0.5					
1984-2013 (whole period)													
		holding (months)						**holding (months)**					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	1.6	2.1	1.9	1.3	0.5	1.1	0.8	1.9	1.8	0.9	0.2	0.7
	3	2.8	2.7	2.8	2.7	2.0	2.1	2.8	2.2	3.0	2.7	2.1	1.9
	6	0.7	1.2	1.2	1.4	1.2	0.2	1.0	1.7	1.6	1.4	1.2	0.2
	9	0.8	0.4	0.7	0.2	-0.1	0.5	2.2	1.0	1.1	0.8	0.2	-0.2
	12	3.1	1.6	0.9	-0.1	-1.1	-1.3	2.4	1.3	1.1	0.4	-0.5	-1.3
	24	-2.2	-1.5	-1.2	-1.5	-1.4	-1.5	-1.6	-1.9	-2.3	-3.2	-3.3	-3.6
1984-1998 (first half)													
look-back	**1**	1.7	1.5	1.6	1.1	0.6	1.1	0.5	1.2	1.8	1.1	0.6	1.1
	3	0.4	0.3	1.4	1.6	1.1	1.6	0.0	-0.3	2.1	2.2	1.7	2.0
	6	0.3	0.7	0.9	1.8	1.8	1.3	0.0	0.8	1.4	1.8	1.8	1.3
	9	-0.2	0.1	0.4	0.2	0.0	1.0	1.6	0.7	1.0	1.0	0.5	0.8
	12	2.3	1.0	0.4	0.1	-0.9	-0.8	2.4	1.3	1.4	1.1	0.3	-0.2
	24	-2.1	-1.5	-1.3	-1.5	-1.5	-1.8	-0.9	-1.5	-2.0	-2.8	-2.6	-2.9
1999-2013 (second half)													
look-back	**1**	0.6	1.5	1.1	0.6	0.0	0.6	0.6	1.5	0.7	0.1	-0.3	0.0
	3	3.6	3.8	2.7	2.4	1.9	1.3	4.3	3.5	2.2	1.6	1.2	0.7
	6	0.7	1.0	0.8	0.2	-0.3	-1.3	1.5	1.7	0.8	0.2	-0.2	-1.0
	9	1.8	1.0	0.8	0.1	-0.5	-1.1	1.6	1.1	0.4	-0.2	-0.5	-1.6
	12	2.3	1.5	1.0	-0.4	-0.7	-1.3	0.6	0.2	-0.2	-1.1	-1.6	-2.2
	24	-0.9	-0.5	-0.2	-0.5	-0.5	-0.4	-1.7	-1.3	-1.1	-1.7	-1.9	-2.2

Table 14: t-statistics of the alpha coefficient for the regression of momentum returns, pooled across 5 interest rate futures: $R^{\mathrm{RAMOM}}_{t,\mathrm{rate}}(k_1,k_2) = \alpha(k_1,k_2) + \beta(k_1,k_2)R^{\mathrm{TSMOM}}_{t,\mathrm{rate}}(k_1,k_2) + \varepsilon_t$. The momentum signals for RAMOM returns are constructed using the returns, adjusted by EWMA(0.87) and the EWMA(0.5) volatilities respectively.

	λ=0.87						λ=0.5					
1984-2013 (whole period)												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	0.4	0.6	0.3	0.8	0.7	1.0	-0.6	0.5	0.4	1.3	1.3	1.2
3	1.9	0.8	1.9	1.9	1.1	0.4	1.9	1.1	2.8	3.3	2.3	1.4
6	0.2	-1.5	-0.9	-0.3	-0.4	0.5	0.9	-0.7	-0.4	0.1	-0.3	0.5
9	1.2	0.6	0.0	0.2	-0.5	-0.2	1.3	1.8	1.3	1.2	0.5	0.0
12	0.1	0.0	0.0	0.0	0.8	0.6	1.7	1.8	1.3	1.6	1.7	1.2
24	1.2	1.3	1.3	1.4	1.4	1.3	0.9	1.0	1.9	1.9	1.6	1.0
1984-1998 (first half)												
look-back												
1	1.4	1.1	1.8	1.8	2.0	1.3	0.5	0.9	1.6	1.7	2.2	1.3
3	2.1	1.8	3.7	2.5	2.5	1.8	2.2	1.8	3.7	3.1	3.0	1.7
6	-0.3	-1.6	-1.5	-0.5	-0.5	-0.1	-0.5	-1.6	-1.3	-0.3	-0.6	0.1
9	1.2	0.2	-0.1	0.3	0.1	-0.2	1.7	1.1	1.4	1.7	1.1	0.0
12	-0.2	0.6	0.1	-0.4	0.0	-0.3	1.0	2.1	1.6	1.5	1.3	0.6
24	1.0	0.7	0.3	0.3	0.0	0.6	0.6	1.0	1.4	1.1	0.8	0.8
1999-2013 (second half)												
look-back												
1	-1.0	-0.3	-1.5	-0.7	-1.0	0.1	-1.5	-0.3	-1.1	0.0	-0.4	0.4
3	0.7	-0.7	-0.7	0.1	-0.8	-1.3	0.5	-0.3	0.5	1.5	0.5	0.3
6	0.6	-0.3	0.2	0.2	0.1	1.0	1.7	0.6	0.9	0.6	0.2	0.9
9	0.5	0.7	0.1	-0.1	-0.7	-0.1	0.3	1.4	0.6	0.3	-0.3	0.0
12	0.3	-0.7	-0.2	0.4	1.1	1.2	1.2	0.4	0.2	0.8	1.1	1.1
24	0.7	1.2	1.7	2.1	2.4	1.5	0.5	0.4	1.2	1.6	1.6	0.7

Table 15: t-statistics of the alpha coefficient for the regression of momentum returns, pooled across 6 currency futures: $R^{\mathrm{RAMOM}}_{t,\mathrm{currency}}(k_1, k_2) = \alpha(k_1, k_2) + \beta(k_1, k_2) R^{\mathrm{TSMOM}}_{t,\mathrm{currency}}(k_1, k_2) + \varepsilon_t$. The momentum signals for RAMOM returns are constructed using the returns, adjusted by EWMA(0.87) and the EWMA(0.5) volatilities respectively.

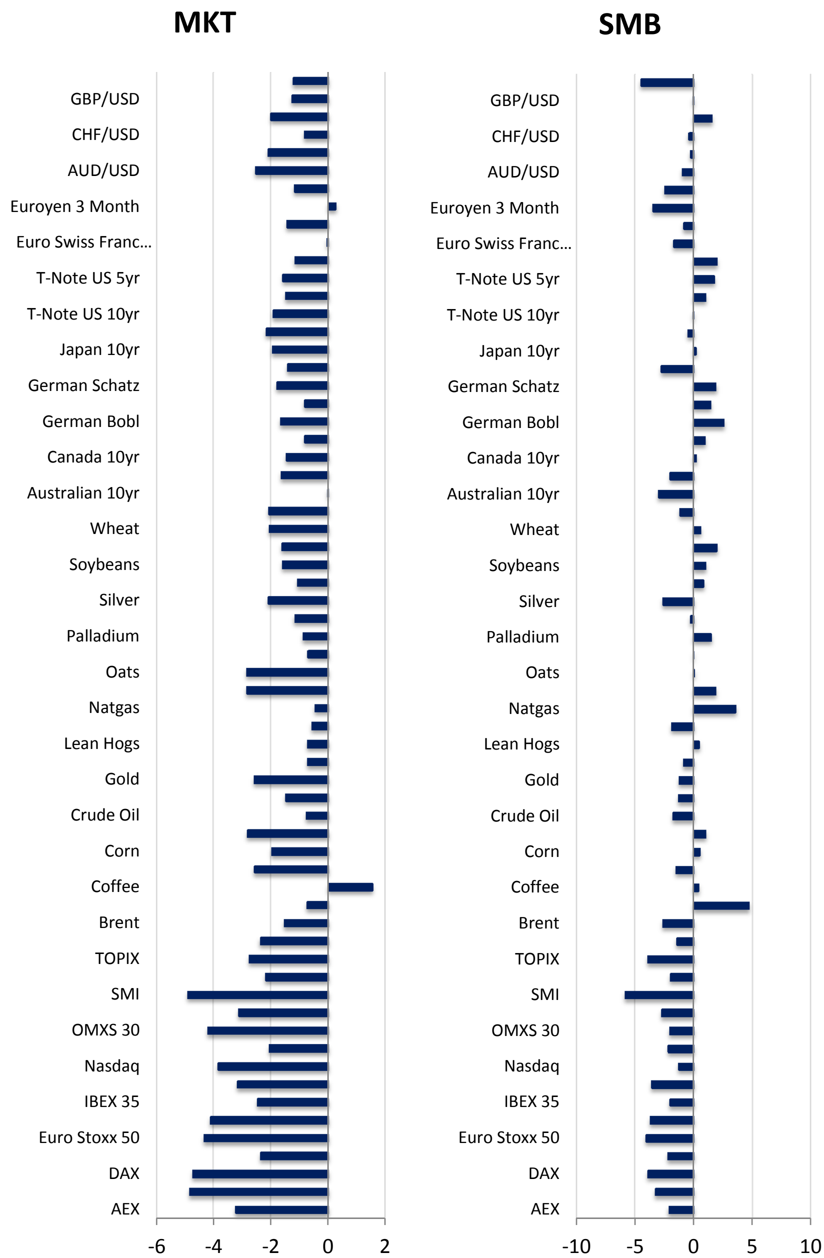


Figure 2: t-statistics of the beta coefficients for MKT and SMB factors of the realized 12-day futures volatilities. Reported are the t-statistics of the beta coefficients from the time series regressions of the realized 12-day futures volatilities on 12-day average returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French. t-statistics for the MKT beta for equity index futures are scaled down by 10 in order to achieve a uniform scale across instruments.

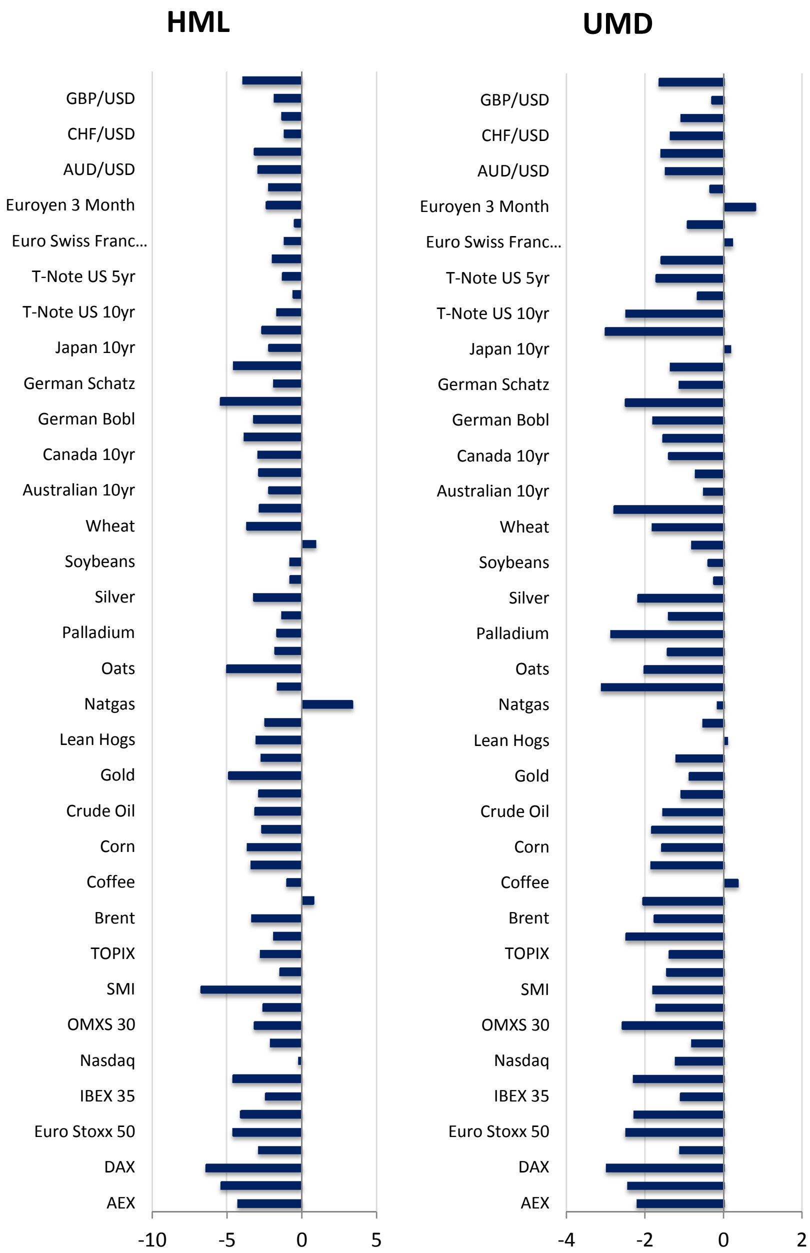


Figure 3: t-statistics of the beta coefficients for HML and UMD factors of the realized 12-day futures volatilities. Reported are the t-statistics of the beta coefficients from the time series regressions of the realized 12-day futures volatilities on 12-day average returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

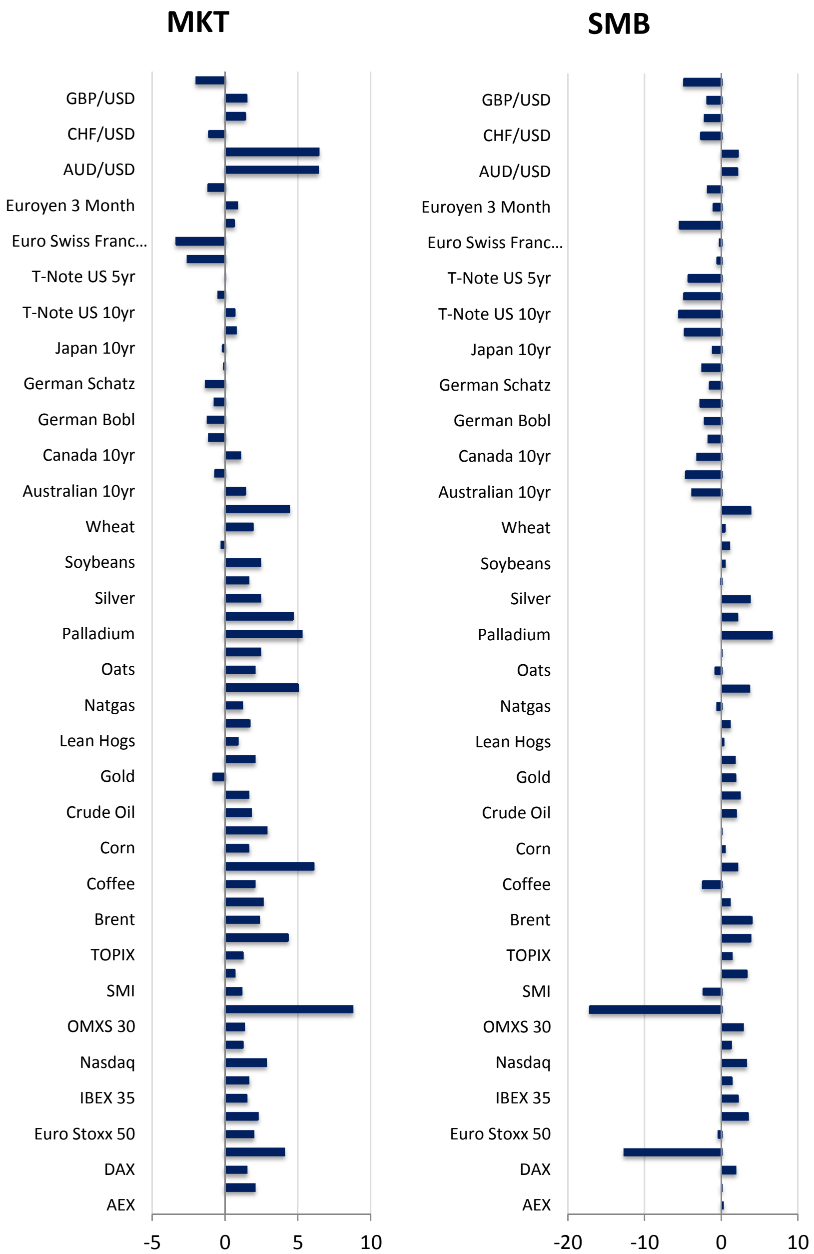


Figure 4: t-statistics of the beta coefficients for MKT and SMB factors of the realized 12-day futures returns. Reported are the t-statistics of the beta coefficients from the time series regressions of the realized 12-day futures returns on 12-day average returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

Figure 5: t-statistics of the beta coefficients for HML and UMD factors of the realized 12-day futures returns. Reported are the t-statistics of the beta coefficients from the time series regressions of the realized 12-day futures returns on 12-day average returns on the MKT, HML, SMB, and UMD Fama and French factors from the Website of Professor Kenneth French.

	turnover(RAMOM)/turnover(TSMOM)						Dollar turnover(RAMOM)/10000					
	1984-2013 (whole period)						1984-2013 (whole period)					
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
λ=0.94												
1	0.6	0.6	0.6	0.7	0.7	0.7	7.0	5.9	5.3	4.9	4.6	3.7
3	0.5	0.5	0.5	0.5	0.5	0.5	3.7	3.1	2.6	2.5	2.3	2.0
6	0.6	0.5	0.5	0.5	0.6	0.6	3.1	2.7	2.4	2.3	2.1	1.8
9	0.6	0.6	0.6	0.6	0.6	0.6	2.7	2.5	2.3	2.2	2.1	1.7
12	0.7	0.7	0.7	0.7	0.7	0.7	2.6	2.4	2.2	2.1	2.0	1.7
24	0.7	0.8	0.8	0.8	0.8	0.8	2.3	2.2	2.1	2.0	2.0	1.8
λ=0.87												
1	0.6	0.6	0.6	0.7	0.7	0.7	7.1	5.9	5.3	4.9	4.6	3.7
3	0.5	0.5	0.5	0.5	0.5	0.6	3.7	3.1	2.7	2.6	2.4	2.0
6	0.6	0.5	0.5	0.6	0.6	0.6	3.0	2.7	2.5	2.3	2.2	1.8
9	0.6	0.6	0.6	0.6	0.6	0.6	2.7	2.5	2.3	2.2	2.1	1.8
12	0.7	0.7	0.7	0.7	0.7	0.7	2.6	2.4	2.2	2.1	2.0	1.7
24	0.7	0.7	0.8	0.8	0.8	0.8	2.3	2.2	2.1	2.0	2.0	1.8
λ=0.5												
1	0.6	0.6	0.6	0.7	0.7	0.7	7.2	6.0	5.4	5.0	4.7	3.8
3	0.5	0.5	0.5	0.5	0.5	0.6	3.7	3.1	2.7	2.6	2.5	2.1
6	0.5	0.5	0.5	0.5	0.6	0.6	2.9	2.6	2.4	2.3	2.1	1.8
9	0.6	0.6	0.6	0.6	0.6	0.6	2.7	2.5	2.3	2.2	2.1	1.8
12	0.7	0.7	0.7	0.7	0.7	0.7	2.6	2.4	2.3	2.1	2.0	1.8
24	0.7	0.8	0.8	0.8	0.8	0.8	2.3	2.2	2.1	2.0	2.0	1.8

Table 16: Comparison of dollar turnovers for RAMOM and TSMOM strategies.

		TSMOM Sharpe Ratio						RAMOM Sharpe Ratio					
1984-2013 (whole period)													
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	-0.9	-1.4	-1.9	-1.8	-1.8	-2.1	-0.1	-0.2	-0.6	-0.6	-0.7	-1.1
look-back	**3**	0.1	-0.1	-0.2	0.0	-0.2	-0.5	0.8	0.7	0.7	0.8	0.6	0.3
look-back	**6**	0.3	0.3	0.4	0.4	0.1	-0.2	0.8	0.9	0.9	0.9	0.6	0.4
look-back	**9**	0.7	0.7	0.6	0.4	0.3	0.0	1.0	1.1	1.0	0.8	0.6	0.4
look-back	**12**	0.7	0.6	0.4	0.3	0.2	0.0	1.0	0.9	0.8	0.6	0.5	0.3
look-back	**24**	0.4	0.3	0.2	0.2	0.1	0.1	0.6	0.6	0.5	0.5	0.4	0.4
1984-1998 (first half)													
look-back	**1**	0.7	0.2	-0.1	0.3	0.2	-0.2	1.2	1.1	0.9	1.2	1.1	0.7
look-back	**3**	1.1	0.8	0.9	1.2	0.8	0.6	1.6	1.4	1.5	1.8	1.5	1.3
look-back	**6**	1.2	1.3	1.4	1.3	0.9	0.8	1.4	1.6	1.8	1.7	1.3	1.2
look-back	**9**	1.6	1.7	1.4	1.2	1.0	0.8	1.8	1.9	1.7	1.5	1.3	1.1
look-back	**12**	1.5	1.3	1.1	0.9	0.8	0.8	1.8	1.6	1.4	1.3	1.1	1.0
look-back	**24**	1.3	1.2	1.1	1.1	1.0	0.8	1.4	1.3	1.2	1.1	1.0	0.9
1999-2013 (second half)													
look-back	**1**	-2.2	-2.7	-3.4	-3.6	-3.6	-3.8	-1.2	-1.2	-1.9	-2.1	-2.2	-2.6
look-back	**3**	-0.7	-0.8	-1.1	-1.1	-1.2	-1.5	0.1	0.1	0.0	0.0	-0.1	-0.5
look-back	**6**	-0.5	-0.5	-0.4	-0.4	-0.5	-0.9	0.3	0.3	0.3	0.2	0.1	-0.2
look-back	**9**	-0.1	0.0	-0.1	-0.2	-0.2	-0.6	0.4	0.5	0.3	0.3	0.2	-0.1
look-back	**12**	0.1	0.0	-0.1	-0.2	-0.3	-0.6	0.4	0.3	0.2	0.1	0.1	-0.2
look-back	**24**	-0.2	-0.3	-0.4	-0.4	-0.5	-0.5	0.0	0.0	-0.1	-0.1	-0.1	-0.1

Table 17: Sharpe ratios of pooled RAMOM and TSMOM returns after transaction costs. Assumed are transaction costs of 0.0005 per dollar traded.

1984-2013

		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
		t-stat for α						t-stat for Market β					
look-back	1	1.4	3.8	3.3	3.2	2.8	2.1	1.7	2.5	3.0	3.1	4.0	7.5
	3	1.6	2.2	2.9	1.7	0.9	-0.4	7.2	8.9	10.6	12.6	16.2	19.6
	6	1.2	1.7	1.3	0.8	-0.1	0.0	8.1	9.6	11.5	13.0	15.0	16.3
	9	1.3	1.4	1.3	1.2	0.5	0.3	9.7	10.4	12.1	13.5	14.0	13.5
	12	1.8	2.1	2.0	1.6	1.6	1.1	11.2	11.0	13.2	14.2	15.5	13.5
	24	0.8	1.0	1.2	0.9	0.7	0.8	14.9	15.2	14.4	14.7	14.3	12.4
		t-stat for SMB β						t-stat for HML β					
look-back	1	-0.5	-0.2	1.2	0.2	0.4	1.4	0.7	0.7	0.4	0.7	0.5	2.6
	3	1.5	6.0	4.7	5.2	3.3	5.6	4.0	3.9	3.1	2.7	3.1	6.1
	6	1.6	2.4	2.3	1.8	1.8	4.1	4.0	2.7	2.4	2.3	4.1	5.3
	9	4.1	4.3	2.7	2.5	3.1	4.7	3.0	2.9	3.1	5.2	7.4	8.0
	12	3.0	2.2	2.2	3.0	3.4	5.9	2.9	3.0	5.1	7.6	9.7	8.9
	24	3.9	4.6	5.3	6.3	7.2	8.6	9.3	10.4	10.4	10.6	10.5	9.2
		t-stat for UMD β						t-stat for TSMOM β					
look-back	1	2.5	2.6	1.5	1.2	0.5	-1.0	85.8	77.8	81.8	88.8	90.0	100.9
	3	6.5	6.6	3.5	0.3	-1.5	-4.3	77.5	99.6	128.8	145.6	137.3	167.7
	6	7.0	4.4	2.0	-0.5	-1.4	-3.1	74.5	113.2	124.3	124.5	137.8	165.8
	9	5.0	0.5	-1.3	-2.6	-3.1	-2.1	86.3	112.7	113.4	123.2	147.6	165.4
	12	3.9	1.4	-0.3	-0.9	-1.7	0.2	78.8	87.5	99.0	110.6	114.5	110.5
	24	0.8	0.0	-0.4	-0.1	0.5	2.6	41.9	46.8	46.1	46.4	45.7	45.0

Table 18: t-statistics of the alpha and beta coefficients from regressing pooled RAMOM daily returns pooled across all 64 instruments on the Fama and French four factors and TSMOM daily returns: $R_t^{\text{RAMOM}}(k_1, k_2, 0.5) = \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \beta_5 R_t^{\text{TSMOM}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

	holding (months)						holding (months)					
	1	3	6	9	12	24	1	3	6	9	12	24
	t-stat for α						t-stat for Market β					
look-back 1	1.4	1.5	0.6	0.9	0.8	-0.4	1.8	3.6	2.5	2.9	4.8	7.1
3	-2.2	0.0	0.4	-0.3	-1.4	-1.5	5.7	11.1	14.2	15.3	12.7	18.2
6	-0.8	0.4	0.5	0.1	-0.8	-0.4	6.3	11.2	13.4	15.0	16.8	19.1
9	0.4	1.0	0.4	0.0	0.3	0.4	9.5	9.8	12.3	14.2	15.7	15.1
12	0.0	0.5	0.4	0.0	0.6	0.4	9.6	10.0	12.9	15.1	16.9	14.2
24	-0.2	-0.5	-0.5	-0.5	-0.4	0.1	15.5	15.5	16.1	16.9	16.6	14.1
	t-stat for SMB β						t-stat for HML β					
look-back 1	0.7	1.5	2.2	2.4	1.9	2.6	0.7	0.7	0.7	1.4	1.4	3.1
3	0.9	4.6	4.1	4.5	1.3	2.9	2.8	2.2	1.1	0.3	1.3	4.3
6	1.1	1.8	1.5	0.9	0.5	2.5	2.6	1.0	0.0	0.2	1.9	3.0
9	4.1	3.7	2.6	2.3	2.8	4.7	0.9	0.9	1.3	2.5	4.0	4.5
12	4.9	4.0	3.4	3.3	3.8	6.0	1.3	1.4	2.6	4.5	6.1	6.2
24	4.5	4.6	5.3	6.2	6.9	8.3	6.5	7.6	8.0	8.2	8.0	7.4
	t-stat for UMD β						t-stat for TSMOM β					
look-back 1	1.6	1.6	0.5	0.5	0.6	-1.4	28.5	49.3	36.2	30.8	32.0	34.9
3	4.2	6.1	3.3	-0.8	-2.1	-4.2	24.6	80.1	79.3	70.4	45.2	84.7
6	5.0	5.1	2.4	-0.3	-1.0	-2.5	48.7	72.6	93.8	116.0	86.2	82.4
9	5.1	2.5	1.3	0.1	-1.3	-1.2	52.2	57.4	64.6	73.1	85.4	46.3
12	4.8	3.1	2.0	1.4	-0.2	0.4	36.5	43.8	52.3	58.0	69.2	51.8
24	1.7	0.9	-0.2	-0.6	-0.3	1.7	20.1	21.0	25.1	28.1	29.1	27.4

Table 19: t-statistics of the alpha and beta coefficients from regressing RAMOM daily returns, pooled across 15 equity index futures on the Fama and French four factors and TSMOM daily returns: $R^{\text{RAMOM}}_{t,\text{equity}}(k_1, k_2, 0.5) = \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \beta_5 R^{\text{TSMOM}}_{t,\text{equity}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
		t-stat for α						t-stat for Market β					
look-back	1	0.1	3.7	3.9	3.9	3.5	1.9	1.4	1.7	1.3	1.2	1.5	2.0
	3	0.0	1.1	1.6	1.4	0.9	-0.3	3.9	4.5	4.9	5.7	6.1	5.9
	6	0.0	1.2	1.0	1.0	0.3	-0.2	5.3	5.6	6.5	7.5	7.4	7.3
	9	0.6	1.1	1.5	2.0	1.0	0.1	5.2	6.3	7.5	7.3	6.9	6.6
	12	1.9	2.6	2.8	2.2	1.7	1.4	6.6	7.6	7.9	7.2	7.3	6.8
	24	0.4	0.6	0.3	0.1	-0.1	0.2	8.5	8.6	7.9	7.7	7.8	7.6
		t-stat for SMB β						t-stat for HML β					
look-back	1	-0.8	0.2	1.3	0.7	0.5	0.4	1.2	1.1	0.0	-0.2	-0.8	0.6
	3	1.5	4.0	3.4	4.1	3.6	4.0	4.4	4.4	3.5	3.2	2.9	3.2
	6	1.1	2.0	2.7	2.7	3.3	3.6	3.9	3.2	4.0	3.5	3.9	4.5
	9	1.2	2.8	3.2	3.9	4.4	4.4	2.8	3.6	3.6	4.5	5.0	5.8
	12	0.6	1.7	3.9	4.6	4.4	5.4	3.3	3.6	4.6	5.2	5.7	6.7
	24	3.4	4.3	4.3	4.8	5.4	6.0	6.3	6.8	6.9	7.1	7.4	7.4
		t-stat for UMD β						t-stat for TSMOM β					
look-back	1	2.4	3.3	2.8	2.9	1.7	-0.2	69.2	64.6	66.9	70.0	73.2	79.0
	3	5.0	4.5	3.0	1.7	1.0	-0.4	57.1	88.3	120.5	119.4	112.9	116.1
	6	5.0	2.5	1.5	0.1	-0.2	-0.5	71.9	98.9	107.5	97.5	96.5	98.4
	9	2.8	-0.9	-2.0	-2.0	-1.2	-1.0	66.5	96.5	105.4	110.0	121.2	139.8
	12	1.8	0.0	-1.3	-0.9	0.4	0.9	78.5	96.4	97.5	100.8	104.0	131.3
	24	1.1	1.0	1.7	2.3	2.7	3.4	52.2	56.9	53.3	52.9	53.0	59.9

Table 20: t-statistics of the alpha and beta coefficients from regressing RAMOM daily returns, pooled across 25 commodity futures on the Fama and French four factors and TSMOM daily returns: $R^{\text{RAMOM}}_{t,\text{commodity}}(k_1, k_2, 0.5) = \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \beta_5 R^{\text{TSMOM}}_{t,\text{commodity}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
		t-stat for α						**t-stat for Market β**					
look-back	1	1.9	2.2	2.1	2.0	1.6	1.9	-1.5	-1.1	-1.8	-1.6	-1.2	-0.2
	3	2.8	2.2	2.1	1.0	1.6	0.5	-1.9	-2.8	-1.5	-0.8	-0.9	-0.9
	6	2.4	2.2	1.6	0.9	1.0	1.2	-0.7	-0.9	-0.3	-0.6	0.7	-0.5
	9	-0.2	-0.2	0.0	-0.1	-0.3	-0.2	1.5	1.9	2.1	2.9	3.3	0.8
	12	0.1	-0.1	0.2	0.5	0.4	0.3	1.8	1.9	2.8	3.3	3.2	2.2
	24	0.9	1.4	1.6	1.2	0.9	1.2	2.1	1.6	1.5	1.4	1.4	-0.4
		t-stat for SMB β						**t-stat for HML β**					
look-back	1	0.2	0.3	0.6	-0.3	0.3	-1.1	-0.6	-1.1	-0.9	-1.3	-1.6	-0.2
	3	-0.8	0.4	-0.4	-1.0	-2.8	-1.7	0.4	0.4	-0.4	-0.6	-0.6	1.9
	6	-0.8	-1.9	-1.8	-1.9	-1.8	-1.1	0.4	-0.3	-1.1	-1.4	0.0	1.9
	9	-1.3	-2.3	-2.0	-1.9	-1.7	-0.9	1.0	-1.1	-1.0	-0.3	1.4	4.0
	12	-2.1	-2.8	-1.9	-2.0	-1.8	-1.0	-0.2	0.1	0.7	1.9	3.2	5.9
	24	-1.5	-1.6	-1.4	-1.3	-1.3	1.4	2.6	3.0	3.3	4.3	4.9	6.4
		t-stat for UMD β						**t-stat for TSMOM β**					
look-back	1	1.0	0.9	0.6	0.9	0.2	0.3	57.6	55.1	52.1	54.1	59.1	84.7
	3	3.4	3.3	2.5	2.8	1.6	-0.7	52.1	43.4	113.3	113.0	123.8	128.2
	6	4.2	2.1	1.7	0.8	0.0	-3.4	89.2	143.7	130.6	131.2	141.5	146.2
	9	4.7	2.4	1.2	0.4	-0.3	-2.1	59.8	84.9	100.2	114.8	123.6	144.9
	12	3.8	2.7	1.4	0.5	-0.2	-0.1	67.8	76.9	87.0	124.5	123.1	127.5
	24	2.0	1.7	0.8	1.1	1.2	1.7	63.0	74.1	77.2	70.7	72.3	74.5

Table 21: t-statistics of the alpha and beta coefficients from regressing RAMOM daily returns, pooled across 13 bond futures on the Fama and French four factors and TSMOM daily returns: $R^{\text{RAMOM}}_{t,\text{bond}}(k_1, k_2, 0.5) = \alpha + \beta_1 R^{MKT}_t + \beta_2 R^{SMB}_t + \beta_3 R^{HML}_t + \beta_4 R^{UMD}_t + \beta_5 R^{\text{TSMOM}}_{t,\text{bond}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

	holding (months)						holding (months)					
	1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
	t-stat for α						**t-stat for Market β**					
look-back 1	0.8	1.8	1.7	0.7	0.1	0.6	-0.8	-1.1	-0.1	0.8	1.5	1.1
3	2.6	2.0	2.8	2.6	2.0	1.8	-1.0	0.3	1.1	1.0	0.9	1.4
6	0.8	1.6	1.4	1.3	1.1	0.1	0.3	-0.3	0.2	-0.1	0.9	2.2
9	1.9	0.9	1.0	0.7	0.1	-0.4	0.6	1.1	1.4	2.4	2.8	3.4
12	2.1	1.2	1.0	0.3	-0.6	-1.4	0.8	0.5	0.9	2.0	2.0	2.2
24	-1.7	-2.0	-2.2	-3.2	-3.3	-3.7	3.0	2.8	3.3	3.5	3.1	3.9
	t-stat for SMB β						**t-stat for HML β**					
look-back 1	0.7	0.5	0.2	0.3	0.3	0.1	0.2	0.0	-0.6	0.2	0.3	0.3
3	-0.3	-0.4	-1.6	-1.2	-1.1	-0.8	1.7	2.1	1.9	2.0	2.0	3.1
6	1.9	1.6	-0.3	-0.4	-0.8	-0.3	1.3	0.9	1.5	1.6	2.4	2.9
9	0.0	-1.0	-1.2	-1.4	-1.8	-1.4	2.7	2.3	1.4	2.5	3.0	4.1
12	-1.5	-1.1	-1.4	-1.3	-1.3	-0.7	2.0	1.4	1.6	2.7	3.3	4.0
24	-2.2	-2.1	-1.5	-1.0	-1.1	0.3	0.5	0.4	0.5	1.5	1.7	2.6
	t-stat for UMD β						**t-stat for TSMOM β**					
look-back 1	1.5	2.3	2.0	2.6	2.0	1.2	48.8	44.1	49.2	54.0	53.5	66.5
3	2.9	2.7	1.8	1.4	0.7	0.6	56.8	100.9	131.4	128.1	142.0	143.4
6	4.3	3.1	2.5	0.9	-0.4	-1.7	51.3	93.5	108.3	119.9	134.2	144.2
9	5.3	3.2	0.7	-1.3	-2.3	-2.1	44.8	63.6	74.7	102.1	115.6	128.7
12	3.3	1.5	-1.0	-2.6	-2.6	-2.5	41.1	45.4	96.8	120.1	139.0	128.2
24	-1.2	-1.6	-2.5	-3.3	-3.0	-2.0	76.8	112.2	121.2	143.5	173.6	210.3

Table 22: t-statistics of the alpha and beta coefficients from regressing RAMOM daily returns, pooled across 5 interest rate futures on the Fama and French four factors and TSMOM daily returns: $R^{\text{RAMOM}}_{t,\text{rate}}(k_1, k_2, 0.5) = \alpha + \beta_1 R^{MKT}_t + \beta_2 R^{SMB}_t + \beta_3 R^{HML}_t + \beta_4 R^{UMD}_t + \beta_5 R^{\text{TSMOM}}_{t,\text{rate}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

look-back	t-stat for α: 1	3	6	9	12	24	t-stat for Market β: 1	3	6	9	12	24
1	-0.8	0.2	0.1	1.0	1.0	0.9	2.1	1.7	3.5	4.0	4.1	3.1
3	1.5	0.8	2.3	2.7	1.8	0.9	3.2	4.3	6.7	7.8	7.7	9.7
6	0.5	-1.2	-0.9	-0.4	-0.9	-0.1	6.1	7.6	8.9	9.3	10.6	10.4
9	1.0	1.4	0.9	0.8	0.0	-0.6	5.4	7.0	8.7	9.7	9.9	9.9
12	1.4	1.4	0.9	1.1	1.1	0.5	5.8	7.0	8.1	9.1	9.0	9.0
24	0.4	0.6	1.4	1.2	0.8	0.0	7.6	8.6	9.0	9.8	9.7	9.4

look-back	t-stat for SMB β: 1	3	6	9	12	24	t-stat for HML β: 1	3	6	9	12	24
1	-0.7	-1.4	-0.8	-1.5	-0.6	0.7	0.5	2.0	1.9	2.3	2.4	1.1
3	0.1	0.9	0.5	0.9	0.2	0.4	1.7	1.9	3.8	4.7	5.1	5.3
6	-0.2	0.2	0.0	-0.2	-0.3	0.8	3.6	4.0	4.8	4.4	6.4	7.2
9	1.4	0.5	0.4	0.7	0.8	0.9	2.2	3.4	4.0	5.5	6.8	6.8
12	0.5	0.4	0.7	1.0	1.4	1.9	2.0	3.7	5.6	7.0	7.7	6.6
24	1.6	3.0	3.8	4.5	4.6	2.5	7.0	7.3	7.9	8.7	8.7	7.6

look-back	t-stat for UMD β: 1	3	6	9	12	24	t-stat for TSMOM β: 1	3	6	9	12	24
1	1.7	2.2	2.1	2.1	2.5	1.8	48.1	43.3	46.4	52.6	60.7	64.6
3	2.8	1.2	0.3	-0.8	-0.9	-1.5	66.0	96.0	116.7	130.9	127.2	121.3
6	1.5	0.5	-0.2	-0.2	-0.5	-0.1	68.3	112.5	123.2	120.1	120.0	111.7
9	-0.9	-1.6	-2.0	-3.2	-3.1	-1.0	76.0	112.4	110.7	121.2	125.6	104.2
12	-1.6	-2.1	-3.1	-3.1	-2.5	0.0	70.9	91.2	127.2	139.6	140.0	145.9
24	-3.9	-4.4	-4.0	-3.0	-1.2	1.6	56.1	71.3	87.1	102.0	114.4	124.1

Columns: holding (months); rows: look-back.

Table 23: t-statistics of the alpha and beta coefficients from regressing RAMOM daily returns, pooled across 6 currency futures on the Fama and French four factors and TSMOM daily returns: $R^{\text{RAMOM}}_{t,\text{currency}}(k_1, k_2, 0.5) = \alpha + \beta_1 R^{MKT}_t + \beta_2 R^{SMB}_t + \beta_3 R^{HML}_t + \beta_4 R^{UMD}_t + \beta_5 R^{\text{TSMOM}}_{t,\text{currency}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

		Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
		1984-2013 (whole period)											
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	1.1	1.1	1.2	1.1	1.1	1.1	1.0	1.1	1.1	1.1	1.1	1.0
	3	1.1	1.1	1.2	1.2	1.2	1.2	1.0	1.1	1.1	1.2	1.1	1.0
	6	1.1	1.2	1.2	1.2	1.2	1.2	1.0	1.1	1.1	1.2	1.1	1.0
	9	1.1	1.2	1.2	1.2	1.2	1.2	1.1	1.1	1.1	1.1	1.0	0.9
	12	1.1	1.2	1.2	1.2	1.2	1.3	1.1	1.1	1.1	1.0	1.0	1.0
	24	1.1	1.1	1.2	1.2	1.2	1.1	0.9	0.9	0.9	0.9	0.8	0.8
		1984-1998 (first half)											
look-back	**1**	1.1	1.1	1.1	1.1	1.1	1.1	0.9	1.0	1.0	1.0	1.0	0.9
	3	1.1	1.1	1.1	1.1	1.1	1.1	0.9	1.0	1.0	1.0	1.0	0.8
	6	1.1	1.1	1.1	1.1	1.1	1.1	0.9	1.0	1.0	1.0	1.0	0.8
	9	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.0	1.0	1.0	1.0	0.8
	12	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.0	1.0	1.0	0.9	0.8
	24	1.1	1.1	1.1	1.1	1.1	1.1	0.9	0.8	0.8	0.8	0.7	0.6
		1999-2013 (second half)											
look-back	**1**	1.0	1.0	1.1	1.1	1.1	1.0	0.9	1.2	1.3	1.2	1.2	1.0
	3	1.1	1.1	1.3	1.3	1.2	1.0	1.0	1.1	1.2	1.3	1.2	1.0
	6	1.1	1.2	1.3	1.2	1.1	1.0	1.0	1.1	1.1	1.2	1.1	1.1
	9	1.1	1.2	1.2	1.1	1.1	1.1	1.0	1.1	1.1	1.0	0.9	1.1
	12	1.2	1.2	1.1	1.1	1.0	1.3	1.1	1.1	1.1	0.9	0.9	1.4
	24	1.0	1.0	1.2	1.3	1.4	1.2	1.0	1.1	1.1	1.0	1.0	1.1

Table 24: Quotients of Sharpe ratios for RAMOM returns adjusted by momentum-specific risk and simple RAMOM returns, pooled across all 64 instruments over different time intervals.

		Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
1984-2013 (whole period)													
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	1.0	0.8	1.0	0.9	1.0	0.8	1.0	1.0	1.1	1.1	1.1	1.2
	3	0.8	0.9	1.1	1.0	0.9	0.9	1.0	1.0	1.2	1.1	1.0	1.0
	6	0.9	1.1	1.1	1.1	0.9	0.9	1.0	1.0	1.0	1.1	1.1	1.3
	9	1.0	1.0	1.1	1.0	0.9	1.0	1.1	1.1	1.1	1.1	1.2	1.4
	12	1.0	1.1	1.0	1.0	0.9	1.0	1.0	1.0	1.1	1.1	1.1	1.6
	24	0.9	0.9	1.0	0.9	0.9	0.8	1.1	1.2	1.2	1.2	1.2	1.0
1984-1998 (first half)													
look-back	**1**	0.9	0.7	0.8	0.7	0.8	0.7	0.9	1.1	1.1	1.0	1.1	1.4
	3	0.4	0.7	0.8	0.7	0.6	0.8	0.9	1.0	1.2	1.0	0.9	1.2
	6	0.8	0.9	1.0	0.9	0.8	0.9	1.1	1.1	1.1	1.0	1.1	1.4
	9	0.9	0.9	0.9	0.8	0.7	0.9	1.1	1.2	1.0	1.1	1.2	1.4
	12	0.8	0.9	0.8	0.8	0.7	0.9	1.0	1.0	0.9	1.0	1.2	1.3
	24	0.9	0.8	0.8	0.9	0.9	0.9	1.1	1.2	1.2	1.2	1.2	1.0
1999-2013 (second half)													
look-back	**1**	1.1	0.9	1.2	1.2	1.3	0.8	1.0	0.9	1.2	1.1	1.0	0.6
	3	1.1	1.1	1.3	1.4	1.3	0.7	1.0	0.9	1.1	1.4	1.1	0.0
	6	1.1	1.2	1.2	1.3	1.2	0.5	1.0	1.0	0.9	1.2	1.1	0.4
	9	1.1	1.2	1.2	1.2	1.1	0.5	1.0	1.0	1.1	1.2	1.0	1.0
	12	1.2	1.3	1.3	1.3	1.1	0.3	1.0	1.0	1.2	1.0	0.5	2.9
	24	0.9	0.9	1.1	1.0	0.7	-1.3	0.8	0.9	0.9	1.1	0.9	-0.4

Table 25: Quotients of Sharpe ratios for RAMOM returns adjusted by momentum-specific risk and simple RAMOM returns, pooled across equity index futures over different time intervals.

	Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
1984-2013 (whole period)												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	1.2	1.0	1.1	1.1	1.0	1.2	1.2	1.1	1.1	1.1	1.2	1.2
3	1.1	1.1	1.1	1.1	1.1	1.2	1.0	1.0	1.1	1.2	1.2	1.4
6	1.0	1.0	1.1	1.2	1.1	1.3	1.0	1.1	1.2	1.2	1.1	1.2
9	1.1	1.1	1.2	1.1	1.0	1.4	1.1	1.1	1.1	1.1	1.1	1.5
12	1.1	1.1	1.1	1.1	1.1	1.7	1.1	1.1	1.2	1.1	1.2	2.3
24	1.0	1.1	1.5	3.3	-0.3	31.5	1.2	1.3	1.6	3.8	-0.6	18.2
1984-1998 (first half)												
look-back												
1	1.1	1.0	1.1	1.0	1.0	1.2	1.0	1.1	1.1	1.0	1.0	1.1
3	1.1	1.0	1.0	1.1	1.0	1.5	1.0	1.0	1.0	1.1	1.1	1.1
6	1.0	0.9	1.0	1.1	1.1	1.9	1.0	1.0	1.1	1.1	1.1	1.2
9	1.0	1.0	1.0	1.1	1.1	5.1	1.0	1.0	1.0	1.0	1.0	2.8
12	1.0	1.0	1.1	1.1	1.3	-0.3	1.0	1.0	1.1	1.1	1.2	0.2
24	1.1	1.3	1.7	5.3	0.0	0.8	1.1	1.1	1.2	2.2	0.8	1.1
1999-2013 (second half)												
look-back												
1	-0.7	1.0	1.1	1.1	1.0	1.0	4.8	1.1	1.1	1.2	1.3	1.3
3	1.0	1.1	1.2	1.1	1.1	0.8	0.9	1.1	1.1	1.2	1.2	1.5
6	1.0	1.1	1.2	1.2	0.9	0.7	1.1	1.1	1.2	1.2	1.1	1.3
9	1.1	1.1	1.2	1.0	0.9	0.7	1.2	1.2	1.2	1.1	1.0	1.3
12	1.2	1.1	1.0	0.9	0.8	0.8	1.1	1.2	1.1	1.1	1.1	1.4
24	0.8	0.6	0.6	0.5	0.7	1.1	1.3	1.4	2.7	4.6	3.7	1.3

Table 26: Quotients of Sharpe ratios for RAMOM returns adjusted by momentum-specific risk and simple RAMOM returns, pooled across commodity futures over different time intervals.

		Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
1984-2013 (whole period)													
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	1.1	1.1	1.2	1.1	1.1	1.1	1.1	1.2	1.2	1.0	1.1	1.0
	3	1.1	1.1	1.2	1.2	1.2	1.1	1.1	1.2	1.3	1.2	1.3	1.2
	6	1.1	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.3	1.2
	9	1.1	1.1	1.1	1.1	1.1	1.2	1.1	1.1	1.2	1.2	1.2	1.1
	12	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.2	1.1	1.2	1.2
	24	1.1	1.1	1.1	1.1	1.2	1.2	1.1	1.1	1.1	1.1	1.1	1.1
1984-1998 (first half)													
look-back	**1**	1.1	1.1	1.2	1.1	1.1	1.1	1.1	1.2	1.2	1.0	1.1	1.0
	3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.3	1.2	1.2	1.2	1.1
	6	1.1	1.1	1.1	1.1	1.2	1.1	1.2	1.2	1.1	1.2	1.3	1.2
	9	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.1	1.2	1.2	1.2	1.0
	12	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.2	1.2	1.1
	24	1.1	1.1	1.1	1.0	1.0	1.0	1.1	1.0	1.1	1.1	1.1	1.0
1999-2013 (second half)													
look-back	**1**	1.0	0.9	0.8	0.9	0.8	0.8	1.0	1.3	1.5	1.3	1.5	1.2
	3	0.9	0.9	1.2	1.1	1.2	1.0	1.2	1.0	1.7	1.5	1.8	1.2
	6	1.1	1.3	1.3	1.0	1.0	1.1	1.3	1.4	1.5	1.5	1.3	1.2
	9	0.9	1.0	0.9	0.9	0.9	1.2	1.1	1.1	1.1	1.0	0.8	1.1
	12	1.0	0.9	0.9	0.9	0.9	1.5	1.1	1.1	0.9	0.7	0.9	1.1
	24	0.9	1.0	1.0	1.2	1.4	1.6	1.0	1.1	1.0	0.8	0.9	1.1

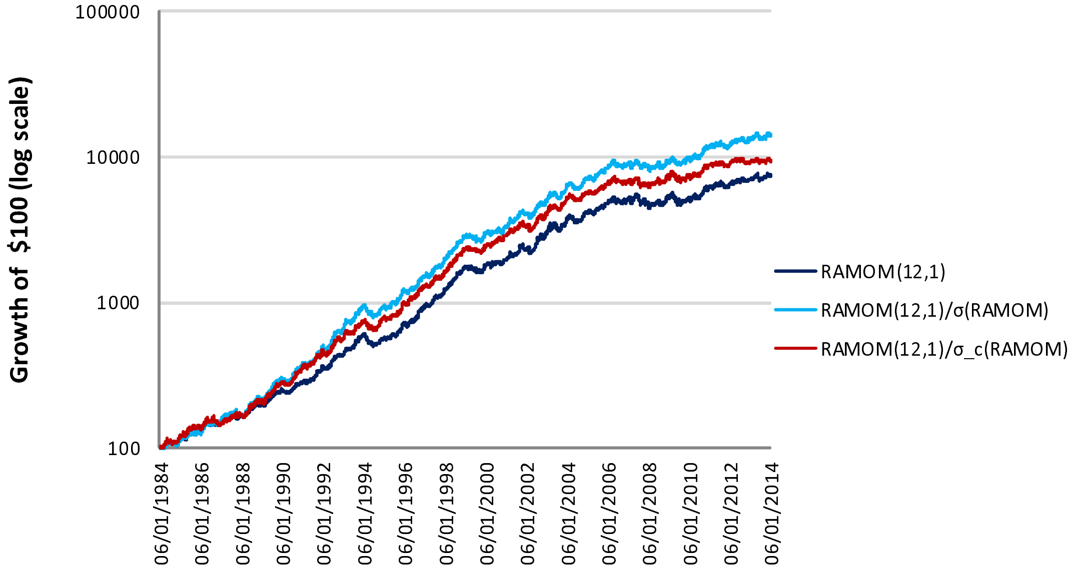
Table 27: Quotients of Sharpe ratios for RAMOM returns adjusted by momentum-specific risk and simple RAMOM returns, pooled across bond futures over different time intervals.

		Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
		1984-2013 (whole period)											
		holding (months)						**holding (months)**					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	1.0	1.0	1.0	0.9	1.0	1.0	1.0	1.1	1.1	1.0	1.1	1.1
	3	1.0	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.1	1.1	1.2
	6	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.2	1.1	1.2	1.1	1.2
	9	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.1	1.1	1.1	1.0	1.1
	12	1.0	1.0	1.0	1.0	1.0	1.2	1.1	1.1	1.0	1.0	1.0	1.1
	24	1.0	1.0	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.0	0.8
		1984-1998 (first half)											
look-back	**1**	1.0	1.1	1.1	0.9	1.0	0.9	1.1	1.2	1.3	1.0	1.2	1.2
	3	1.1	1.2	1.1	1.0	1.1	1.0	1.1	1.2	1.3	1.0	1.3	1.5
	6	1.2	1.1	1.0	1.1	1.0	1.0	1.3	1.3	1.1	1.3	1.5	1.5
	9	1.1	1.0	1.0	1.0	0.9	0.9	1.2	1.2	1.3	1.2	1.4	1.3
	12	1.1	1.1	1.0	1.0	0.9	0.8	1.2	1.3	1.2	1.3	1.4	0.9
	24	1.0	1.0	1.0	0.9	0.9	0.6	1.2	1.2	1.2	1.1	1.1	0.5
		1999-2013 (second half)											
look-back	**1**	1.0	0.9	0.9	0.8	1.0	1.0	1.0	1.1	0.9	0.9	1.1	0.9
	3	1.0	1.0	1.1	1.1	1.2	1.1	1.0	1.0	1.1	1.2	1.0	0.9
	6	1.0	1.1	1.1	1.0	1.1	1.2	1.0	1.1	1.0	1.0	0.9	0.9
	9	0.9	1.0	1.0	1.0	1.1	1.3	1.0	1.0	0.9	0.9	0.8	1.1
	12	1.0	1.0	1.0	1.0	1.0	1.5	0.9	0.9	0.9	0.7	0.7	1.2
	24	1.1	1.1	1.1	1.2	1.3	1.5	0.9	0.9	1.0	1.0	1.0	1.0

Table 28: Quotients of Sharpe ratios for RAMOM returns adjusted by momentum-specific risk and simple RAMOM returns, pooled across interest rate futures over different time intervals.

	Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
1984-2013 (whole period)												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	1.1	1.1	1.3	1.1	1.1	1.2	0.9	1.1	1.3	1.1	1.1	1.3
3	1.1	1.1	1.2	1.1	1.1	1.2	1.0	1.2	0.9	1.2	1.1	1.4
6	1.1	1.1	1.0	1.0	0.9	1.2	1.1	1.0	1.1	1.1	1.0	1.8
9	1.0	1.0	1.0	0.9	0.9	1.2	1.0	1.1	1.2	1.1	1.1	1.6
12	1.0	1.0	1.0	1.0	1.0	1.2	1.1	1.1	1.1	1.0	1.1	2.0
24	1.1	1.1	1.1	1.1	1.1	0.0	1.1	1.2	1.4	1.4	1.3	0.0
1984-1998 (first half)												
look-back												
1	1.0	1.0	1.1	1.1	1.1	1.1	1.0	1.1	1.2	1.2	1.2	1.3
3	1.0	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.0	1.2	1.2	1.2
6	1.1	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.0	1.1	1.0	1.2
9	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.1	1.1	1.1	1.0	1.1
12	1.0	1.0	1.0	1.0	1.1	0.9	1.1	1.1	1.1	1.0	1.0	1.5
24	1.1	1.0	1.0	0.9	0.9	0.0	1.1	1.1	1.1	1.2	1.1	0.0
1999-2013 (second half)												
look-back												
1	0.0	1.3	0.0	1.1	1.2	1.3	0.0	1.3	0.0	1.0	1.0	1.4
3	1.7	1.0	1.1	1.1	0.9	1.2	0.7	1.4	0.8	1.2	1.0	2.1
6	1.1	1.1	1.2	1.1	0.8	1.6	1.1	1.0	1.2	1.2	1.0	3.5
9	1.0	1.0	1.0	0.8	0.8	2.0	1.1	1.2	1.3	1.1	1.1	4.6
12	1.2	1.0	0.9	0.8	0.9	3.1	1.3	1.2	1.2	1.0	1.3	8.8
24	1.2	1.3	1.4	1.5	1.6	0.0	1.3	1.6	2.0	2.1	2.0	0.0

Table 29: Quotients of Sharpe ratios for RAMOM returns adjusted by momentum-specific risk and simple RAMOM returns, pooled across currency futures over different time intervals.



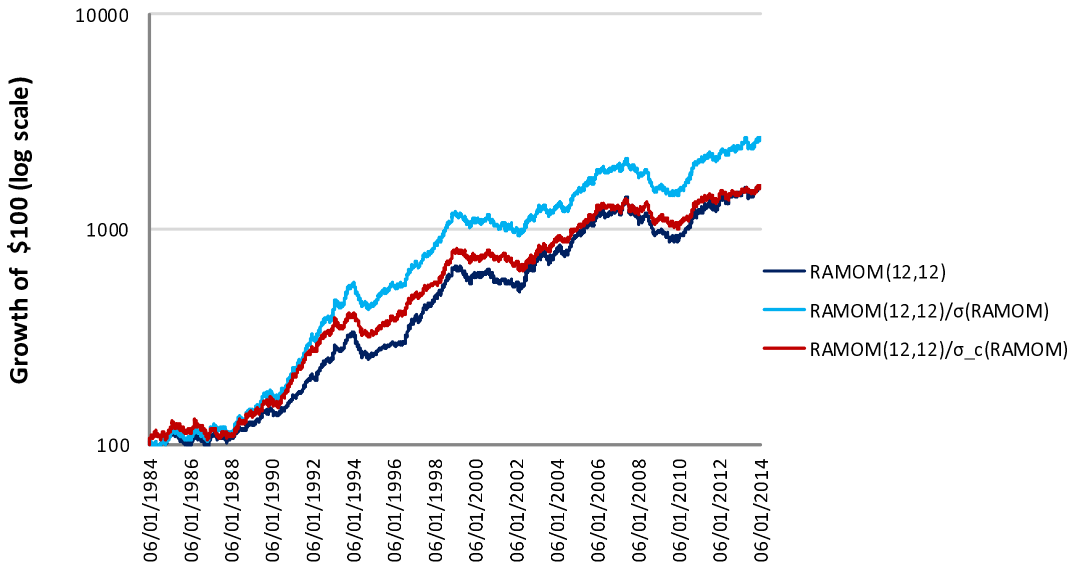


Figure 6: Cumulative excess return of the plain RAMOM strategy and the RAMOM strategy adjusted by the aggregate momentum volatility (denoted vRAMOM in the plot legend) and the class-specific momentum volatilities (denoted vRAMOM_class in the plot legend), January 1984 to January 2014. Plotted are the cumulative excess returns of the diversified RAMOM portfolios. The RAMOM and adjusted portfolios are defined in (3.6), (5.1), and (5.2). Sample period is January 1984 to January 2014. All three return series are normalized to have an identical annualized ex-post volatility of 10%.

		t-stat for β w.r.t. volatility of class-specific RAMOM returns						t-stat for β w.r.t. volatility of pooled RAMOM returns					
		holding (months)						holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
Equities													
look-back	1	-0.3	-0.2	1.0	1.4	1.8	1.9	-0.6	-0.2	-3.1	-3.6	-3.5	-1.2
look-back	3	0.6	2.0	3.5	2.4	3.4	1.5	-1.6	-2.3	-4.3	-4.3	-4.4	-1.2
look-back	6	1.5	3.3	4.0	3.2	2.5	1.1	-2.6	-4.1	-4.7	-4.5	-3.0	-0.5
look-back	9	2.8	3.0	2.7	2.4	2.8	0.9	-3.8	-4.0	-4.1	-2.9	-2.1	0.0
look-back	12	2.0	2.5	1.7	2.5	3.0	0.5	-3.6	-4.0	-3.1	-2.2	-1.8	0.1
look-back	24	1.1	1.5	1.5	1.0	0.4	-0.7	-0.7	-1.0	-1.2	-0.8	-0.3	2.4
Commodities													
look-back	1	-1.8	-0.4	0.4	-0.9	-1.0	-0.2	2.0	1.2	-2.1	-0.9	-0.3	0.6
look-back	3	1.6	1.0	0.3	-0.9	-0.4	-0.6	0.2	-0.8	-1.3	-0.2	0.1	1.2
look-back	6	0.7	0.1	-1.0	-0.6	0.1	-0.2	-0.7	-0.9	-1.0	-0.9	0.7	1.5
look-back	9	-0.5	-1.1	-0.6	-0.2	0.2	-0.1	-0.3	-0.3	-1.2	0.0	1.0	1.7
look-back	12	0.4	-0.4	-0.1	0.1	-0.1	-0.2	-1.9	-1.0	-0.2	0.8	0.9	1.1
look-back	24	-0.7	-1.0	-1.4	-1.5	-1.5	-0.3	1.8	2.0	1.6	1.2	0.8	0.2
Bonds													
look-back	1	0.4	-2.1	-1.2	-0.1	-2.0	-1.0	0.7	3.0	1.2	0.7	1.5	2.4
look-back	3	-2.4	-1.2	-0.6	-0.6	-2.3	0.0	2.1	0.7	-1.0	-0.4	-0.2	0.6
look-back	6	-1.6	-1.2	-0.6	-1.2	-1.1	0.5	0.2	-1.1	-0.8	0.6	0.7	0.0
look-back	9	-0.3	-0.6	-0.4	0.4	0.5	1.1	0.5	0.6	1.6	1.7	1.2	-1.2
look-back	12	-0.4	-0.5	0.6	1.1	0.9	1.5	0.7	0.9	1.2	1.0	0.7	-2.6
look-back	24	0.1	0.3	1.3	1.9	1.7	0.3	0.4	0.2	-0.7	-1.9	-3.2	-4.2
Interest Rates													
look-back	1	-0.6	-1.2	1.1	1.0	0.8	2.0	0.8	2.9	0.4	1.2	-0.6	-0.2
look-back	3	-0.6	0.2	0.9	1.3	2.0	2.3	1.7	-0.2	-1.2	-1.5	-2.5	-2.1
look-back	6	0.3	0.0	0.9	1.3	2.2	1.7	-0.1	-0.5	-0.3	0.0	-1.1	-2.3
look-back	9	-0.6	0.1	1.2	1.1	1.3	1.6	1.6	0.9	0.7	0.2	-0.2	-2.7
look-back	12	1.0	0.9	1.5	1.6	1.4	1.1	0.5	0.0	-0.3	-0.4	-0.5	-3.5
look-back	24	1.3	1.5	1.2	1.5	1.4	0.7	-1.5	-1.8	-2.3	-3.0	-4.2	-5.4
Currencies													
look-back	1	-0.6	-0.9	-1.3	0.0	-0.1	-0.5	1.0	0.7	-0.6	-0.4	-0.6	0.0
look-back	3	1.5	-1.8	0.5	0.4	-0.5	-1.1	-1.3	0.9	-0.1	0.0	1.1	0.8
look-back	6	-0.4	0.7	0.4	0.5	0.5	-0.6	-0.3	-0.4	-0.9	0.1	1.6	0.8
look-back	9	0.2	-0.4	-0.1	0.1	0.1	-0.5	-0.7	-0.3	0.1	1.8	2.1	0.3
look-back	12	-0.6	-0.4	-0.3	-0.1	-0.5	-0.5	-1.1	0.1	1.1	1.8	1.2	-0.4
look-back	24	-1.1	-2.2	-2.5	-1.7	-1.1	-1.5	0.2	0.4	-0.1	-0.7	-1.2	0.1

Table 30: t-statistics of the beta coefficients from regressing class-specific RAMOM 12-day returns on the class-specific momentum volatility (left panel) and aggregate momentum volatility (right panel), both volatilities are lagged by 12 days. Reported are t-statistics of beta coefficients from the regressions 12-day RAMOM returns, pooled across a given asset class (equity, commodities, bonds, interest rates, or currencies) on $\sigma^{\mathrm{RAMOM}}_{t,-12}(k_1, k_2)$ and $\sigma^{\mathrm{RAMOM}}_{t-12,c}(k_1, k_2)$.

		t-stat for β w.r.t. volatility of class-specific RAMOM returns						t-stat for β w.r.t. volatility of pooled RAMOM returns					
Equities													
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	11.3	14.4	13.6	19.3	18.3	25.9	-0.9	-1.6	-1.8	-2.1	-2.2	-1.0
look-back	**3**	11.7	19.8	21.2	21.8	26.2	30.3	-0.8	-2.1	-1.3	-1.9	-1.3	-1.1
look-back	**6**	13.6	18.3	21.4	26.3	28.4	30.8	-0.7	-1.0	-1.2	-1.7	-2.1	-1.4
look-back	**9**	15.0	17.7	21.7	24.4	28.4	33.2	-0.7	-1.4	-1.2	-2.0	-1.8	-1.3
look-back	**12**	14.3	16.9	19.2	25.6	29.5	34.6	-0.2	-0.6	-1.4	-1.8	-2.3	-1.3
look-back	**24**	17.6	22.5	25.9	29.0	28.4	31.5	-0.2	-0.2	-0.2	-0.7	-0.9	-1.2
Commodities													
look-back	**1**	10.5	12.4	15.7	19.3	19.1	25.3	1.2	1.5	0.5	-0.1	-0.1	1.0
look-back	**3**	13.3	20.1	21.8	24.4	24.4	25.7	1.3	0.7	0.3	0.4	-0.1	0.5
look-back	**6**	16.2	22.3	23.4	25.5	27.3	27.4	1.5	0.6	0.3	0.0	-0.6	-0.2
look-back	**9**	15.5	20.1	23.1	23.6	24.6	30.0	1.3	0.9	0.3	-0.7	-1.0	-0.3
look-back	**12**	19.0	22.0	23.4	23.7	25.6	27.5	0.2	-0.1	-0.4	-0.6	-0.5	-0.5
look-back	**24**	21.4	20.7	21.9	22.3	20.2	19.3	0.4	-0.1	-0.7	-1.0	-1.1	-1.7
Bonds													
look-back	**1**	15.2	12.4	15.0	17.4	19.1	28.6	-2.2	-0.8	-0.3	0.0	-1.6	-1.3
look-back	**3**	17.0	20.2	29.1	29.9	30.3	39.0	-1.2	0.4	0.4	-0.4	-2.0	-2.8
look-back	**6**	22.2	28.2	30.0	33.8	34.3	49.1	0.2	0.5	-0.1	-1.1	-2.8	-2.2
look-back	**9**	23.3	26.8	28.6	31.7	35.3	51.5	-0.4	-0.3	-1.0	-2.1	-2.8	-3.0
look-back	**12**	20.8	23.9	27.8	30.5	35.8	49.0	-0.9	-0.8	-2.2	-2.8	-2.9	-3.2
look-back	**24**	31.8	34.9	35.8	36.7	37.3	49.6	-1.7	-1.7	-1.7	-1.8	-2.3	-2.8
Interest Rates													
look-back	**1**	13.2	12.7	16.5	16.1	13.7	27.4	0.0	0.7	2.3	2.8	1.2	-0.7
look-back	**3**	15.5	16.7	24.3	24.6	27.0	35.7	2.1	3.4	2.2	1.1	-1.2	-2.4
look-back	**6**	16.2	21.3	24.3	25.1	25.5	30.7	2.0	2.5	1.3	0.5	-0.4	-1.0
look-back	**9**	16.1	18.3	19.6	20.7	22.9	27.1	1.4	1.2	0.9	0.5	0.6	0.0
look-back	**12**	14.6	17.1	18.6	20.4	24.8	28.3	1.8	0.9	0.7	0.4	0.1	0.1
look-back	**24**	17.2	18.7	21.5	22.4	24.5	31.4	0.7	0.3	0.0	-0.1	-0.2	-1.1
Currencies													
look-back	**1**	13.1	12.3	17.2	20.7	21.8	25.5	-0.1	-1.2	-0.5	-1.4	-2.3	0.1
look-back	**3**	17.4	23.8	30.6	32.3	33.8	45.0	1.0	-1.2	-0.6	-0.9	-0.5	-0.4
look-back	**6**	24.5	31.3	37.7	41.4	44.1	50.5	-1.4	-0.9	-1.1	-1.8	-0.2	-0.5
look-back	**9**	29.0	37.3	43.0	44.8	47.7	54.6	0.3	-0.4	-0.5	-0.1	0.3	-0.8
look-back	**12**	26.5	36.2	39.5	42.2	45.6	53.4	-1.3	-1.0	0.1	0.4	0.3	-0.6
look-back	**24**	33.6	38.4	40.3	39.8	38.0	30.7	-1.1	-2.2	-2.1	-1.3	-1.1	-0.3

Table 31: t-statistics of the beta coefficients from regressing class-specific RAMOM volatility $\sigma^{\mathrm{RAMOM}}_{c,t}$ on lagged by 12 days the class-specific momentum volatility and aggregate momentum volatility: $\sigma^{\mathrm{RAMOM}}_{t,c} = \alpha + \beta_1 \sigma^{\mathrm{RAMOM}}_{t-12,c} + \beta_2 \sigma^{\mathrm{RAMOM}}_{t-12} + \varepsilon_t$.

	Kurtosis(TSMOM)						Kurtosis(RAMOM)/Kurtosis(TSMOM)					
1984-2013 (whole period)												
	holding (months)						holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	17.9	29.7	24.4	28.3	25.6	22.5	0.9	1.0	1.0	0.9	0.9	0.9
3	21.1	19.3	21.9	23.0	18.2	19.1	0.9	1.0	1.0	1.0	1.0	1.0
6	21.6	20.7	23.4	21.5	19.6	19.9	0.7	0.8	0.8	0.8	0.9	0.9
9	18.4	17.4	17.3	17.0	16.8	16.5	0.9	1.0	0.9	0.9	1.0	1.0
12	21.4	18.8	17.2	16.5	16.7	15.9	0.8	0.8	0.9	0.9	0.9	1.0
24	14.1	12.9	12.8	12.6	12.4	13.3	1.0	1.0	1.0	1.1	1.1	1.2
1984-1998 (first half)												
look-back												
1	27.2	37.8	26.6	41.4	35.4	21.6	0.8	0.6	1.1	0.8	0.9	1.2
3	28.5	15.6	27.6	35.6	28.1	20.2	0.6	1.4	1.1	1.0	1.0	1.0
6	38.6	35.0	44.6	39.1	33.4	23.8	0.5	0.6	0.6	0.7	0.8	0.8
9	30.1	26.7	28.2	27.3	25.8	15.5	0.8	0.9	0.8	0.8	0.9	1.0
12	38.5	32.5	28.2	24.9	24.4	14.3	0.6	0.6	0.7	0.8	0.8	0.9
24	17.1	14.2	13.6	12.6	11.7	13.4	0.8	0.9	0.9	0.9	1.0	1.1
1999-2013 (second half)												
look-back												
1	13.0	24.3	21.6	20.7	19.8	21.5	0.9	1.2	1.0	1.1	0.9	0.7
3	16.6	18.1	18.0	16.0	12.4	17.3	1.1	0.9	1.0	1.0	1.0	0.9
6	13.0	13.5	12.8	12.0	11.9	16.7	1.1	1.0	1.0	1.0	1.1	0.9
9	12.5	12.6	12.0	12.0	12.3	14.4	1.0	1.0	1.0	1.1	1.1	1.0
12	13.5	12.5	12.0	12.2	12.5	13.8	0.9	1.0	1.0	1.0	1.0	1.0
24	11.5	10.8	10.9	10.9	11.0	12.2	1.1	1.1	1.1	1.2	1.2	1.3

Table 32: The kurtosis of TSMOM and RAMOM returns, pooled across all 64 instruments over different time intervals.

Kurtosis(adjusted RAMOM) /Kurtosis(RAMOM)

		Adjusting by volatility of pooled RAMOM returns						Adjusting by volatility of class-specific RAMOM returns					
1984-2013 (whole period)													
		holding (months)						holding (months)					
		1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
look-back	**1**	0.9	0.7	0.7	0.9	0.9	1.6	1.1	0.5	0.6	0.5	0.5	0.8
	3	0.8	1.4	1.0	1.8	2.1	1.0	0.7	0.7	0.6	0.8	0.7	0.7
	6	0.9	0.8	1.1	1.6	1.6	1.0	0.7	0.6	0.7	0.8	0.7	0.6
	9	1.2	1.5	1.3	1.3	1.2	0.8	0.8	0.8	0.8	0.7	0.7	0.7
	12	1.2	1.2	1.2	1.1	1.1	0.8	0.7	0.8	0.8	0.8	0.7	0.7
	24	1.1	1.1	0.9	0.9	0.9	0.7	0.8	0.9	0.9	0.9	0.9	0.8
1984-1998 (first half)													
look-back	**1**	0.8	1.1	0.8	1.3	1.1	2.0	1.1	0.6	0.6	0.5	0.5	0.8
	3	0.9	1.9	1.1	2.1	2.3	1.3	0.8	0.8	0.5	0.7	0.6	0.8
	6	1.0	0.9	1.1	1.6	1.7	1.2	0.7	0.5	0.6	0.6	0.6	0.7
	9	1.2	1.6	1.3	1.3	1.2	0.9	0.7	0.8	0.7	0.7	0.7	0.9
	12	1.1	1.1	1.1	1.1	1.0	1.0	0.6	0.7	0.7	0.8	0.7	1.0
	24	1.1	1.2	1.1	1.1	1.0	0.9	0.9	1.1	1.2	1.2	1.2	0.9
1999-2013 (second half)													
look-back	**1**	1.0	0.5	0.6	0.5	0.6	0.9	0.9	0.5	0.6	0.4	0.5	0.6
	3	0.8	0.9	0.8	0.7	1.0	0.9	0.7	0.7	0.6	0.6	0.8	0.6
	6	0.9	0.7	0.8	1.1	1.1	0.9	0.7	0.7	0.7	0.8	0.8	0.7
	9	1.0	1.0	1.1	1.1	1.1	0.9	0.7	0.7	0.8	0.7	0.7	0.7
	12	1.2	1.1	1.2	1.2	1.2	0.8	0.8	0.8	0.8	0.7	0.7	0.7
	24	1.1	1.1	1.0	0.9	0.9	0.7	0.8	0.8	0.7	0.8	0.8	0.7

Table 33: The effect of managing momentum-specific risk on the kurtosis of RAMOM returns, pooled across all 64 instruments over different time intervals.

1984-2013

look-back	t-stat for α holding (months)						t-stat for Market β holding (months)					
	1	**3**	**6**	**9**	**12**	**24**	**1**	**3**	**6**	**9**	**12**	**24**
1	3.5	3.7	5.0	3.8	4.3	3.5	4.9	4.1	2.3	2.6	1.1	1.8
3	4.1	4.1	5.8	5.7	5.1	3.9	4.1	3.0	-0.9	-1.4	-1.9	-1.2
6	3.9	4.7	5.5	5.5	4.5	4.0	3.3	1.8	0.4	-0.4	-0.8	-0.9
9	4.2	5.0	4.9	4.5	3.6	3.7	4.2	2.9	1.7	1.3	2.2	-0.4
12	4.8	5.0	4.5	4.0	3.5	3.9	4.1	2.7	1.7	2.3	1.4	-1.2
24	3.1	3.0	3.5	3.8	3.8	2.4	0.8	0.7	0.3	0.0	-0.3	-1.7

look-back	t-stat for SMB β						t-stat for HML β					
1	-2.2	0.3	-0.6	-0.4	-1.4	-0.4	1.9	0.8	-1.6	-2.1	-2.3	-2.8
3	-0.3	-0.1	-1.0	-0.6	-0.9	-1.0	0.8	-0.4	-1.1	-2.0	-4.0	-4.9
6	-2.1	-2.1	-1.8	-1.3	-0.8	-1.5	0.1	-0.1	-0.7	-2.6	-4.8	-6.0
9	-1.0	-0.6	-0.7	-0.3	-0.1	-1.3	0.4	-0.1	-1.1	-2.4	-3.1	-5.7
12	-0.7	-0.8	-0.3	0.2	-0.3	-0.4	0.2	-0.7	-1.3	-1.0	-2.9	-5.1
24	0.2	0.3	0.7	1.3	1.6	0.2	-4.5	-3.5	-3.3	-3.2	-2.9	-4.1

look-back	t-stat for UMD β						t-stat for RAMOM β					
1	0.7	-3.7	-6.0	-4.3	-1.8	-1.9	80.2	49.4	62.5	54.4	59.5	66.9
3	-4.7	-5.5	-4.2	-2.4	-1.3	-2.1	57.9	57.0	53.1	54.0	65.6	60.3
6	-5.8	-6.4	-4.4	-3.2	-1.4	-1.4	74.1	71.5	68.3	72.9	74.0	60.3
9	-7.6	-5.7	-3.7	-1.7	-1.2	-2.2	81.3	76.7	76.1	74.5	70.4	64.9
12	-6.3	-4.8	-2.7	-1.1	-0.5	-2.1	84.1	83.1	79.3	75.5	73.0	69.3
24	-1.5	-0.6	-0.8	-0.1	1.0	2.1	77.9	75.5	75.9	78.2	81.4	88.1

Table 34: t-statistics of the alpha and beta coefficients from regressing pooled RAMOM daily returns, adjusted by the aggregate volatility (as defined in (5.1)) on the Fama and French four factors and RAMOM daily returns: $\hat{R}_t^{\text{RAMOM}}(k_1, k_2) = \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \beta_5 R_t^{\text{RAMOM}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

		t-stat for α holding (months)						t-stat for Market β holding (months)					
		1	3	6	9	12	24	1	3	6	9	12	24
look-back	1	0.1	3.6	4.5	3.4	4.1	1.3	5.3	2.8	-0.9	-2.4	-3.4	-1.7
	3	1.6	2.9	4.3	5.1	4.0	1.0	2.0	-0.5	-4.4	-4.5	-5.9	-2.5
	6	1.9	3.5	4.0	4.1	2.9	1.2	-1.2	-3.5	-3.3	-3.5	-5.5	-3.1
	9	2.9	3.7	3.4	2.7	1.6	0.7	-2.1	-2.7	-3.3	-4.5	-4.2	-2.5
	12	2.7	2.9	2.6	1.6	1.2	0.9	-2.2	-3.3	-5.6	-5.6	-4.2	-2.7
	24	0.4	0.4	0.1	-0.5	-0.9	-1.1	-6.6	-6.2	-5.9	-5.1	-4.4	-6.6
		t-stat for SMB β						t-stat for HML β					
look-back	1	-1.5	-0.5	-1.4	-1.5	-2.2	-1.8	1.5	0.8	-2.4	-3.2	-2.6	-1.2
	3	-1.9	-1.3	-1.6	-1.0	-1.7	0.0	0.2	-1.0	-0.6	0.1	-0.4	1.1
	6	-3.8	-3.2	-2.2	-2.2	-2.2	-0.5	-0.8	-0.2	0.8	0.5	-0.5	0.1
	9	-2.5	-1.8	-1.6	-1.2	0.3	0.8	0.2	0.3	0.6	-0.1	0.3	0.9
	12	-3.0	-3.0	-1.5	-0.1	0.1	1.3	-0.4	0.4	0.6	1.0	0.9	1.4
	24	0.3	0.6	1.1	2.1	2.5	1.1	0.6	1.5	2.0	2.6	2.3	0.1
		t-stat for UMD β						t-stat for RAMOM β					
look-back	1	0.6	-3.4	-5.5	-5.3	-2.9	-1.5	94.7	58.6	66.9	55.9	58.6	63.6
	3	-5.3	-6.8	-5.2	-1.8	-0.3	0.6	77.2	75.1	64.6	63.2	72.5	63.0
	6	-7.7	-7.5	-4.3	-1.8	-1.2	0.4	99.0	91.1	80.6	82.1	83.3	66.5
	9	-8.5	-6.4	-3.6	-2.0	-0.3	-0.1	101.3	96.9	90.7	88.5	83.2	66.4
	12	-6.6	-4.7	-2.6	-0.3	0.2	0.3	99.2	96.8	91.2	89.3	85.9	71.5
	24	-1.4	0.5	1.4	2.3	2.5	1.0	93.7	90.1	89.3	90.8	89.8	88.7

Table 35: t-statistics from regressing pooled RAMOM daily returns, adjusted by class-specific volatilities (as defined in (5.2)) on the Fama and French four factors and RAMOM daily returns: $\widetilde{R}_t^{\text{RAMOM}}(k_1, k_2, 0.5) = \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \beta_5 R_t^{\text{RAMOM}}(k_1, k_2) + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.

1984-2013

	t-stat for Market β holding (months)						t-stat for SMB β holding (months)					
look-back	1	3	6	9	12	24	1	3	6	9	12	24
1	-2.2	-3.0	-3.2	-4.2	-4.2	-2.3	-1.5	-2.5	-0.7	-0.6	-0.2	-1.0
3	-2.9	-2.5	-2.7	-3.1	-3.0	-2.3	-1.3	-1.8	-0.9	-0.8	-1.1	-1.7
6	-3.8	-3.7	-4.0	-3.7	-2.9	-2.6	-1.3	-0.9	-0.6	-0.7	-1.1	-1.0
9	-4.8	-4.5	-3.8	-2.8	-2.1	-2.7	-1.3	-0.9	-0.7	-1.0	-0.7	-0.5
12	-4.6	-4.3	-3.2	-2.6	-2.5	-2.7	-0.8	-0.7	-0.8	-0.5	-0.5	-0.1
24	-3.9	-3.6	-3.3	-2.9	-2.5	-2.0	-1.6	-1.7	-1.4	-0.9	-0.5	-0.4
	t-stat for HML β						**t-stat for UMD β**					
look-back												
1	-3.4	-4.4	-3.8	-3.7	-3.3	-1.4	-2.9	-2.6	-4.5	-4.6	-4.4	-0.9
3	-3.9	-3.9	-4.1	-3.3	-2.6	-2.0	-3.4	-5.0	-4.7	-4.2	-4.7	-0.7
6	-4.5	-4.2	-3.0	-1.9	-1.4	-1.9	-4.8	-4.6	-3.8	-4.1	-4.2	-0.6
9	-4.5	-3.4	-1.9	-1.3	-0.8	-1.9	-4.5	-4.0	-4.0	-3.8	-2.9	-0.4
12	-3.0	-2.3	-1.2	-0.7	-0.6	-1.8	-5.2	-5.0	-4.2	-3.3	-1.7	-0.2
24	-3.4	-3.3	-3.0	-2.5	-1.9	-1.0	-1.9	-1.3	-1.1	-1.2	-1.4	-1.4

Table 36: t-statistics from regressing aggregate momentum volatility σ_t^{RAMOM} on the Fama and French four factors: $\sigma_t^{\text{RAMOM}} = \alpha + \beta_1 R_t^{MKT} + \beta_2 R_t^{SMB} + \beta_3 R_t^{HML} + \beta_4 R_t^{UMD} + \varepsilon_t$. Factor returns are from the Website of Professor Kenneth French.