Demystifying Time-Series Momentum Strategies: Volatility Estimators, Trading Rules and Pairwise Correlations*

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June 3, 2014

ABSTRACT

Motivated by the recent asset pricing literature that examines the effect of frictions on asset prices, we examine the effect of volatility estimation error, trading rule and pairwise correlations on turnover and performance of time-series momentum strategies from 1974 until 2013. Volatility estimators with desirable theoretical properties, such as range-based estimators, improve the performance of the strategies after transaction costs. Price trend-based momentum trading rules lead to the highest out-of-sample performance, because they reduce portfolio turnover significantly. A weighting scheme that incorporates pairwise correlations sheds light on recent performance drivers and improves performance during the post 2008 financial crisis period.

KEY WORDS: Trend-following; Momentum; Constant-volatility; Volatility-targeting; Volatility-timing; Volatility estimation; Trading rules; Correlation; Diversification; Transaction costs; Turnover.

*Comments by Yoav Git, Nadia Linciano, Stephen Satchell, Laurens Swinkels and participants at the 67th European Meeting of the Econometric Society (Aug. 2013), the IV World Finance Conference (July 2013) and the UBS Annual Quantitative Conference (April 2013) are gratefully acknowledged. Further comments are warmly welcomed, including references to related papers that have been inadvertently overlooked. Financial support from INQUIRE Europe is gratefully acknowledged. The views expressed in this article are those of the authors only and no other representation to INQUIRE Europe or UBS Investment Bank should be attributed. The paper has been previously circulated with the title "Improving Time-Series Momentum Strategies: The Role of Volatility Estimators and Trading Signals".

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1. Introduction

Volatility, correlations and frictions play a key role in real-world portfolio construction. Early work on mean-variance portfolio construction (Markowitz 1952) shows that portfolio weights are inversely related to volatility. Recent theoretical work studies the effect of frictions and turnover on asset prices (see for example Luttmer 1996, Dorn and Huberman 2009). However, few recent empirical asset pricing studies examine the effects of volatility-timing and associated portfolio turnover on portfolio performance. The objective of this paper is to study the effects of the volatility estimation efficiency, the trading rules employed and the pairwise correlations of portfolio constituents on the turnover and performance of time-series momentum strategies.

Time-series momentum strategies, initially studied in the academic literature by Moskowitz, Ooi and Pedersen (2012), are formed by aggregating together long and short positions of assets on a volatility-adjusted basis. They have been claimed by Hurst, Ooi and Pedersen (2013) and Baltas and Kosowski (2013) to be followed by Commodity Trading Advisor (CTA) funds and have recently received increased investor attention because, on one hand, as in previous business cycle downturns, they provided impressive diversification benefits during the financial crisis of 2008, but on the other hand, they have exhibited very poor performance during the subsequent post-crisis period 2009 to 2013. One of the reasons that has been claimed to be responsible for this underperformance has been the increased correlations across markets and asset classes after 2008 (Baltas and Kosowski 2013). To the best of our knowledge, no paper on time-series momentum strategies examines explicitly the effects and benefits from incorporating information from the correlation matrix of the assets into the portfolio weighting scheme. We specifically address this issue both theoretically and empirically.

Our paper makes three main contributions. First, we focus on the effect of volatility estimation error and frictions on the performance of the time-series momentum strategy and hence, document the economic value of using volatility estimators with desirable theoretical properties. In particular, in line with Fleming, Kirby and Ostdiek (2003), we hypothesise that more efficient and precise estimators, than those constructed using daily close-to-close returns, can safeguard against over-trading and therefore reduce the excessive turnover and improve the after costs performance of the strategy. We find that the range-based estimators, which make use of opening, high, low and closing price data do empirically reduce the turnover of the strategy and consequently improve its net of transaction costs performance. The term “range” refers to the daily high-low price difference and its major advantage is that it can even successfully capture the high volatility of an erratically moving price path intra-daily, which happens to exhibit similar opening and closing prices and therefore a low daily return. We employ the range

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1Time-series momentum strategies are genuinely different from the cross-sectional momentum strategies, “winners minus losers”, that have been heavily studied in the academic literature, starting from the works of Jegadeesh and Titman (1993, 2001) in the equity markets. The time-series momentum strategies rely heavily on return serial correlation patterns, whereas the cross-sectional momentum strategy is a long-short zero-cost portfolio of securities with the best and worst relative performance during the lookback period.

2As an indicative example, on Tuesday, August 9, 2011, most major exchanges demonstrated price erratic behaviour, following the previous day’s large losses and the downgrade of the US’s sovereign debt rating from AAA to AA+ by Standard &
estimators of Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991) and Yang and Zhang (2000) and find that the Yang and Zhang (2000) estimator dominates the other estimators, not just because it is theoretically the most efficient range estimator and exhibits the smallest bias when compared to the ex-post realised variance, but also because it reduces the turnover of the strategy by around 10%, hence minimising the costs of rebalancing the portfolio.

The standard time-series momentum trading rule in the literature is the sign of the past return over some lookback horizon such as 12 months (Moskowitz et al. 2012, Baltas and Kosowski 2013). As part of our second main contribution we carry out a detailed methodological investigation of the time-series momentum trading rule. Our analysis shows that the frequency at which a trading rule switches between long and short positions can dramatically affect the portfolio turnover. Intuitively, avoiding the excessive position changes when no significant trend exists can significantly improve the after transaction costs performance of the strategy. We therefore suggest using a trading rule that only instructs taking a long or a short position when the underlying price trend is statistically significant. Avoiding over-trading in this way reduces the turnover of the strategy by two thirds without significantly reducing its before cost Sharpe ratio.

Our third and final contribution is to show that incorporating correlation into portfolio construction and the weighting scheme not only sheds light on the return drivers of time-series momentum strategies, but can also significantly improve their out-of-sample performance. We investigate the interplay between the pairwise correlations of the portfolio constituents and the portfolio volatility and extend the formulation of the standard time-series momentum strategy by introducing a correlation factor in the weighting scheme that increases (decreases) the leverage of portfolio constituents in periods of low (high) average pairwise correlation. This adjustment is shown to genuinely improve the performance of the strategy by safeguarding against crash risk. The improvement is relatively more pronounced over the most recent post-crisis period 2009-2013 during which pairwise correlations across assets and asset classes dramatically increased, thus, diminishing diversification benefits. Thus, our results also shed light on the drivers of the recent underperformance of trend-following CTA strategies.

By using one of the most comprehensive datasets examined to date that includes a large cross-section of 75 futures contracts over a period of 36 years, we are able to study all these effects over several business cycles and draw conclusions about the underlying performance drivers of time-series momentum strategies. Overall, our results imply that the choice of the volatility estimator has a significant impact on portfolio turnover, but the choice of trading rule and the incorporation of pairwise correlation into the weighting scheme can have a more pronounced economically and statistically significant effect on the Sharpe ratio of the strategy after accounting for transaction costs.

This paper is related to three streams of the literature. First, our work builds on recent studies focusing Poor’s late on Friday, August 6, 2011. On that Tuesday, FTSE100 exhibited intra-daily a 5.48% loss and a 2.10% gain compared to its opening price, before closing 1.89% up. An article in the Financial Times entitled “Investors shaken after rollercoaster ride” on August 12 mentions that “...the high volatility in asset prices has been striking. On Tuesday, for example, the FTSE100 crossed the zero per cent line between being up or down on that day at least 13 times...”.

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on momentum patterns in futures markets. Moskowitz et al. (2012), Hurst et al. (2013) and Baltas and Kosowski (2013) study the construction and performance of time-series momentum patterns. Even though genuinely different to time-series momentum patterns, the cross-sectional momentum effects in futures markets (Pirrong 2005, Miffre and Rallis 2007) are also of significant relevance. It is worth noting that none of the existing papers on momentum strategies model explicitly the pairwise correlations of the assets into the weighting scheme.

Second, the paper is related to recent work on the effect of volatility-timing and on the importance of volatility estimation efficiency on dynamic portfolio construction and turnover. Fleming, Kirby and Ostdiek (2001) and more recently Ilmanen and Kizer (2012), Kirby and Ostdiek (2012) and Hallerbach (2012) highlight the benefits of volatility-timing, while Daniel and Moskowitz (2013) and Barroso and Santa-Clara (2014) examine its effect on the performance of cross-sectional equity momentum strategies. Fleming et al. (2003) investigate the performance and turnover benefits for a mean-variance portfolio from using more efficient estimates of volatility. In our paper, we make use of range volatility estimators by Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991) and Yang and Zhang (2000) in order increase the estimation of efficiency of daily estimators. Alizadeh, Brandt and Diebold (2002) investigate the statistical properties of these estimators and show that they generate approximately Gaussian estimates (contrary to return-based volatility estimates that are far from Gaussian) and therefore constitute a more appropriate choice for the calibration of stochastic volatility models using a Gaussian quasi-maximum likelihood procedure.

Finally, our paper is related to a literature on the interplay between investor behaviour, turnover and volatility. Lo and Wang (2009) report that turnover in a given stock is higher when the stock’s (idiosyncratic) volatility is higher. This positive correlation between turnover and volatility across stocks is distinct from the well-known temporal relation between trading activity and volatility (summarized, for example, by Karpoff 1987). In a recent theoretical paper, Dorn and Huberman (2009) present a model in which individuals hold and trade stocks with volatilities commensurate with their attitudes to risk, which they label the preferred risk habitat hypothesis.

The rest of the paper is organized as follows. Section 2 provides an overview of the dataset and Section 3 describes the construction of the time-series momentum strategy, introduces the correlation adjustment and explores the dependence of the strategy’s turnover on volatility estimator and trading rule. The empirical results of the effects of volatility estimator and trading rule on the performance of time-series momentum strategies are presented in Sections 4 and 5 respectively. Section 6 presents our empirical results on the effect of incorporating pairwise correlations in the weighting scheme onto the performance of time-series momentum strategies. Finally, Section 7 concludes.
2. Data Description

The dataset that we use is identical to the one used in Baltas and Kosowski (2013) and consists of daily opening, high, low and closing futures prices for 75 assets across all asset classes: 26 commodities, 23 equity indices, 7 currencies and 19 short-term, medium-term and long-term government bonds; see Table I. It is obtained from Tick Data and the sample period is from December 1974 (not all contracts start in December 1974; Table I reports the starting month and year of each contract) to February 2013. Since the contracts of different assets are traded in various exchanges each with different trading hours and holidays, the data series are appropriately aligned by filling forward any missing prices. Finally and especially for equity indices, we also obtain spot prices from Datastream and backfill the respective futures series for periods prior to the availability of futures data.

Futures contracts are short-lived instruments and are only active for a few months until the delivery date. Additionally, entering a futures contract is, in theory, a free of cost investment and in practice only implies a small (relative to a spot transaction) initial margin payment, hence rendering futures highly levered investments. These features of futures contracts give rise to two key issues that we carefully address below, namely (a) the construction of single continuous price time-series per asset suitable for backtesting and (b) the calculation of holding period returns.

First, in order to construct a continuous series of futures prices for each asset, we appropriately splice together different contracts. Following the standard approach in the literature (e.g. de Roon et al. 2000, Miffre and Rallis 2007, Moskowitz et al. 2012), we use the most liquid futures contract at each point in time and we roll over contracts so that we always trade the most liquid contract (based on daily tick volume). In practice, the most liquid contract is almost always the nearest-to-delivery (“front”) contract up until a few days/weeks before delivery, when the second-to-delivery (“first-back”) contract becomes the most liquid one and a rollover takes place.

An important issue for the construction of continuous price series of a futures contract is the price adjustment on a roll date. The two contracts that participate in a rollover do not typically trade at the same price. If the time-series of these contracts were to be spliced together without any further adjustment, then an artificial non-traded return would appear on the rollover day, which would bias the mean return upwards or downwards for an asset that is on average in contango or backwardation respectively. For that purpose, we backwards ratio-adjust the futures series at each roll date, i.e. we multiply the entire history of the asset by the ratio of the prevailing futures prices of the new and the old contracts. Hence, the entire price history up to the roll date is scaled accordingly so that no artificial return exists in the single data series.

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3de Roon, Nijman and Veld (2000) and Moskowitz et al. (2012) find that equity index returns calculated using spot price series or nearest-to-delivery futures series are largely correlated. In unreported results, we confirm this and find that our results remain qualitatively unchanged without the equity spot price backfill.

4Another price adjustment technique is to add/subtract to the entire history the level difference between the prevailing futures prices of the two contracts involved in a rollover (backwards difference adjustment). The disadvantage of this technique is that it distorts the historical returns as the price level changes in absolute terms. In fact, the historical returns are upwards.
Second, having obtained single price data series for each asset, we need to construct daily excess returns. As already mentioned, calculating futures holding period returns is not as straightforward as it is for spot transactions and requires additional assumptions regarding the initial margin payments. For that purpose, let $F_{t,T}$ and $F_{t+1,T}$ denote the prevailing futures prices of a futures contract with maturity $T$ at the end of months $t$ and $t+1$ respectively. Additionally, assume that the contract is not within its delivery month, hence $t < t+1 < T$. Entering a futures contract at time $t$ implies an initial margin payment of $M_t$ that earns the risk-free rate, $r_f^t$ during the life of the contract. During the course of a month, assuming no variation margin payments, the margin account will have accumulated an amount equal to $M_t \left(1 + r_f^t\right) + (F_{t+1,T} - F_{t,T})$. Therefore, the holding period return for the futures contract in excess of the risk-free rate is:

$$r_{t,t+1}^{\text{margin}} = \left[ M_t \left(1 + r_f^t\right) + (F_{t+1,T} - F_{t,T}) \right] - M_t - r_f^t = \frac{F_{t+1,T} - F_{t,T}}{M_t}$$

If we assume that the initial margin requirement equals the prevailing futures price, i.e. $M_t = F_{t,T}$ then we can calculate the fully collateralised return in excess of the risk-free rate as follows:

$$r_{t,t+1} = \frac{F_{t+1,T} - F_{t,T}}{F_{t,T}}$$

Interestingly, the excess return calculation for a fully collateralised futures transaction takes the same form as a total return calculation for a cash equity spot transaction.

Using equation (2), we construct daily excess close-to-close fully collateralised returns, which are then compounded to generate monthly returns. Table I presents summary monthly return statistics for all assets and asset classes. In line with the futures literature (e.g. see de Roon et al. 2000, Moskowitz et al. 2012), we find that there is large cross-sectional variation in the return distributions of the different assets. In total, 67 out of 75 futures contracts have a positive unconditional mean excess return, 29 of which statistically significant at the 10% level. Currency and commodity futures have insignificant mean returns with only few exceptions. All but four assets have leptokurtic return distributions (fat tails) and, as expected, almost all equity futures have negative skewness. More importantly, the cross-sectional variation in volatility is substantial. Commodity and equity futures exhibit the largest volatilities, followed by the currencies and lastly by the bond futures, which have lowest volatilities in the cross-section.

Table [about here]

3. Methodology

The objective of the paper is to investigate the effect of the efficiency of volatility estimation, the momentum trading rule and the pairwise correlations on portfolio turnover and the profitability of time-series momentum strategies. This section first provides insight into the construction of Moskowitz et al.’s (2012), Hurst et al.’s (2013) and Baltas and Kosowski’s (2013) time-series momentum strategies as an extension of constant-volatility (volatility-targeting) strategies. It then extends the strategy design by explicitly incorporating the pairwise correlations of the constituents. Finally this section explains the dependence of the turnover of the strategy on the efficiency of the volatility estimation and on the nature of the trading rule.

3.1. Constant-Volatility and Time-Series Momentum Strategies

In the previous section we discussed the return construction of a fully collateralised futures position. In practice, the initial margin requirement is a fraction of the prevailing futures price and is typically a function of the historical risk profile of the underlying asset. If we therefore express the initial margin requirement as the product of the underlying asset’s volatility and its futures price, i.e. \( M_t = \sigma_t \cdot F_t, T \), then we can deduce from equation (1) a levered holding period return in excess of the risk-free rate as follows:

\[
r_{lev}^{t+1} = \frac{F_{t+1, T} - F_{t, T}}{\sigma_t \cdot F_t, T} = \frac{1}{\sigma_t} \cdot r_{t+1}
\]

(3)

It is worth noting that the above result can also be interpreted as a long-only constant-volatility strategy, with the target level of volatility being equal to 100%. Denoting by \( \sigma_{tgt} \) a desired level of target volatility, we can generalise the concept to a single-asset constant-volatility (cvol) strategy:

\[
r_{cvol}^{t+1} = \frac{\sigma_{tgt}}{\sigma_t} \cdot r_{t+1}
\]

(4)

The concept of constant-volatility (also known as volatility-targeting or volatility-timing) has been first highlighted by Fleming et al. (2001, 2003) and more recently by Kirby and Ostdiek (2012), Ilmanen and Kizer (2012) and Hallerbach (2012). This series of papers documents that volatility-timing can result in desirable properties for the portfolio like lower turnover and larger Sharpe ratio.

A constant-volatility strategy across assets (to differentiate from the single-asset strategy, we hereafter use capital letters, CVOL) can be simply formed as the average (equally-weighted portfolio) of individual constant-volatility strategies:

\[
r_{CVOL}^{t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} r_{cvol}^{t+1}
\]

(5)

\[
r_{CVOL}^{t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{\sigma_{tgt}}{\sigma_t} \cdot r_{t+1}
\]

(6)
where $N_t$ is the number of available assets at time $t$. The target volatility of each asset remains $\sigma_{tgt}$, however the volatility of the portfolio is expected to be relatively lower due to diversification. In fact, the volatility of the portfolio would only be equal to this upper bound of $\sigma_{tgt}$, if all the assets were perfectly correlated, which is not typically the case. Further details on the effect of pairwise correlations are presented later in this section.

A time-series momentum strategy (TSMOM, hereafter), also known as a trend-following strategy, is an extension to the long-only CVOL strategy of equation (6) and involves both long and short positions. These are determined by each asset’s recent performance over some lookback period, as captured by an appropriately designed trading rule denoted by $X$:

$$r_{t,t+1}^{TSMOM} = \frac{1}{N_t} \sum_{i=1}^{N_t} X_i^j \cdot r_{t,t+1}^{i,cvol}$$

$$= \frac{1}{N_t} \sum_{i=1}^{N_t} X_i^j \cdot \frac{\sigma_{tgt}}{\sigma_i} \cdot r_{t,t+1}$$

Arguably, the nature of the trading rule is critical for the performance of the strategy. We study these effects in detail in Section 5. In its simplest form (as in Moskowitz et al. 2012, Hurst et al. 2013, Baltas and Kosowski 2013), the TSMOM strategy uses the sign of the past 12-month return to determine the type of position for each portfolio constituent, i.e. $X_i^j = \text{sign}[r_{t-12,t}^i]$:

$$r_{t,t+1}^{TSMOM} = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{sign}[r_{t-12,t}^i] \cdot \frac{\sigma_{tgt}}{\sigma_i} \cdot r_{t,t+1}$$

### 3.2. Incorporating Pairwise Correlations

The construction of the TSMOM strategy, which follows the standard specification used by other papers in the literature (Moskowitz et al. 2012, Hurst et al. 2013, Baltas and Kosowski 2013) does not explicitly model the pairwise correlations between futures contracts as part of the weighting scheme. One of the major methodological contributions of this paper is to extend the formulation of the TSMOM strategy by taking into account the average pairwise correlation of portfolio constituents. We then test whether allowing portfolio weights to depend on correlation can increase the out-of-sample performance of the strategy especially in periods, such as the most recent post-crisis period, when correlation increase.

To do so we first investigate the interplay between the portfolio volatility and the pairwise correlations of portfolio constituents. Assume a portfolio of $N$ assets with weights and volatilities denoted by $w_i$ and $\sigma_i$ for $i = 1, \cdots, N$ respectively. To facilitate the notation, we drop the dependence on time in the
following derivations. The portfolio volatility, \( \sigma_P \), is trivially deduced as follows:

\[
\sigma_P = \sqrt{\sum_{i=1}^{N} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} w_i w_j \sigma_i \sigma_j \rho_{i,j}}
\]  

(10)

where \( \rho_{i,j} \) denotes the pairwise correlation between assets \( i \) and \( j \). The TSMOM strategy of equations (8) and (9) consists of assets whose weights are such that they all have an ex-ante volatility equal to a pre-determined target level of volatility \( \sigma_{tgt} \). In particular, each asset has an absolute weight/leverage factor equal to \( \sigma_{tgt}/(\sqrt{N} \cdot \sigma_i) \). Substituting the portfolio weights of equation (10) with this quantity leads to the following result:

\[
\sigma_P = \sigma_{tgt} \sqrt{\sum_{i=1}^{N} \frac{1}{N^2} + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} \frac{1}{N^2} \rho_{i,j}}
\]  

\[
= \frac{\sigma_{tgt}}{N} \sqrt{N + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{i,j}}
\]  

(11)

The double summation \( \sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{i,j} \) is effectively the sum of all the elements of the upper right triangle of the correlation matrix of the assets. Normalising this quantity by the number of pairs formed by \( N \) assets (which can be trivially shown to be \( \frac{N(N-1)}{2} \)) results to the average pairwise correlation of the universe, \( \bar{\rho} \):

\[
\bar{\rho} = 2 \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{i,j}}{N(N-1)}
\]  

(12)

Solving for the double summation and substituting back into equation (11) yields:

\[
\sigma_P = \sigma_{tgt} \sqrt{\frac{1 + (N-1)\bar{\rho}}{N}}
\]  

(13)

The above result lies at the heart of diversification. Given that \( \bar{\rho} \leq 1 \), we deduce that \( \sqrt{\frac{1 + (N-1)\bar{\rho}}{N}} \leq 1 \), and therefore that \( \sigma_P \leq \sigma_{tgt} \). In other words, the fact that correlation across assets is empirically less than perfect results in a portfolio of assets with lower volatility than the target level of volatility of each asset. Thus, when correlation falls, diversification benefits increase and portfolio volatility drops further.

Following from equation (13), we can introduce the average pairwise correlation as a factor that controls the target level of volatility of each asset. When average pairwise correlation increases (decreases) we would optimally want to lower (increase) the per asset target level of volatility. Solving equation (13)
for a dynamic level of target volatility for each asset results in:

\[ \sigma_{tgt} (\hat{\rho}) = \sigma_p \sqrt{N \over 1 + (N-1)\hat{\rho}} \]

(14)

\[ = \sigma_p \cdot CF (\hat{\rho}) \]

(15)

where

\[ CF (\hat{\rho}) = \sqrt{N \over 1 + (N-1)\hat{\rho}} \]

(16)

denotes a correlation factor that adjusts the level of leverage applied to each portfolio constituent as a function of their average pairwise correlation.\(^6\)

Following the above, the generalised TSMOM strategy of equation (8) can be accordingly adjusted by replacing the volatility target for each asset, \(\sigma_{tgt}\) with a time-varying target level of volatility that is determined by a target level of volatility for the overall strategy, \(\sigma_{P, tgt}\) and a measure of the contemporaneous average pairwise correlation of the assets. This gives rise to the correlation-adjusted time-series momentum strategy (TSMOM-CF):

\[ r_{TSMOM-CF, t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} X_i \cdot \frac{\sigma_{P, tgt} \cdot \sigma_i \cdot CF (\hat{\rho}_t) \cdot r_{i, t+1}}{\sigma_{tgt}} \]

(17)

We empirically study the effect of the correlation adjustment in Section 6.\(^6\)

3.3. Turnover Dynamics

The correlation adjustment that was presented above affects all asset weights in the same way, whereas the volatility and any trending behaviour that is captured by the trading rule of the strategy are asset-specific components and affect the portfolio performance and turnover in a distinct manner.

A long-only CVOL strategy involves frequent rebalancing due to the fact that the volatility of the assets changes from time to time and appropriate adjustment is necessary so that each asset maintains the same ex-ante target volatility. In contrast to this, a TSMOM strategy requires rebalancing because of two genuinely different effects: (i) because, similar to the CVOL strategy, the volatility profiles of the portfolio constituents changes and (ii) because the trading rule of some assets changes from positive to negative and vice versa, due to the change in the direction of the trends.

Building on these observations, we next illustrate and disentangle the two channels through which portfolio turnover is affected: (a) the volatility channel and (ii) the trading rule channel (for TSMOM strategies only). We do so using a single-asset paradigm in order to facilitate the exposition of the effects. For simplicity, we assume a single period defined by two rebalancing dates \(t - 1\) and \(t\).

\(^6\)A similar result has been used by S&P Dow Jones Indices for the construction of their S&P Systematic Global Macro Index. For further details see: [http://us.spindices.com/indices/commodities/sp-systematic-global-macro-index](http://us.spindices.com/indices/commodities/sp-systematic-global-macro-index)
First, consider a single-asset constant-volatility strategy, or, alternatively, a single-asset time-series momentum strategy, whose trading rule at dates \( t - 1 \) and \( t \) remains constant (either long or short). The turnover of the strategy will be proportional to the change of the reciprocal of volatility. From equation (4), we can deduce the marginal effect of volatility on portfolio turnover of a single-asset constant-volatility or time-series momentum strategy:

\[
\text{turnover}_{\text{vol}}(t - 1, t) \propto \left| \frac{1}{\sigma_t} - \frac{1}{\sigma_{t-1}} \right| = \left| \Delta \left( \frac{1}{\sigma_t} \right) \right|
\]

Arguably, the smoother the transition between different states of volatility, the lower the turnover of a strategy. However, volatility is not directly observable, but instead needs to be estimated. The objective of the econometrician is to estimate \( \sigma_t \). Volatility is estimated with error, that is \( \hat{\sigma}_t = \sigma_t + \varepsilon_t \), where \( \varepsilon_t \) denotes the estimation error. Consequently, the turnover of the strategy is not only a function of the underlying volatility path, but more importantly of the error inherent in the estimation of the unobserved volatility path.

We hypothesise that larger estimation error (either in magnitude or error variance) results in over-trading and therefore in increased turnover in line with Fleming et al. (2003). Our related conjecture is that a more efficient volatility estimator can significantly reduce the turnover of a CVOL or TSMOM strategy and hence improve the performance of the strategies after accounting for transaction costs. We empirically test this hypothesis in Section 4.

Apart from the volatility component, the rebalancing of a TSMOM strategy could alternatively be due to the switching of a position from long to short or vice versa. In order to focus on the marginal effect of the trading rule, assume that the volatility \( \sigma \) of an asset stays constant between the rebalancing dates \( t - 1 \) and \( t \), but the position switches sign. The marginal effect of a trading rule on the turnover of a single-asset time-series momentum strategy illustrated by the following relationship:

\[
\text{turnover}_{\text{rule}}(t - 1, t) \propto \left| \frac{X_t}{\sigma} - \frac{X_{t-1}}{\sigma} \right| = \left| \frac{\Delta X_t}{\sigma} \right|
\]

For a binomial trading rule, such as the sign of the past return that only takes the values +1 or -1, \( |\Delta X_t| = 2 \), when the position switches sign. In a more general setup, in which the trading rule has more than two states or even becomes a continuous function of past performance, the turnover of the TSMOM strategy would largely depend on the speed or frequency with which the trading rule changes states. The effect is also expected to be magnified for lower volatility assets, such as interest rate futures, since volatility appears in the denominator of equation (19). This leads to the conjecture that a trading rule, which can avoid unnecessary and frequent swings between long and short positions, can significantly reduce the turnover of a TSMOM strategy and therefore improve the performance of the strategy after accounting for transaction costs. We empirically test this hypothesis in Section 5.
4. The Effect of Volatility Estimator

Fleming et al. (2003) show that increasing the efficiency of volatility estimates can result in significant economic benefits for a risk-averse investor that dynamically rebalances a mean-variance optimised portfolio. The efficiency gain is achieved by switching from daily to high-frequency returns in order to estimate the conditional covariance matrix that is used in the optimisation. Extending this finding, we hypothesise that more efficient volatility estimates can significantly reduce portfolio turnover and consequently improve the net of transaction costs profitability of CVOL and TSMOM strategies.

In the absence of high-frequency data in our dataset, we use intraday open, high, low and close daily prices in an effort to increase the efficiency of close-to-close daily volatility estimates. The volatility estimators that make use of open, high, low and close prices are known in the literature as range estimators and have been shown to offer additional robustness against microstructure noise such as bid-ask bounce and asynchronous trading and therefore increase the efficiency of the estimation (Alizadeh et al. 2002).

As we need to move to daily frequency for the description of the estimators, we change the notation for the purposes of this section. Let us denote by $t_m$ the last trading day of month $m$ and let $N_D$ denote the number of trading days over the past month $[t_{m-1}, t_m]$. Additionally, denote the opening, high, low and closing daily log-prices of day $t$ by $O(t), H(t), L(t), C(t)$ and define:

- Normalised Opening price (“overnight jump”): $o(t) = O(t) - C(t - 1)$
- Normalised Closing price: $c(t) = C(t) - O(t)$
- Normalised High price: $h(t) = H(t) - O(t)$
- Normalised Low price: $l(t) = L(t) - O(t)$
- Daily Close-to-Close return: $r(t) = C(t) - C(t - 1)$

The ordinary measure of volatility of an asset over the past month is the **standard deviation of past daily returns** (STDEV) and is given by:

$$\sigma_{\text{STDEV}}^2 (t_{m-1}, t_m) = \frac{261}{N_D - 1} \sum_{i=0}^{N_D-1} [r(t_m - i) - \bar{r}]^2,$$

where $\bar{r}$ denotes the average daily return over the month and 261 is the number of trading days per year.

The STDEV estimator, even though an unbiased estimator, makes only use of daily closing prices and therefore is subject to large estimation error when compared to volatility estimators that make use of intraday information. We next list several range volatility estimators from the literature that have been claimed to increase estimation efficiency.

**Parkinson (1980) estimator** (PK): Parkinson is the first to propose the use of intraday high and low
prices in order to estimate day-\( t \) volatility as follows:

\[
\sigma_{PK}^2(t) = \frac{1}{4\log 2} [h(t) - l(t)]^2
\]  

(21)

This estimator assumes that the asset price follows a driftless diffusion process and is shown (Garman and Klass 1980) to be theoretically around 5.2 times more efficient than STDEV.\(^7\)

**Garman and Klass (1980) estimator** (GK): Garman and Klass extend Parkinson’s (1980) estimator and include opening and closing prices and increase the efficiency of the PK estimator. However, their estimator still assumes a driftless price process and does not take into account the overnight jump. The day-\( t \) GK estimator is given by:\(^8\)

\[
\sigma_{GK}^2(t) = 0.511 [h(t) - l(t)]^2 - 0.019 \{c(t) [h(t) + l(t)] - 2h(t) l(t)\} - 0.383c^2(t)
\]  

(22)

The GK estimator is shown to be 7.4 times more efficient than STDEV (Garman and Klass 1980).

**Rogers and Satchell (1991) estimator** (RS): Rogers and Satchell are the first to introduce an unbiased estimator that allows for a non-zero drift in the price process. However, the RS estimator does not account for the overnight jump. The day-\( t \) RS estimator is given by:

\[
\sigma_{RS}^2(t) = h(t) [h(t) - c(t)] + l(t) [l(t) - c(t)]
\]  

(23)

The RS estimator is not significantly worse in terms of efficiency when compared to the GK estimator. Rogers and Satchell (1991) show that GK is just 1.2 times more efficient than RS, or in other words RS is 6.2 times more efficient than STDEV. Besides, Rogers, Satchell and Yoon (1994) show that the RS estimator can also efficiently deal with time-variation in the drift component of the price process.

The above three range estimators, PK, GK and RS provide daily estimates of volatility. Monthly measures of volatility can be therefore easily deduced by averaging the \( N_D \) intra-monthly estimates:

\[
\sigma_{PK/GK/RS}^2(t_{m-1}, t_m) = \frac{261}{N_D} \sum_{i=0}^{N_D-1} \sigma_{PK/GK/RS}^2(t_{m-i})
\]  

(24)

**Yang and Zhang (2000) estimator** (YZ): None of the above range estimators takes into account the overnight jump of the price. Yang and Zhang are the first to introduce an unbiased volatility estimator that is independent of both the opening jump and the drift of the price process. By construction, such an estimator has to have a multi-period specification, as it needs to incorporate information about the past.

\(^7\)This means that the estimation variance of the PK estimator is theoretically 5.2 times lower than that of STDEV or in other words STDEV needs 5.2 times more data points in order to achieve the same level of efficiency.

\(^8\)The authors also offer a computationally faster expression that eliminates the cross-product terms, but still achieves virtually the same efficiency:

\[
\sigma_{GK}^2(t) = 0.5 [h(t) - l(t)]^2 - (2\log 2 - 1)c^2(t)
\]
The YZ estimator is a linear combination of the STDEV estimator, the RS estimator and the standard deviation of past overnight jump log-returns. The volatility of an asset over the past month as estimated by the YZ estimator is given by:

\[
\sigma_{YZ}^2(t_{m-1}, t_m) = \sigma_{OJ}^2(t_{m-1}, t_m) + k \sigma_{STDEV}^2(t_{m-1}, t_m) + (1 - k) \sigma_{RS}^2(t_{m-1}, t_m)
\]  \(25\)

where \(\sigma_{OJ}(t_{m-1}, t_m)\) is estimated like STDEV in equation (20) using overnight close-to-open log-returns instead of daily close-to-close log-returns. The parameter \(k\) is chosen so that the variance of the estimator is minimised and is shown by Yang and Zhang to be a function of the number of days used in the estimation. Yang and Zhang also show that the YZ estimator is \(1 + \frac{1}{k}\) times more efficient than STDEV. This expression is maximised for a 2-day estimator (i.e. \(N_D = 2\)), when YZ is almost 14 times more efficient than STDEV. For our purposes, a monthly YZ estimator with -on average- \(N_D = 21\) daily returns would be 8.2 times more efficient than the monthly STDEV estimator.

To summarise, the theoretical properties of the four range estimators are reported in Table [II].

Finally, we note that the discretization of a continuous price process will almost always lead to an estimate of the maximum (minimum) price that resides below (above) the true maximum (minimum) of the continuous price path. Consequently, the approximated range \(h(t) - l(t)\) always underestimates the true range and therefore the estimated volatility is downward biased. See Rogers and Satchell (1991) for a discussion on this matter and an effort to bias-correct the RS and GK estimators.

### 4.1. Empirical Comparison of Volatility Estimators

Scaling each asset by a measure of its ex-ante volatility is the key feature of a CVOL or TSMOM strategy as presented in Section [3]. A volatility estimate is always subject to estimation error. Consequently, the ex-post volatility of the asset deviates in practice from the target volatility, because either the ex-ante volatility estimate inherently bears estimation error and/or the volatility of the asset changes dramatically during the holding month. Moreover, the estimation error can give rise to excessive turnover, hence reducing the performance of the strategies after accounting for transaction costs.

In order to empirically assess the performance of the various volatility estimators, we estimate the monthly volatility of the 75 futures contracts of our dataset at the end of each month and estimate two statistics for each asset and for each volatility estimator.

---

\(9\) The parameter \(k\) is chosen using the following equation:

\[
k = \frac{0.34}{1.34 + \frac{N_D+1}{N_D-1}}
\]
First, we calculate the time-series average difference between the ex-ante volatility estimate over the estimation month \((t_{m-1}, t_m]\) and the ex-post realised volatility, \(RV\) (sum of squared daily returns) over the portfolio holding month \((t_m, t_{m+1}]\) for each asset \(i\) and each estimator. We label this statistic the “Forecast Bias”\(^\text{[11]}\):

\[
\text{Forecast Bias (} i, \text{estimator} \rangle = \sum_{\gamma = m} \left| \sigma_{i, RV} (t_{m-1}, t_{m+1}) - \sigma_{i, \text{estimator}} (t_{m-1}, t_m) \right| \tag{26}
\]

Second, for each asset \(i\) and each volatility estimator, we calculate the time-series average difference in the reciprocal of volatility estimates, which is a quantity that, as shown in equation (18), directly affects the turnover of a strategy. For that purpose, we call this statistic the “Volatility Turnover”:

\[
\text{Volatility Turnover (} i, \text{estimator} \rangle = \sum_{\gamma = m} \left| \frac{1}{\sigma_{i, \text{estimator}} (t_{m-1}, t_{m+1})} - \frac{1}{\sigma_{i, \text{estimator}} (t_{m-1}, t_m)} \right| \tag{27}
\]

In principle, the most efficient volatility estimator should minimise both the forecast bias and the volatility turnover statistics for each asset. Given the large cross-sectional deviation in volatility profiles of futures contracts (see Table I), it is impossible to directly compare the statistics across assets. We therefore first rank the five volatility estimators (STDEV, PK, GK, RS YZ) for each asset based on the values of the two statistics and then average the ranks of each estimator across assets in order to obtain the average rank of each estimator.

Figure 1 shows the average rank of each volatility estimator across the 75 futures contracts in the dataset (rank 1: best - minimising statistics, rank 2: worst). The empirical evidence largely supports the theoretical features of the estimators. The STDEV estimator is the least efficient estimator and it produces on average the largest forecast bias and results in excessive turnover. In contrast, the range estimators, due to their superior statistical properties discussed above, reduce both statistics on average across assets with the YZ estimator being by far the best estimator for almost every contract with regards to the volatility turnover statistic.

The results from Figure 1 are important in that they confirm our conjecture that more efficient estimators can indeed reduce the turnover of a CVOL or TSMOM strategy. However, the average rank of the estimators cannot quantify the benefit. For that purpose, Figure 2 presents the percentage drop in the volatility turnover statistic when switching from the STDEV estimator to the YZ estimator, i.e. from the daily estimator to the most efficient range estimator. In other words, we plot in a bar chart the value

\[
100 \cdot \left( \frac{\text{Volatility Turnover (} i, \text{YZ} \rangle}{\text{Volatility Turnover (} i, \text{STDEV} \rangle} - 1 \right)
\]

for each asset \(i\). The empirical evidence is again very strong. Across

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10 The assumption that the realised volatility estimator (Andersen, Bollerslev, Christoffersen and Diebold 2006) provides a good proxy of the volatility process is also made by Brandt and Kinlay (2005) and Shu and Zhang (2006), who carry out volatility estimator comparison analyses.

11 We note that volatility forecasting is not our main objective; see Andersen et al. (2006) for a detailed overview.
all 75 contracts, the time-series average change in the reciprocal of volatility is reduced when a more efficient volatility estimator is used. The effects are, as expected, more pronounced for low volatility contracts, like the interest rate contracts, but even for equity contracts the average drop is above 10%, with the maximum drop being exhibited for the S&P500 contract at about 26%. These results suggest that the large error variance of the STDEV volatility estimator is the main reason for potentially excessive overtrading in a CVOL or TSMOM strategy.

4.2. Performance Evaluation

Next, we evaluate the effect of efficiency in volatility estimation on the performance of CVOL and TSMOM portfolios that are constructed as in equations (6) and (9) respectively. For the target level of volatility of each asset, we follow Moskowitz et al. (2012) and Baltas and Kosowski (2013) and use $\sigma_{tgt} = 40\%$, because this choice is claimed in these studies to generate ex-post portfolio volatilities that are comparable to those of commonly used factors such as those constructed by Fama and French (1993) and Asness, Moskowitz and Pedersen (2013).

Table III presents out-of-sample performance statistics for long-only CVOL strategies that employ a different volatility estimator at a time. The period of volatility estimation is one month; robustness results using longer windows of estimation follow later in this section. The last column of the table reports statistics for a hypothetical strategy that uses the ex-post realised volatility over the holding month to ex-ante scale the futures positions. This strategy cannot be implemented in real-time and only constitutes a benchmark for the purpose of our analysis; for that reason, it is called the “perfect forecast” strategy (PF).

In terms of risk-adjusted returns, all strategies except for PF, deliver a Sharpe ratio of approximately 0.60, which means that the different volatility estimators do not have an economically significant effect on the performance of the strategy before accounting for transaction costs. However, the turnover estimate for the strategy that uses the conventional STDEV estimator drops by about one fifth if one uses a more efficient range volatility estimator. This result supports our conjecture that more efficient volatility estimators can significantly reduce the turnover of constant-volatility strategies hence delivering greater risk-adjusted returns after accounting for transaction costs.

Comparing the results of implementable strategies to the PF benchmark, it is obvious that the strategy with perfect forecast delivers larger risk-adjusted performance with a Sharpe ratio of 0.89, which is significantly different from the Sharpe ratios of the rest of the strategies as deduced by the very low p-values of the Ledoit and Wolf (2008) statistical test. The rejection of the null of equality in Sharpe
ratios shows that there is room of improvement in terms of forecasting accurately increases (decreases) in volatility and therefore better timing the downscaling (upscaling) of positions before an impending drawdown (uptrend). This task is beyond the objectives of this paper. Our main objective is to show that increased estimation efficiency can significantly reduce the turnover and therefore the transaction costs of a CVOL or TSMOM strategy and not to forecast future realised volatility.

Finally, we turn our attention to the effect of efficiency in volatility estimation on the performance of TSMOM strategies. Similarly to the CVOL results above, Table IV shows that the choice of volatility estimator does not have an economically important effect on the Sharpe Ratio of the strategy (before transaction costs) which varies between 0.82 and 0.90. However, range-based volatility estimators reduce portfolio turnover by around a tenth, which is likely to have a significant effect on the after transaction costs performance. Needless to say that a strategy with perfect volatility forecast generates significantly higher Sharpe ratio, equal to 1.30.

4.2.1. Robustness Test - The Effect of Estimation Period

In Tables III and IV we studied the economic value of different volatility estimators using an estimation window of one month. Next, we examine whether the choice of the volatility estimation window affects the marginal benefit of using a range estimator and in particular the YZ estimator over the standard STDEV estimator. Figures 3 and 4 report different performance statistics as well as the turnover benefit for the CVOL and TSMOM strategies respectively for different sizes of the estimation window ranging from one to twelve months.

One of the key insights from Figure 4 is that the Sharpe ratio of the TSMOM strategy is maximised when using a three month estimation window. Although this recommendation is empirically motivated, it lends support to the choice of a three month volatility estimation window in Baltas and Kosowski (2013) and a 60-business day centre of mass of the weights of the exponentially weighted volatility estimator in Moskowitz et al. (2012) and Hurst et al. (2013). Following this result, we will be using an estimation window of three months for the remainder of the paper.

5. The Effect of Trading Rule

Apart from the efficiency of the volatility estimator, the economic performance of a TSMOM trading strategy is also strongly driven by the choice of the trading rule. In this section, we study two different
trading rules in detail and explore how they affect the performance of the strategy. In particular, we compare the standard momentum rule (sign of the past return) with a rule that identifies statistically significant trends and therefore allows exiting a position in the absence of one.

**Return Sign (SIGN):** The ordinary measure of past performance that has been used in the literature (Moskowitz et al. 2012, Hurst et al. 2013, Baltas and Kosowski 2013) as well as in our paper so far is the sign of the past 12-month return. A positive (negative) past return dictates a long (short) position:

\[
\text{SIGN}_{t}^{12M} = \text{sign}[r_{t-12,t}] = \begin{cases} 
+1, & r_{t-12,t} \geq 0 \\
-1, & \text{otherwise}
\end{cases}
\] (28)

**Time-Trend t-statistic (TREND):** Another way to capture the trend of a price series is through fitting a trend on the past 12-month daily futures log-price series using least-squares. The momentum trading rule can then be determined by the significance of the slope coefficient of the trend fit. Assume the linear regression model:

\[
\log (F_t) = \alpha + \beta \cdot \tau + \epsilon_t, \quad \tau \in [t_{12}, t]
\] (29)

The significance of the time-trend is determined by the Newey and West (1987) t-statistic of \( \beta \), \( t(\beta) \), and the cutoff points for the long/short position of the trading rule are chosen to be +2/-2 respectively:

\[
\text{TREND}_{t}^{12M} = \begin{cases} 
+1, & \text{if } t(\beta) > +2 \\
-1, & \text{if } t(\beta) < -2 \\
0, & \text{otherwise}
\end{cases}
\] (30)

The TREND rule effectively instructs staying out of certain assets if no significant price trends are identified. This is the reason why we introduce this trading rule. Our aim is to investigate how the rules sparse trading feature affects the performance and turnover of the TSMOM strategy. This allows us to address the question of whether statistically significant price trends are the main performance drivers of the TSMOM strategy.

### 5.1. Return Predictability

Following Moskowitz et al. (2012) and Baltas and Kosowski (2013), we first assess the amount of in-sample return predictability that is inherent in lagged excess returns or lagged trading rules by running the following pooled panel regressions:

\[
\frac{r_{t-1,t}}{\sigma_{t-1}} = \alpha + \beta \cdot \frac{r_{t-\lambda,t-\lambda}}{\sigma_{t-\lambda-1}} + \epsilon_t
\] (31)

\[\text{Clearly, more sophisticated methodologies in contracting momentum strategies can be devised, but our objective is to maintain a simple and tractable framework and avoid data mining.}\]
and
\[
\frac{r_{t-1,t}}{\sigma_{t-1}} = \alpha + \beta_{\lambda} \cdot X^{1M}_{t-\lambda} + \varepsilon_t
\]  
(32)
where \( \lambda \) denotes the lag that ranges between 1 and 60 months and the lagged one month rule \( X^{1M}_{t-\lambda} \) is either the \( \text{SIGN}_{t-\lambda} \) or the \( \text{TREND}_{t-\lambda} \) rule.

The regressions (31) and (32) are estimated for each lag by pooling together all \( T_i \) (where \( i = 1, \cdots, N \)) monthly returns/trading rules for the \( N = 75 \) contracts. We are interested in the \( t \)-statistic of the coefficient \( \beta_{\lambda} \) for each lag. Large and significant \( t \)-statistics support the hypothesis of time-series return predictability. The \( t \)-statistics \( t(\beta_{\lambda}) \) are computed using standard errors that are clustered by time and asset\(^{13}\) in order to account for potential cross-sectional dependence (correlation between contemporaneous returns of the contracts) or time-series dependence (serial correlation in the return series of each individual contract). Briefly, the variance-covariance matrix of the regressions (31) and (32) is given by (Cameron, Gelbach and Miller 2011, Thompson 2011):

\[
V_{\text{TIME}&\text{ASSET}} = V_{\text{TIME}} + V_{\text{ASSET}} - V_{\text{WHITE}},
\]  
(33)

where \( V_{\text{TIME}} \) and \( V_{\text{ASSET}} \) are the variance-covariance matrices of one-way clustering across time and asset respectively, and \( V_{\text{WHITE}} \) is the White (1980) heteroscedasticity-robust OLS variance-covariance matrix. In fact, Petersen (2009) shows that when \( T >> N \) and \( N >> T \) then standard errors computed via one-way clustering by time (by asset) are close to the two-way clustered standard errors; nevertheless, one-way clustering across the “wrong” dimension produces downward biased standard errors, hence inflating the resulting \( t \)-statistics and leading to over-rejection rates of the null hypothesis. Our panel dataset is unbalanced as not all assets have the same number of monthly observations. On average, we have \( \frac{1}{N} \sum_{i=1}^{N} T_i \approx 319 \) months of data per asset. We can therefore argue that \( T > N \) and we document that two-way clustering or one-way clustering by time (i.e. estimating \( T \) cross-sectional regressions as in Fama and MacBeth 1973) produces similar results, whereas clustering by asset produces inflated \( t \)-statistics that are similar to simple OLS \( t \)-statistics. Two-way clustering is also used by Baltas and Kosowski (2013), who study the return predictability over monthly, weekly and daily frequencies, whereas one-way clustering by time is used by Moskowitz et al. (2012).

Following the above, Figure 5 presents the two-way clustered \( t \)-statistics \( t(\beta_{\lambda}) \) for regressions (31) and (32) and lags \( \lambda = 1, 2, \cdots, 60 \) months. The \( t \)-statistics are almost always positive for the first twelve months for all regressor choices, hence indicating strong momentum patterns of past year’s returns. Moreover, the fact that the TREND rule is sparsely active does not seem to affect its return predictability, which also remains statistically strong for the first twelve months. Apparently, it is the statistical significance of the price trends that drive the documented momentum behaviour. In line with Moskowitz et al. (2012) and Baltas and Kosowski (2013), there exist statistically strong signs of return reversals after the

\[^{13}\text{Petersen (2009) and Gow, Ormazabal and Taylor (2010) study a series of empirical applications with panel datasets and recognise the importance of correcting for both forms of dependence.}\]
first year\textsuperscript{14} that subsequently attenuate and only seem to gain some significance for a lag of around three years.

5.2. Performance Evaluation

Similar to the analysis in Table \text{IV}, which studies the impact of the volatility estimator choice on turnover and out-of-sample Sharpe ratio, in Table \text{V} we examine the economic value of using the SIGN or TREND trading rule. It is clear from the results that the choice of the trading rule does not have an economically significant impact on the Sharpe ratio before transaction costs. The Ledoit and Wolf (2008) p-value shows that the Sharpe ratios of 1.04 and 0.99 are not statistically different from each other. However, the choice of trading rule has a very pronounced effect on turnover, which for the TREND rule is about a third of that resulting from the use of the SIGN rule. This implies that the TREND rule leads to a similar before transaction costs Sharpe ratio, but only requires one third of the trading and associated cost. This is evidently the consequence of staying out of certain assets in periods of statistically insignificant trends.

To gain deeper understanding of this finding for the aggregate strategy, we next study the asset by asset effects on the Sharpe ratio (before transaction costs) and turnover from switching between the two trading rules. Panel A of Figure \text{6} presents the Sharpe ratio of single-asset time-series momentum strategies that use the SIGN rule, as well as the change in the Sharpe ratio from using the TREND instead. Across all assets the change is on average insignificant as the TREND rule leads to an increase for some contracts and a decrease for others. The reductions appear to be concentrated among fixed income and commodities contracts. Panel B of Figure \text{6} shows the effect on turnover from switching between SIGN and TREND rules and supports earlier conclusions that using the latter has an economically large effect on performance net of transaction costs. The reduction in turnover is around two thirds for most contracts (ranging overall between 55\% and 85\%).

To shed further light on the performance drivers of the time-series momentum strategy over time we study the number of contracts that the strategy employs over time. Baltas and Kosowski (2013) show that the time-series momentum strategy has the attractive feature of generating higher performance in

\textsuperscript{14}Part of this severe transition from largely positive and significant t-statistic to largely negative and significant t-statistic after the lag of twelve months can be potentially attributed to seasonal patterns in the commodity futures returns. In undocumented results, we repeat the pooled panel regression only on commodity contracts, after removing contracts that for various reasons might exhibit seasonality, like the agricultural and energy contracts. In general the patterns become relatively less pronounced, but our conclusions remain qualitatively the same and the momentum/reversal transition is still apparent.
recessions rather than in booms. Therefore, we also examine when the strategy is net long or net short across all contracts. Panel A of Figure 7 plots the number of contracts that are traded as a result of using the SIGN or TREND rules. As we can see the TREND rule, due to its sparse activity, consistently leads to a lower number of contracts employed and therefore lower turnover. Panel B of Figure 7 shows that the TSMOM strategy tends to be on average net short during recessions independent of the trading rule used. This result is not obvious since the investment opportunity set for the strategy includes many futures contracts across asset classes, whose prices can be expected to be both pro and counter-cyclical. However, it appears that many of the prices are pro-cyclical and by going short these assets in recessions the TSMOM strategy offers a hedge against an equity market downturn.

Apart from documenting the business cycle performance of the TSMOM strategy, Baltas and Kosowski (2013) also highlight the poor performance of the strategy after 2008. The authors explain that the underperformance can be due to (i) capacity contracts in the futures markets, (ii) a lack of trends for each asset or (iii) increased correlations across assets. They find no evidence of capacity constraints based on two different methodologies, but they do show that correlations between futures markets have increased in the period from 2008 to 2013. To shed further light on this performance decrease Panel A of Figure 8 shows the percentage of contracts for which the SIGN and TREND have the same value (either 1 of -1). It illustrates that there is a drop at the end of the period, which implies that the TREND rule is likely to return more 0’s (hence documenting fewer significantly trending assets). Panel B of Figure 8 presents the percentage of TREND=0 contracts, i.e. contracts that show no signs of significant trend. We confirm that after 2008 the number of contracts without a significant TREND rule increases significantly and almost doubles. This absence of strong momentum patterns is, therefore, one possible reason for the performance decrease in the TSMOM strategy over time. In the following section, we investigate whether the increased correlations-based explanation of the poor performance is also viable.

6. The Effect of Pairwise Correlations

In the specification of the TSMOM strategy that has been used so far in the paper, the pairwise correlation between futures contracts is not explicitly modelled as part of the weighting scheme. As already mentioned in the previous section, one of the hypotheses regarding the recent poor performance of the Commodity Trading Advisor (CTA) funds, which have been shown to employ trend-following strategies (Hurst et al. 2013, Baltas and Kosowski 2013), has been the increase in correlations between markets following the recent financial crisis. The objective of this section is to evaluate the benefits from in-

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15See for example, “CTA trend-followers suffer in market dominated by intervention” by Emma Cusworth, Hedge Funds Review, 10 October 2013.
corporating information from the correlation matrix of the assets into the portfolio construction. As explained in Section 3, this can be achieved by using the contemporaneous level of average pairwise correlation to dynamically adjust the target level of volatility of each asset in the TSMOM strategy. The correlation-adjusted TSMOM strategy of equation (17) is repeated below for convenience, using the SIGN trading rule:

\[ r_{TSMOM-CF}^{t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{sign}\left(r_{i,t-12,t}^{t} \right) \cdot \frac{\sigma_{Ptgt}}{\sigma_{t}} \cdot CF \cdot \left( \frac{\bar{r}_{t}}{\rho_{t}} \right) \cdot r_{i,t+1}^{t} \]  

(34)

Before proceeding with the evaluation of the performance of the correlation-adjusted TSMOM strategy, it is important to first explore how the average pairwise correlation and consequently the correlation factor CF have fluctuated over time. Panel A of Figure 9 plots the average pairwise correlation across all contracts in our sample over time (the values prior to 1983 should be treated with caution as during that period the dataset consists of less than 20 traded contracts as deduced by Panel A of Figure 7). It is apparent that the correlation between contracts increased significantly in 2009 and remained at elevated levels before returning to pre-crisis levels in early 2013. The correlation factor plotted in Panel B of Figure 9 depends on the average pairwise correlation as per equation (16). As expected, the plot shows that incorporating correlation into the weighting scheme acts to reduce leverage in the period 2009-2012 when correlations increase.

[Figure 9 about here]

6.1. Performance Evaluation

Following the above, it is reasonable to ask whether incorporating the level of the average pairwise correlation into the portfolio weighting scheme can add economic value to the TSMOM strategy and more interestingly whether the benefit is pronounced over the whole sample period or after the recent financial crisis when correlations have been relatively higher to historical averages. Table VI reports performance statistics for the standard TSMOM strategy (with a per asset target level of volatility \( \sigma_{tgt} = 40\% \)) and the correlation-adjusted strategy with a portfolio target level of volatility \( \sigma_{Ptgt} = 12\% \).

[Table VI about here]

Several interesting insights emerge from the analysis. Over the full sample, the Sharpe ratio does not increase significantly with a marginal increase from 1.04 to 1.05 when the correlation adjustment is used. However, the use of correlation renders the portfolio more robust to crash risk. This is evidenced by the relatively larger values of performance ratios that measure risk using downside volatility (the so-called Sortino ratio; see Sortino and Van Der Meer 1991) or by the maximum drawdown (the so-called Calmar ratio; see Young 1991). Taking into account pairwise correlations can positively affect the diversification benefits of the portfolio. However, this benefit does not come without cost. As expected the effect of modeling and incorporating correlation does increase portfolio turnover (from 162.38\% to 240.21\%).

21
More importantly, incorporating the information from the correlation matrix has a relatively stronger effect during the period after the 2008 Financial Crisis (January 2009 to February 2013). This has been a period of elevated levels of co-movement across asset classes (as seen in Figure 9) and therefore of diminished diversification benefits. During this period, incorporating correlation in the construction of a time-series momentum strategy has an economically significant effect since it more than doubles the Sharpe ratio from 0.14 to 0.29. Other risk-adjusted performance ratios also increase significantly.

Overall, our results highlight the role that the increased pairwise correlations have played in the recent performance of simple unadjusted TSMOM strategies. The implication for fund managers and investors is two-fold. First, allowing correlation to determine portfolio weights can be beneficial during periods of high correlation. Second, adjusting for correlation can increase trading costs. Therefore, any correlation adjustment has to be carefully incorporated into portfolio construction so that net of transaction cost performance does not suffer.

7. Concluding Remarks

This paper studies the effect of volatility estimation, trading rules and pairwise correlations on the turnover and performance of time series momentum strategies.

We find that range-based estimators, which are known to be more efficient than daily volatility estimators, reduce the turnover of the time-series momentum strategy and therefore improve the net of transaction costs performance. The most efficient range estimator that we study, the Yang and Zhang (2000) estimator, reduces the turnover of the strategy by around 10%. Extrapolating from our results, it is plausible that high-frequency volatility estimators could potentially have additional turnover benefit in line with Fleming et al. (2003). This is an interesting avenue for future research.

Regarding the standard momentum trading rule, which is typically based on the sign of the past return over some lookback horizon, our theoretical investigation shows that the frequency at which a trading rule switches between long and short positions can dramatically affect the portfolio turnover. Therefore, we recommend using a trading rule that only instructs taking a long or a short position when the underlying price trend is statistically significant. We show that avoiding overtrading in this way reduces the turnover of the strategy by 66% without significantly reducing its before cost Sharpe ratio. Intuitively, avoiding the excessive position changes when no significant trend exists can significantly improve the after transaction costs performance of the strategy.

Finally, we introduce a correlation factor in the weighting scheme which extends the standard time-series momentum strategy. This factor increases (decreases) the leverage of the individual assets that comprise the portfolio in periods of low (high) average pairwise correlation. This adjustment is shown to genuinely improve the performance of the strategy by safeguarding against crash risk. The improvement is relatively more pronounced over the most recent post-crisis period 2009-2013 during which pairwise correlations across assets and asset classes dramatically increased, thus, diminishing diversification ben-
efits. Thus, our results shed light on the drivers of the recent underperformance of trend-following CTA strategies.

References


Volatility Estimator Ranks (1: Best, 5: Worst)

The bar chart presents the average rank (across 75 futures contracts) for five volatility estimators, with respect to the absolute change in the reciprocal of estimated 1-month volatility and with respect to the forecast bias of future 1-month realized volatility. The volatility estimators are: (a) standard deviation of past returns (STDEV), (b) Parkinson (1980) estimator (PK), (c) Garman and Klass (1980) estimator (GK), (d) Rogers and Satchell (1991) estimator (RS) and (e) Yang and Zhang (2000) estimator (YZ). The sample period of the dataset is December 1974 to February 2013; for the specific sample period of each contract see Table I.
Figure 2: Effect of Volatility Estimator choice on Reciprocal of Volatility

The figure presents the percentage drop of the average absolute change in the reciprocal of volatility for each of the 75 futures contracts of the dataset when switching from the standard deviation of past returns (STDEV) volatility estimator to the Yang and Zhang (2000) estimator (YZ). The specific sample period of each contract is reported in Table I.
Figure 3: Long-Only Constant Volatility Statistics for Different Estimation Periods

The figure presents the annualised mean return, the Sharpe ratio, the annualised turnover, the skewness and the kurtosis of a long-only constant volatility strategy using Yang and Zhang (2000) volatility estimates across various estimation periods ranging between one to twelve past months. Additionally, the turnover benefit for switching from the standard deviation of past returns (STDEV) volatility estimator to the Yang and Zhang (2000) estimator (this turnover benefit denotes a drop in the turnover, but is presented as a positive number) is also presented.
Figure 4: Time-Series Momentum Statistics for Different Estimation Periods

The figure presents the annualised mean return, the Sharpe ratio, the annualised turnover, the skewness and the kurtosis of a time-series momentum strategy using Yang and Zhang (2000) volatility estimates across various estimation periods ranging between one to twelve past months. Additionally, the turnover benefit for switching from the standard deviation of past returns (STDEV) volatility estimator to the Yang and Zhang (2000) estimator (this turnover benefit denotes a drop in the turnover, but is presented as a positive number) is also presented.
Figure 5: Time-Series Return Predictability

The figure presents the \( t \)-statistics of the pooled regression coefficient from regressing monthly excess returns of the futures contracts on lagged excess returns or lagged excess momentum trading rules. Panel A presents the results when lagged excess returns are used as the regressor, Panel B when the regressor is the lagged SIGN rule and Panel C when the regressor is the lagged TREND rule. The \( t \)-statistics are computed using standard errors clustered by asset and time (Cameron, Gelbach and Miller 2011, Thompson 2011). The volatility estimates are computed using the Yang and Zhang (2000) estimator on a one-month rolling window. The dashed lines represent significance at the 5% and 10% level. The dataset covers the period December 1974 to February 2013.
Figure 6: The Effect of Sparse Trading Rule
Panel A presents annualised Sharpe ratios for univariate time-series momentum strategies with 40% target volatility that use the SIGN of past return as trading rule. Additionally, the change in the Sharpe ratio from applying the TREND sparse trading rule is also presented. Panel B presents the percentage drop in the turnover of each univariate strategy when switching between SIGN and TREND momentum trading rules. The volatility estimator that is used across all strategies is the Yang and Zhang (2000) estimator with an estimation period of three months. The specific sample period of each contract is reported in Table I.
Figure 7: Number of Contracts Traded and Net Positions
Panel A presents the number of contracts that are traded at the end of each month for the SIGN and TREND rules. The SIGN rule is always +1 or -1, hence the number of contracts traded for this rule equals the number of available contracts. Panel B presents the net position of the time-series momentum strategy using the SIGN or the TREND rule. The net position is calculated as the sum of long contracts minus the sum of short contracts and then the result is expressed in percentage of the total number of contracts available at the end of each month. The sample period is December 1975 to February 2013.
Figure 8: Comparison between SIGN and TREND Rules

Panel A presents the 12-month moving average of the percentage of contracts at the end of each month for which SIGN and TREND rules agree (i.e. both long or short for each and every contract). Panel B presents the 12-month moving average of the percentage of available contracts at the end of each month for which the TREND rule does not identify a significant upward or downward trend and is therefore equal to zero. The lookback period for which the rules are generated is 12 months and the sample period is December 1975 (first observation in December 1976 due to the 12-month moving average) to February 2013.
Figure 9: Average Pairwise Correlation and Correlation Factor
Panel A presents the 6-month average pairwise correlation of the available contracts at the end of each month. Panel B presents the correlation factor that is deduced from the average pairwise correlation. The sample period is from February 1975 to February 2013.
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<th>Exchange</th>
<th>From</th>
<th>Mean</th>
<th>Vol</th>
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<td>CME</td>
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<td>TSE</td>
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<td>Korean 3Yr</td>
<td>KRX</td>
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<td>1.63</td>
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(Continued on next page)
Table I: Summary Statistics for Futures Contracts

The table presents summary statistics for the 75 futures contracts of the dataset, which are estimated using monthly fully collateralised excess return series. The statistics are: annualised mean return in %, Newey and West (1987) t-statistic, annualised volatility in %, skewness, kurtosis and annualised Sharpe ratio (SR).

The table also indicates the exchange that each contract is traded at the end of the sample period as well as the starting month and year for each contract. All but 7 contracts have data up until February 2013. The remaining 7 contracts are indicated by an asterisk (*) next to the starting date and their sample ends prior to February 2013: NYSE Composite up to January 2012, ASX SPI 200 up to January 2012, KOSPI 200 up to January 2012, US Treasury Bills 3Mo up to August 2003, Municipal Bonds up to March 2006, Korean 3Yr up to June 2011 and Pork Bellies up to April 2011. The EUR/USD contract is spliced with the DEM/USD (Deutche Mark) contract for dates prior to January 1999 and the RBOB Gasoline contract is spliced with the Unleaded Gasoline contract for dates prior to January 2007, following Moskowitz, Ooi and Pedersen (2012). The exchanges that appear in the table are listed next: CME: Chicago Mercantile Exchange, CBOT: Chicago Board of Trade, ICE: IntercontinentalExchange, Eurex: European Exchange, NYSE Liffe: New York Stock Exchange / Euronext - London International Financial Futures and Options Exchange, MEFF: Mercado Español de Futuros Financieros, BI: Borsa Italiana, MX: Montreal Exchange, TSE: Tokyo Stock Exchange, ASX: Australian Securities Exchange, SEHK: Hong Kong Stock Exchange, KRX: Korea Exchange, SGX: Singapore Exchange, NYMEX: New York Mercantile Exchange, COMEX: Commodity Exchange, Inc.
### Table II: Theoretical Features of Range Volatility Estimators


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<th>Range Estimator</th>
<th>Drift of diffusion process</th>
<th>Overnight Jump</th>
<th>Efficiency vs. STDEV</th>
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<tr>
<td>Parkinson (1980)</td>
<td>Assumes zero drift</td>
<td>Assumes no jump</td>
<td>5.2x</td>
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<tr>
<td>Garman and Klass (1980)</td>
<td>Assumes zero drift</td>
<td>Assumes no jump</td>
<td>7.4x</td>
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<tr>
<td>Rogers and Satchell (1991)</td>
<td>Allows for non-zero drift</td>
<td>Assumes no jump</td>
<td>6.2x</td>
</tr>
<tr>
<td>Yang and Zhang (2000)</td>
<td>Allows for non-zero drift</td>
<td>Allows for jump</td>
<td>8.2x (21-day estimator)</td>
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### Panel A: Performance Statistics

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<th>RS</th>
<th>YZ</th>
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<td>Turnover (%)</td>
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### Panel B: Correlation Matrix

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</table>

### Table III: Long-Only Constant Volatility Strategies and the Effect of Volatility Estimator

The table presents in Panel A performance statistics for various long-only constant volatility strategies that differ between each other in the volatility estimator used: (a) standard deviation of past returns (STDEV), (b) Parkinson (1980) estimator (PK), (c) Garman and Klass (1980) estimator (GK), (d) Rogers and Satchell (1991) estimator (RS) and (e) Yang and Zhang (2000) estimator (YZ). The ex-ante volatility estimation period is one month. For comparison purposes, the last column reports statistics for a strategy that uses the ex-post realised volatility over the holding period, i.e. the Perfect Foresight estimator (PF). The reported statistics are: annualised mean return in %, annualised volatility in %, skewness, kurtosis, CAPM beta with the respective Newey and West (1987) t-statistic, annualised Sharpe ratio, Ledoit and Wolf (2008) p-value for the null hypothesis of equality of Sharpe ratios between all different strategies with the PF strategy, annualised turnover in % and benefit in annualised turnover from switching between STDEV estimator and any other volatility estimator. Panel B reports the unconditional correlation matrix of the above strategies. The dataset covers the period December 1975 to February 2013.
### Panel A: Performance Statistics

<table>
<thead>
<tr>
<th></th>
<th>STDEV</th>
<th>PK</th>
<th>GK</th>
<th>RS</th>
<th>YZ</th>
<th>PF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (%)</td>
<td>14.95</td>
<td>17.95</td>
<td>18.23</td>
<td>18.33</td>
<td>14.72</td>
<td>17.33</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>17.96</td>
<td>19.95</td>
<td>20.27</td>
<td>20.39</td>
<td>17.91</td>
<td>13.34</td>
</tr>
<tr>
<td>Skewness</td>
<td>-2.38</td>
<td>-1.93</td>
<td>-1.88</td>
<td>-1.83</td>
<td>-2.31</td>
<td>-0.03</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>27.88</td>
<td>21.80</td>
<td>20.87</td>
<td>20.35</td>
<td>26.79</td>
<td>3.02</td>
</tr>
<tr>
<td>CAPM Beta</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.08</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.51)</td>
<td>(0.50)</td>
<td>(0.49)</td>
<td>(0.68)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.83</td>
<td>0.90</td>
<td>0.90</td>
<td>0.90</td>
<td>0.82</td>
<td>1.30</td>
</tr>
<tr>
<td>LW p-value (%)</td>
<td>0.08</td>
<td>0.15</td>
<td>0.16</td>
<td>0.14</td>
<td>0.09</td>
<td>$H_0$</td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>250.14</td>
<td>219.49</td>
<td>217.79</td>
<td>219.67</td>
<td>225.00</td>
<td>243.42</td>
</tr>
<tr>
<td>Benefit vs. STDEV (%)</td>
<td>0.00</td>
<td>-12.25</td>
<td>-12.93</td>
<td>-12.18</td>
<td>-10.05</td>
<td>-2.68</td>
</tr>
</tbody>
</table>

### Panel B: Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>STDEV</th>
<th>PK</th>
<th>GK</th>
<th>RS</th>
<th>YZ</th>
<th>PF</th>
</tr>
</thead>
<tbody>
<tr>
<td>STDEV</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PK</td>
<td>0.990</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GK</td>
<td>0.988</td>
<td>0.999</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RS</td>
<td>0.986</td>
<td>0.999</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YZ</td>
<td>0.997</td>
<td>0.992</td>
<td>0.992</td>
<td>0.991</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>PF</td>
<td>0.833</td>
<td>0.850</td>
<td>0.852</td>
<td>0.853</td>
<td>0.838</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table IV: Time-Series Momentum Strategies and the Effect of Volatility Estimator**

The table presents in Panel A performance statistics for various time-series momentum strategies that differ between each other in the volatility estimator used: (a) standard deviation of past returns (STDEV), (b) Parkinson (1980) estimator (PK), (c) Garman and Klass (1980) estimator (GK), (d) Rogers and Satchell (1991) estimator (RS) and (e) Yang and Zhang (2000) estimator (YZ). The ex-ante volatility estimation period is one month. For comparison purposes, the last column reports statistics for a strategy that uses the ex-post realised volatility over the holding period, i.e. the Perfect Foresight estimator (PF).

The reported statistics are: annualised mean return in %, annualised volatility in %, skewness, kurtosis, CAPM beta with the respective Newey and West (1987) t-statistic, annualised Sharpe ratio, Ledoit and Wolf (2008) p-value for the null hypothesis of equality of Sharpe ratios between all different strategies with the PF strategy, annualised turnover in % and benefit in annualised turnover from switching between STDEV estimator and any other volatility estimator. Panel B reports the unconditional correlation matrix of the above strategies. The dataset covers the period December 1975 to February 2013.
<table>
<thead>
<tr>
<th></th>
<th>SIGN</th>
<th>TREND</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (%)</td>
<td>15.28</td>
<td>14.83</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>14.74</td>
<td>14.96</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.20</td>
<td>-0.28</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.99</td>
<td>3.86</td>
</tr>
<tr>
<td>CAPM Beta</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>(0.45)</td>
<td>(0.79)</td>
<td></td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>1.04</td>
<td>0.99</td>
</tr>
<tr>
<td>LW p-value(%)</td>
<td>53.31</td>
<td></td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>162.38</td>
<td>54.76</td>
</tr>
<tr>
<td>Benefit (%)</td>
<td>0.00</td>
<td>-66.2</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.92</td>
<td></td>
</tr>
</tbody>
</table>

Table V: *Time-Series Momentum Strategies and the Effect of Sparse Trading*

The table presents performance statistics for the time-series momentum strategies that differ between each other in the momentum trading rule used: sign of past return (SIGN) versus the t-statistic of a linear trend fit on the price path (TREND). The volatility estimator that is used is the Yang and Zhang (2000) estimator with an estimation period of three months. The reported statistics are: annualised mean return in %, annualised volatility in %, skewness, kurtosis, CAPM beta with the respective Newey and West (1987) t-statistic, annualised Sharpe ratio, Ledoit and Wolf (2008) p-value for the null hypothesis of equality of Sharpe ratios, annualised turnover in %, benefit in annualised turnover from switching between SIGN to TREND rule and finally correlation between the two strategies. The dataset covers the period December 1975 to February 2013.
### Table VI: Time-Series Momentum Strategies and the Effect of Correlation

The table presents performance statistics for the standard time-series momentum strategy and the correlation-adjusted strategy. The volatility estimator that is used is the Yang and Zhang (2000) estimator with an estimation period of three months. The average pairwise correlation is also estimated using a window of three months. The reported statistics are: annualised mean return in %, annualised volatility in %, skewness, kurtosis, annualised Sharpe ratio, annualised Sortino ratio (defined as the ratio of the mean return and the downside volatility), Calmar ratio (defined as the ratio of the mean return and the maximum drawdown), annualised turnover in %, and finally correlation between the two strategies.

Panel A covers the entire sample period December 1975 to February 2013, whereas Panel B covers the most recent period following the financial crisis, from January 2009 to February 2013.

<table>
<thead>
<tr>
<th></th>
<th>Unadjusted</th>
<th>Correlation-Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Full-Sample: December 1978 - February 2013</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (%)</td>
<td>15.28</td>
<td>15.98</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>14.74</td>
<td>15.17</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.20</td>
<td>0.32</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.99</td>
<td>7.29</td>
</tr>
<tr>
<td>Sharpe Ratio (Mean/Volatility)</td>
<td>1.04</td>
<td>1.05</td>
</tr>
<tr>
<td>Sortino Ratio (Mean/Downside Vol.)</td>
<td>1.81</td>
<td>1.98</td>
</tr>
<tr>
<td>Calmar Ratio (Mean/Max Drawdown)</td>
<td>0.57</td>
<td>0.70</td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>162.38</td>
<td>240.21</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td>0.94</td>
</tr>
<tr>
<td><strong>Panel B: After Financial Crisis: January 2009 - February 2013</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (%)</td>
<td>2.00</td>
<td>3.52</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>14.27</td>
<td>12.21</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.07</td>
<td>0.64</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.69</td>
<td>6.86</td>
</tr>
<tr>
<td>Sharpe Ratio (Mean/Volatility)</td>
<td>0.14</td>
<td>0.29</td>
</tr>
<tr>
<td>Sortino Ratio (Mean/Downside Volatility)</td>
<td>0.20</td>
<td>0.46</td>
</tr>
<tr>
<td>Calmar Ratio (Mean/Max Drawdown)</td>
<td>0.12</td>
<td>0.24</td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>119.54</td>
<td>177.31</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td>0.96</td>
</tr>
</tbody>
</table>