Improving Time-Series Momentum Strategies: The Role of Volatility Estimators and Trading Signals*

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ABSTRACT

The aim of this paper is to examine the effect of risk-weighting and of the choice of trading signal on the performance of time-series momentum strategies using a broad dataset of 75 futures contracts over the period 1974-2013. Time-series momentum strategies have received increased attention after they provided again, as in previous business cycle downturns, impressive diversification benefits during the recent financial crisis in 2008. Motivated by recent asset pricing literature that examines the effect of frictions on asset prices and the link between portfolio volatility and turnover, we highlight the effect of the choice of volatility estimator and trading signal on turnover and performance of time-series momentum strategies. We find that by increasing the efficiency of volatility estimation using estimators with desirable theoretical properties, such as range-based estimators, the net of transaction costs performance improves, but the effect on turnover is relatively small compared to that of the trading signal. Momentum trading signals generated by fitting a linear trend on the asset price path maximise the out-of-sample performance by reducing portfolio turnover by about two thirds, hence dominating other momentum trading signals commonly used in the literature.

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KEY WORDS: Trend-following; Time-Series Momentum; Constant Volatility Strategy; Volatility Estimation; Trading Signals; Transaction Costs, Turnover.

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1. Introduction

Volatility and frictions play a key role in real-world portfolio construction. Although early work on mean-variance portfolio construction implies that more volatile assets are penalised and recent theoretical work studies the effect of frictions and turnover on asset prices[1], many recent empirical asset pricing studies do not examine effects of risk weighting or volatility scaling and associated portfolio turnover on portfolio performance. Some recent exceptions to this are the work by Moskowitz, Ooi and Pedersen (2012) and Baltas and Kosowski (2013) who study time series momentum strategies and Barroso and Santa-Clara (2013) and Daniel and Moskowitz (2013) who study the effect of volatility scaling on the performance of cross-sectional momentum strategies.

The aim of this paper is to examine the effect of risk-weighting and choice of volatility estimator on the performance of time-series momentum strategies which have received increased attention after they again provided impressive diversification benefits during the recent financial crisis in 2008 as in previous business cycle downturns. We generalise earlier work on time-series momentum strategies and highlight the effect of the choice of volatility estimator and trading signal on turnover and strategy performance. We then build on the recent literature on volatility forecasting[2] and document the economic value of using volatility estimators with desirable theoretical properties, such as range-based estimators, in the construction of time-series momentum strategies.

By using a long time-series of more than 36 years and a large cross-section of 75 futures contracts we are able to study the effect of different volatility estimators and trading signals over several business cycles and draw conclusions about the underlying performance drivers in one of the most comprehensive datasets examined to date. We show that the choice of volatility estimator has a relatively small impact on portfolio turnover, but that the choice of trading signal can reduce turnover and associated transaction costs by two thirds. This has an economically and statistically significant effect on the Sharpe ratio net of transaction costs.

It is well-known that financial markets exhibit strong momentum patterns. Until recently, the "*cross-sectional momentum*" effect in equity markets (Jegadeesh and Titman 1993, Jegadeesh and Titman 2001) and in futures markets (Pirrong 2005, Miffre and Rallis 2007) has received most of the academic interest. Moskowitz et al. (2012) and Baltas and Kosowski (2013) offer the first concrete piece of empirical evidence on "*time-series momentum*", using a broad daily dataset of futures contracts. Time-series momentum refers to the trading strategy that results from the aggregation of a number of univariate momentum strategies on a volatility-adjusted basis. The univariate time-series momentum strategy relies heavily on the serial correlation/predictability of the asset's return series, in contrast to the cross-sectional momentum strategy, which is constructed as a long-short zero-cost portfolio of securities with the best and worst relative performance during the lookback period[3].

[1] See Luttmer (1996) and Dorn and Huberman (2009) for example.

[2] See Alizadeh, Brandt and Diebold (2002) and Andersen, Bollerslev, Christoffersen and Diebold (2006)) for example.

[3] In the absence of transaction costs, a cross-sectional momentum strategy needs no capital to be constructed. The short portfolio finances the long portfolio and each of these two portfolios consists of a fraction of the available N instruments, for instance when decile portfolios are used, then each of these two portfolios consists of $N/10$ securities. Instead, a time-series

We investigate the dependence of time-series momentum strategy performance on key parameters and focus on (a) the volatility estimation that is crucial for the aggregation of the individual momentum strategies (b) the momentum trading signals. We show that the choice between various available methodologies for these two components of the strategy heavily affects the ex-post momentum profitability and portfolio turnover and is therefore very important for a momentum investor. We study a family of volatility estimators and assess their efficiency from a momentum investing viewpoint.

Finally, we show that traditional daily volatility estimators, like the standard deviation of daily past returns, provide relatively noisy volatility estimates, hence worsening the turnover of the time-series momentum portfolio. We employ the estimators by Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991) and Yang and Zhang (2000). 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[4]. Alizadeh et al. (2002) show that the range-based volatility estimates are approximately Gaussian, whereas return-based volatility estimates are far from Gaussian, hence rendering the former estimators more appropriate for the calibration of stochastic volatility models using a Gaussian quasi-maximum likelihood procedure.

It is found that the Yang and Zhang (2000) estimator dominates the remaining estimators because (a) it is theoretically the most efficient range estimator, (b) it exhibits the smallest bias when compared to the ex-post realised variance and (c) it generates the lowest turnover, hence minimising the costs of rebalancing the momentum portfolio. In unreported results we show that the realized variance estimator is superior among the volatility estimators. This is due to the fact that it uses the complete high-frequency price path information leads to greater theoretical efficiency (Barndorff-Nielsen and Shephard 2002) and therefore is used as the benchmark for the comparison among the rest of estimators. However, we choose to use the Yang and Zhang (2000) estimator, because it constitutes an optimal tradeoff between efficiency, turnover and the necessity of high-frequency data, since it can be satisfactorily computed using daily information on opening, closing, high and low prices. It is shown that the numerical difference between these two estimators is relatively small and consequently they lead to statistically indistinguishable results for the performance of the momentum strategies.

We then focus on the information content of traditional momentum trading signals and then devise new signals that capture a price trend, in an effort to maximise the out-of-sample performance and to minimise the transaction costs incurred by the portfolio rebalancing. The results show that the traditional momentum trading signal, that of the sign of the past return (Moskowitz et al. 2012, Baltas and Kosowski 2013) can induce excessive trading in the absence of a true price trend, hence dramatically increasing

momentum strategy always consists of N open positions, which in the extreme case can even simultaneously be N long or N short positions.

[4] As an indicative example, on Tuesday, August 9, 2011, most major exchanges demonstrated a very erratic behaviour, as a result of previous day's aggressive losses, following the downgrade of the US's sovereign debt rating from AAA to AA+ by Standard & 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...*".

the transaction costs. For that purpose, we introduce another methodology that focuses on the trend behaviour of the price path. Through fitting a linear trend on the price path, we introduce the idea of sparse trading that only instructs taking a position when there exists a statistically significant trend. Momentum strategies that make use of this trend signal have insignificantly different Sharpe ratio to the original strategies, but reduce the amount of trading by two thirds, hence constituting a significant improvement.

This paper is related to three streams of the literature. First, our work builds on recent studies of time-series momentum (Moskowitz et al. 2012, Baltas and Kosowski 2013) and the role of risk-weighting in cross-sectional momentum studies (Barroso and Santa-Clara 2013, Daniel and Moskowitz 2013). Second, we build on recent work on volatility forecasting. Alizadeh et al. (2002) show that the range-based volatility estimates are approximately Gaussian, whereas return-based volatility estimates are far from Gaussian, hence rendering the former estimators more appropriate for the calibration of stochastic volatility models using a Gaussian quasi-maximum likelihood procedure. Third, there is a literature on investor behaviour, turnover and volatility. Time-series momentum strategies are implemented in a systematic way by trend-following funds and CTAs. Nevertheless it is instructive to highlight the links to the behavioural (Barber and Odean 2000) and rational asset pricing literature. Lo and Wang (2009) report that turnover in a given stock is higher when the stock's (idiosyncratic) volatility is higher. The 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, section 3 describes the construction of time-series momentum strategies and the dependence of the strategy's turnover on volatility estimator and trading signal. The empirical results regarding the effects of volatility estimator and trading signal on the performance of time-series momentum strategies are presented in Sections 4 and 5 respectively. Finally, section 6 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: 26 commodities, 23 equity indices, 7 currencies and 19 short-term, medium-term and long-term bonds. It is obtained from Tick Data and the sample period is December 1974 (not all contracts start in December 1974; see Table I below for 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.[5]

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 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 roll over takes place.

An important issue in the construction of continuous price series for 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 one were to splice these contracts 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 ratio-adjust backwards 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.[6]

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_t^f during the life of the contract. During the course of month, assuming no variation margin payments, the margin account will have accumulated an amount equal to $M_t\left(1+r_t^f\right)+(F_{t+1,T}-F_{t,T})$. Therefore, the holding period return for the futures contract in excess of

[5] de 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 observation and that our results remain qualitatively unchanged without the equity spot price backfill.

[6] Another 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 or downwards biased for contracts that are on average in backwardation or contango respectively. Instead, backwards-ratio adjustment only scales the price series, hence it leaves percentage changes unaffected and results in a tradable series that can be used for backtesting.

the risk-free rate is:

$$r^{xs}(t,t+1) = \frac{\left[M_t\left(1+r_t^f\right)+(F_{t+1,T}-F_{t,T})\right]-M_t}{M_t} - r_t^f = \frac{F_{t+1,T}-F_{t,T}}{M_t} \tag{1}$$

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:

$$r^{xs,fc}(t,t+1) = \frac{F_{t+1,T}-F_{t,T}}{F_{t,T}} \tag{2}$$

An interesting observation that follows from the above result is that a total return calculation for a cash equity transaction takes a similar form as an excess return calculation for a fully collateralised futures transaction.

Using equation (2), we construct daily excess close-to-close fully collateralised returns, which are then compounded to generate monthly returns.[7] Table I presents summary monthly return statistics for all assets. 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 monthly 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 very low volatilities in the cross-section.

[Table I about here]

3. Methodology

Our objective is to study the effect of the volatility estimator and momentum signal choice on portfolio turnover and the profitability of time-series momentum strategies. This section illustrates (i) the construction of our time-series momentum strategies as an extension of constant-volatility strategies and (ii) it explains the dependence of the turnover of a time-series momentum strategy on the efficiency of the volatility estimation and on the momentum signals.

[7] Among others, Bessembinder (1992), Bessembinder (1993), Gorton, Hayashi and Rouwenhorst (2007), Miffre and Rallis (2007), Pesaran, Schleicher and Zaffaroni (2009), Fuertes, Miffre and Rallis (2010) and Moskowitz et al. (2012) similarly compute returns as the percentage change in the price level, whereas Pirrong (2005) and Gorton and Rouwenhorst (2006) also take into account interest rate accruals on a fully-collateralized basis.

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 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. $M_t = \sigma_t F_{t,T}$, then we can deduce from equation (1) a leveraged holding period return in excess of the risk-free rate as follows:

$$r^{xs,l}(t,t+1) = \frac{F_{t+1,T} - F_{t,T}}{\sigma_t F_{t,T}} = \frac{1}{\sigma_t} r^{xs,fc}(t,t+1) \tag{3}$$

It is worth noting that equation (3) can also be interpreted as a long-only constant-volatility strategy, with the target volatility being equal to 100%. Denoting by σ_{target} the desired level of target volatility, we can generalise the concept to a single-asset constant-volatility strategy:

$$r^{xs,c.vol}(t,t+1) = \frac{\sigma_{target}}{\sigma_t} r^{xs,fc}(t,t+1) \tag{4}$$

Equation (4) defines a long-only single-asset constant-volatility strategy that can also be interpreted as the return-series of a leveraged futures position. A constant-volatility strategy (CVOL, hereafter) across assets can therefore simply be formed by the average return series of individual constant-volatility strategies:

$$\begin{aligned} r^{xs}_{CVOL}(t,t+1) &= \frac{1}{N_t} \sum_{i=1}^{N_t} r_i^{xs,c.vol}(t,t+1) & (5) \\ &= \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{\sigma_{target}}{\sigma_{i,t}} r_i^{xs,fc}(t,t+1) & (6) \end{aligned}$$

where N_t is the number of available assets at time t. The target volatility of each asset remains σ_{target}, however the volatility of the portfolio is expected to be relatively lower than this threshold due to diversification. In fact, the volatility of the portfolio would only be equal to this upper bound of σ_{target}, if all the assets were perfectly correlated, which is not typically the case.

A time-series momentum strategy (TSMOM, hereafter), also known as as a trend-following strategy, is a simple extension of the long-only constant-volatility strategy of equation (6) that involves both long and short position as defined by each asset's recent performance over some lookback period.

$$\begin{aligned} r^{xs}_{TSMOM}(t,t+1) &= \frac{1}{N_t} \sum_{i=1}^{N_t} signal_{i,t} r_i^{xs,c.vol}(t,t+1) & (7) \\ &= \frac{1}{N_t} \sum_{i=1}^{N_t} signal_{i,t} \frac{\sigma_{target}}{\sigma_{i,t}} r_i^{xs,fc}(t,t+1) & (8) \end{aligned}$$

The above generalises the work of Moskowitz et al. (2012) and Baltas and Kosowski (2013) who take the functional form of the time-series momentum strategy return as given and make a range of assumptions regarding the parameters in equation (8). These studies employ a monthly time-series momentum strategy that takes a long position in assets with a positive past 12-month return and a short position in assets with a negative past 12-month return. Additionally, the target volatility for each asset is chosen to be equal to 40%, in order for the strategy to exhibit ex-post annualised volatility that is comparable to that of commonly used factors such as those of Fama and French (1993) and Asness, Moskowitz and Pedersen (2010). Finally, the volatility of each asset is estimated over the past w months. Following these specifications, equation (8) becomes:

$$r_{TSMOM}^{xs}(t,t+1) = \frac{1}{N_t}\sum_{i=1}^{N_t} sign\left[r_i^{xs,fc}(t-12,t)\right]\frac{40\%}{\sigma_i(t-w,t)} r_i^{xs,fc}(t,t+1) \tag{9}$$

3.2. Turnover Dynamics

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. Instead, a TSMOM strategy requires rebalancing because of two genuinely different effects: (i) because similarly to the CVOL strategy, the volatility profiles of the portfolio constituents changes and (ii) because the trading signal of some assets changes from positive to negative and vice versa, signalling the change in the direction of the trends.

Building on these observations, we next illustrate and disentangle the two channels through which the portfolio turnover of CVOL and most importantly TSMOM strategies is affected: (a) the volatility channel and (ii) the trading signal channel. We do so with a single-asset paradigm in order to facilitate the exposition of effects. Also, assume a single period defined by two rebalancing dates $t-1$ and t.

First, consider a single-asset CVOL strategy, or equally a TSMOM strategy on a single asset whose trading signal 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 therefore deduce that the marginal effect of volatility on portfolio turnover of a single-asset CVOL or TSMOM strategy:

$$turnover_{vol}(t-1,t) \propto \left|\frac{1}{\sigma_t} - \frac{1}{\sigma_{t-1}}\right| = \left|\Delta\left(\frac{1}{\sigma_t}\right)\right| \tag{10}$$

The changes in the reciprocal of volatility over time is the dominant factor of the turnover of both the CVOL and TSMOM strategies. 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 σ_t, but volatility is estimated with error, that is $\hat{\sigma}_t = \sigma_t + \varepsilon_t$, where ε_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.

Below, we test the hypothesis that a greater estimation error (either in magnitude or error variance) results in over-trading and therefore in increased turnover. Along these lines, our 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 of vice versa. In order to focus on the marginal effect of the trading signal, assume that the volatility of an asset stays constant between dates $t-1$ and t equal to σ, but the position switches sign. Along these lines, the marginal effect of trading signal on portfolio turnover of a single-asset TSMOM strategy is schematically given below:

$$turnover_{signal}(t-1,t) \propto \left| \frac{signal_t}{\sigma} - \frac{signal_{t-1}}{\sigma} \right| = \frac{|\Delta signal_t|}{\sigma} \tag{11}$$

For a binomial trading signal, like the sign of the past return, $|\Delta signal_t|$ will always be equal to two. However, in a more general setup where the trading signal has more than two states or in the limit becomes a continuous function of past performance, the turnover of the TSMOM strategy would largely depend on the speed/frequency by which the trading signal changes states. The effect is also expected to be magnified for lower volatility assets, like interest rate futures, since volatility appears in the denominator of equation (11). Our conjecture is that a trading signal that can avoid unnecessary and frequent swings between 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

Before studying the effect of the volatility estimator choice on turnover and the profitability of momentum strategies we briefly review key volatility estimators that have been proposed in the literature including range based estimators. Recently, Alizadeh et al. (2002) discuss the advantages of range-based estimators such as high efficiency and robustness to microstructure noise such as bid-ask bounce and asynchronous trading.

Let t_m denote the last trading day of month m and 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:

$$\begin{aligned}
\text{Normalised Opening price ("overnight jump"): } o(t) &= O(t) - C(t-1) && (12)\\
\text{Normalised Closing price: } c(t) &= C(t) - O(t) && (13)\\
\text{Normalised High price: } h(t) &= H(t) - O(t) && (14)\\
\text{Normalised Low price: } l(t) &= L(t) - O(t) && (15)\\
\text{Daily Close-to-Close return: } r(t) &= C(t) - C(t-1) && (16)
\end{aligned}$$

Following the above, the standard measure of volatility of an asset over the past month, i.e. the **standard deviation of past daily returns** (STDEV), is given by:

$$\sigma^2_{\text{STDEV}}(t_{m-1}, t_m) = \frac{261}{N_D - 1} \sum_{i=0}^{N_D-1} \left[r(t_m - i) - \bar{r} \right]^2, \tag{17}$$

where $\bar{r} = \frac{1}{N_D} \sum_{i=0}^{N_D-1} r(t_m - i)$ 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 swamped by large estimation error when compared to volatility estimators that make use of intra-day information. In an effort to increase the efficiency of the estimation, we next list a number of range volatility estimators from the literature that make use of daily opening, high, low and closing estimators.

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

$$\sigma^2_{\text{PK}}(t) = \frac{1}{4 \log 2} \left[h(t) - l(t) \right]^2 \tag{18}$$

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. 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.

Garman and Klass (1980) estimator (GK): Garman and Klass extend Parkinson's (1980) estimator and include opening and closing prices in an effort to increase the efficiency of the PK estimator. However, their estimator still assumes that a driftless price process and does not take into account the opening jump. The day-t GK estimator is given by:

$$\sigma^2_{\text{GK}}(t) = 0.511 \left[h(t) - l(t) \right]^2 - 0.019 \left\{ c(t) \left[h(t) + l(t) \right] - 2h(t)\, l(t) \right\} - 0.383 c^2(t) \tag{19}$$

Garman and Klass (1980) show that the GK estimator is 7.4 times more efficient than STDEV. The authors also offer a computationally faster expression that eliminates the cross-product terms, but still achieves virtually the same efficiency:

$$\sigma^2_{\mathrm{GK}}(t) = 0.5\left[h(t) - l(t)\right]^2 - (2\log 2 - 1)\, c^2(t) \tag{20}$$

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 opening jump. The day-t RS estimator is given by:

$$\sigma^2_{\mathrm{RS}}(t) = h(t)\left[h(t) - c(t)\right] + l(t)\left[l(t) - c(t)\right] \tag{21}$$

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:

$$\sigma^2_{\mathrm{PK/GK/RS}}(t_{m-1}, t_m) = \frac{261}{N_D} \sum_{i=0}^{N_D-1} \sigma^2_{\mathrm{PK/GK/RS}}(t_{m-1}, t_m) \tag{22}$$

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 day's closing price in order to account for the overnight jump. 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:

$$\sigma^2_{\mathrm{YZ}}(t_{m-1}, t_m) = \sigma^2_{\mathrm{OJ}}(t_{m-1}, t_m) + k\sigma^2_{\mathrm{STDEV}}(t_{m-1}, t_m) + (1-k)\,\sigma^2_{\mathrm{RS}}(t_{m-1}, t_m) \tag{23}$$

where $\sigma_{\mathrm{OJ}}(t_{m-1}, t_m)$ is estimated like STDEV in equation (17) using overnight close-to-open log-returns instead of daily close-to-close log-returns. k is chosen so that the variance of the estimator is minimised and is shown by Yang and Zhang to a function of the number of days, D, used in the estimation:

$$k = \frac{0.34}{1.34 + \frac{D+1}{D-1}} \tag{24}$$

Yang and Zhang also show that the YZ estimator is $1 + \frac{1}{k}$ times more efficient than STDEV. This expression is maximised for 2-day estimator (i.e. $D = 2$), when YZ is almost 14 times more efficient than YZ. For our purposes, an monthly YZ estimator with -on average- $D = N_D = 21$ daily returns would be 8.2 times more efficient than the monthly STDEV estimator.

The theoretical features of the four range estimators are summarised in Table II.

[Table II about here]

The range estimators only require opening, closing, high and low price daily information. Using higher frequency information can be expected to further improve the volatility estimates Andersen et al. (2006). The more high-frequent the data, the finer the discretization of the true price process and the more precise the estimation of the high and low prices. The measurement of realisations of the latent volatility process has the advantage that it does not rely on an explicitly model. As such, the realised volatility provides *the* natural benchmark for forecast evaluation purposes. The discretization of a continuous price process will almost always lead to an estimate of the maximum (minimum) that resides below (above) the true maximum (minimum) of the continuous price path. Consequently, the approximated range $h(t) - l(t)$ will always underestimate the true range and therefore the estimated volatility will be underestimated. See Rogers and Satchell (1991) for a discussion on this matter and an effort to bias-correct the RS and GK estimators.

On the other hand, the advantage of the range is that it can even successfully capture the high volatility of an erratically moving price path during a day that simply happens to exhibit similar opening and closing prices and therefore exhibits a low daily return (this applies for instance to the STDEV estimator, but not to the Realized Volatility (RV) estimator, because of its high-frequency nature). Furthermore, Alizadeh et al. (2002) show that the range-based volatility estimates are approximately Gaussian, whereas return-based volatility estimates are far from Gaussian, hence rendering the former estimators more appropriate for the calibration of stochastic volatility models using a Gaussian quasi-maximum likelihood procedure.

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 would potentially deviate from the target volatility, because either the ex-ante volatility estimate inherently bore an estimation error (that on average is zero for unbiased estimators) and/or the volatility of the asset changed dramatically during the holding month. Moreover, the estimation error can give rise to unnecessary 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, at the end of each month we estimate the volatility of the 75 futures contracts in our dataset and estimate two statistics for each asset and for each volatility estimator.

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 realised ex-post volatility (sum of squared daily returns[8]) over the

[8]The assumption that the RV estimator provides a good proxy of the volatility process is also made by Brandt and Kinlay

portfolio holding month $(t_m, t_{m+1}]$ for each asset and each estimator. We label this statistic the "Forecast Bias"[9]:

$$\text{Forecast Bias}\,(i, estimator) = \sum_{\forall m} \left|\sigma_{i,\text{RV}}\,(t_m, t_{m+1}) - \sigma_{i,estimator}\,(t_{m-1}, t_m)\right| \tag{25}$$

Second, for each asset 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 (10), directly affects the turnover of a strategy. For that purpose, we call this statistic the "Volatility Turnover":

$$\text{Volatility Turnover}\,(i, estimator) = \sum_{\forall m} \left| \frac{1}{\sigma_{i,estimator}\,(t_m, t_{m+1})} - \frac{1}{\sigma_{i,estimator}\,(t_{m-1}, t_m)} \right| \tag{26}$$

In principle, the most efficient volatility estimator should minimise both forecast bias and 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 from the estimator with the smallest statistic (rank 1) to the estimator with the largest statistic (rank 5) and then average the ranks of each estimator across assets in order to get the average rank of each estimator.

Figure 1 shows the average rank of each volatility estimator across the 75 futures contracts in the dataset. 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 biases and causes excessive turnover. In contrast, the range estimators, due to their superior statistical features 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.

[Figure 1 about here]

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 between the STDEV to the YZ estimator. In other words, we plot in a bar chart the value $100 \cdot \left(\frac{\text{Volatility Turnover}(i,\text{YZ})}{\text{Volatility Turnover}(i,\text{STDEV})} - 1\right)$ for each asset i. The empirical evidence is again very strong. Across 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.

(2005) and Shu and Zhang (2006), who carry out volatility estimator comparison analyses.

[9] We note forecasting volatility is not our main objective.

[Figure 2 about here]

4.2. Performance Evaluation

Following the empirical documentation of the benefits of volatility estimation efficiency, we next evaluate the performance of long-only and time-series momentum portfolios as presented in equations (6) and (9) respectively.

Panel A of Table III presents out-of-sample performance statistics for the long-only strategy using various volatility estimators. The last column of the table reports these statistics for a hypothetical strategy that uses the ex-post realised volatility 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 purpose, it is named 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 annualised turnover estimate for the strategy that uses 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 PF delivers greater 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.[10] The rejection of the null of equality in Sharpe ratios shows that there is room of improvement in the form of superior volatility forecasts and in particular in the form of forecasting unexpected increases in volatility and therefore better timing the downscaling of positions before an impending drawdown. 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. A word of caution related to the latter task would be that a volatility forecast that can successfully predict unexpected changes in volatility can lead to better ex-post performance, as shown by the PF results, but at the same time, if predicted volatility changes do not end up realising themselves, this would lead to excessive turnover and lower ex-post returns of the strategy.

[Table III about here]

Above we documented the advantage of superior volatility estimators for long-only CVOL strategies. Next, we turn to the effect of different volatility estimators on the performance of the time-series momentum strategies. Table IV shows that the choice of ex-ante volatility estimators does not have an

[10] SETTINGS FOR LW TEST

economically important effect on the Sharpe Ratio (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 after transaction cost performance.

[Table IV about here]

4.2.1. Robustness Tests - The Effect of Estimation Period

In Tables III and IV we studied the economic value of different volatility estimators based on the assumption of a one month volatility estimation window. Next we examine whether the choice of the volatility estimation window affects the marginal benefit of using the YZ estimator. Figures 3 and 4 report different performance statistics and moments for estimation windows ranging from one to twelve months. They also show the turnover benefit.

[Figure 3 about here]

One of the key insights from Figure 4 is that the Sharpe ratio 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).

[Figure 4 about here]

5. The Effect of Trading Signal

As discussed in the methodology section, the economic performance of a time-series momentum trading strategy is chiefly driven by the volatility estimator and the choice of trading signal. In this section we study two potential trading signals in detail and their effect on the performance of the trading strategy. The two trading signals are return sign and time-trend t-statistic.

Return Sign (SIGN): The standard measure of past performance in the momentum literature as in Moskowitz et al. (2012) and Baltas and Kosowski (2013) is the sign of the past 12-month past return. A positive (negative) past return dictates a long (short) position:

$$\text{SIGN}\left(t_{m-12}, t_m\right) = \begin{cases} +1, & r\left(t_{m-12}, t_m\right) \geq 0 \\ -1, & \text{otherwise} \end{cases} \tag{27}$$

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

$$F_\tau = \alpha + \beta\tau + e_\tau, \quad \tau = 1, \cdots, t_{m-12} - t_m \tag{28}$$

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

$$\text{TREND}(t_{m-12}, t_m) = \begin{cases} +1, & \text{if } t(\beta) > +2 \\ -1, & \text{if } t(\beta) < -2 \\ 0, & \text{otherwise} \end{cases} \tag{29}$$

In order to account for potential autocorrelation and heteroskedasticity in the price process, Newey and West (1987) t-statistics are used.

5.1. Return Predictability

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

$$\frac{r^{xs,fc}(t_{m-1}, t_m)}{\sigma(t_{m-2}, t_{m-1})} = \alpha + \beta_\lambda \frac{r^{xs,fc}(t_{m-\lambda-1}, t_{m-\lambda})}{\sigma(t_{m-\lambda-2}, t_{m-\lambda-1})} + \varepsilon(t_m) \tag{30}$$

and

$$\frac{r^{xs,fc}(t_{m-1}, t_m)}{\sigma(t_{m-2}, t_{m-1})} = \alpha + \beta_\lambda \, signal(t_{m-\lambda-1}, t_{m-\lambda}) + \varepsilon(t_m) \tag{31}$$

where λ denotes the lag that ranges between 1 and 60 months and the lagged $signal(t_{m-\lambda-1}, t_{m-\lambda})$ is either $\text{SIGN}(t_{m-\lambda-1}, t_{m-\lambda})$ or $\text{TREND}(t_{m-\lambda-1}, t_{m-\lambda})$.

The regressions (30) and (31) is estimated for each lag by pooling together all T_i (where $i = 1, \cdots, N$) monthly returns/trading signals for the $N = 75$ contracts. We are interested in the t-statistic of the coefficient β_λ for each lag. Large and significant t-statistics essentially 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,[11] 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 (30) and (31) is given by (Cameron, Gelbach and Miller 2011, Thompson 2011):

$$V_{\text{TIME\&ASSET}} = V_{\text{TIME}} + V_{\text{ASSET}} - V_{\text{WHITE}}, \tag{32}$$

where V_{TIME} and V_{ASSET} are the variance-covariance matrices of one-way clustering across time and asset respectively, and V_{WHITE} is the White (1980) heteroscedasticity-robust OLS variance-covariance matrix. In fact, Petersen (2009) shows that when $T >> N$ ($N >> T$) 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

[11] 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.

inflating the resulting t-statistics and leading to over-rejection rates of the null hypothesis. In our dataset, not all assets have the same number of monthly observations. On average, we have $\bar{T} = \frac{1}{N}\sum_{i=1}^{N} T_i \cong 319$ months of data per asset. We can therefore argue that $\bar{T} > N$ 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 (30) and (31) 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 signal 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. Similarly to the evidence in Moskowitz et al. (2012) and Baltas and Kosowski (2013), there exist statistically strong signs of return reversals after the first year[12] that subsequently attenuate and only seem to gain some significance for a lag of around three years.

[Figure 5 about here]

5.2. Performance Evaluation

Similar to the analysis in Table IV, which studies the impact of the volatility estimator choice on turnover and out of sample Sharpe ratio, in Table V we examine the economic value of using the SIGN or TREND signal. It is clear from the table that the choice of the trading signal 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 signal has a huge effect on turnover which for the TREND signal is about a third of that resulting from the use of the SIGN signal. This implies that the TREND signal leads to a similar before transaction cost Sharpe ratio, but only requires one third of the trading and associated cost.

[Table V about here]

So far we have analysed the economic value of using different signals on the time-series momentum strategy portfolio. To gain a deeper understanding of the effect of trading signals in Figure 6 we study the effect on the Sharpe ratio (before transaction costs) and turnover asset by asset. Panel A of Figure 6

[12]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

shows that the Sharpe ratio of each asset in blue and the change in the Sharpe ratio that would result from the use of the TREND instead of the SIGN signal. Across all assets, on-average, the change is insignificant as the TREND signal 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 6 shows the effect on turnover and supports earlier conclusions that using the TREND instead of the SIGN signal has an economically large effect on performance net of transaction costs. The reduction in turnover is around two thirds for most contracts but ranges from around 55 to around 85 percent.

[Figure 6 about here]

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 recessions rather than in booms. Therefore, we also examine when the strategy is net long or net short on average 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 signals. As we can see the TREND signal consistently leads to a lower number of contracts employed and lower turnover. Panel B of Figure 7 shows that the time-series momentum strategy tends to be on average more short in recessions than in booms independent of the trading signal used. Panel B shows shows the net position (i.e. Long positions - Short positions/(sum of absolute Long + absolute Short)). This results is not obvious since the investment opportunity set for the strategy includes many futures contracts 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 time-series momentum strategy offers a hedge against an equity market downturn and thus diversification benefits.

[Figure 7 about here]

Apart form documenting the business cycle performance of the time-series momentum strategy, Baltas and Kosowski (2013) also highlighted the decrease in the performance after 2008. Baltas and Kosowski (2013) explain that the underperformance can be due to (i) capacity contracts, (ii) a lack of trends for each asset or (iii) increase correlations across assets. The authors do not find 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 signal is likely to return more 0's. Panel B of the figure shows the percentage of TREND=0 contracts, i.e. contracts that show no signs of significant trend. We find that after 2008 the number of contracts without a significant trend signal increases significantly and almost doubles. This is one potential reason for the performance decrease in the time-series momentum strategy over time.

[Figure 8 about here]

6. Concluding Remarks

The time-series momentum strategy refers to the trading strategy that results from the aggregation of various univariate momentum strategies on a volatility-adjusted basis. Such strategies have received increased attention after they again provided impressive diversification benefits during the recent financial crisis in 2008 as in previous business cycle downturns. This paper builds on recent works by Moskowitz et al. (2012) and Baltas and Kosowski (2013) that focus on the profitability of time-series momentum strategies in futures markets and examines the effect of risk-weighting and choice of the trading signal on the performance of time-series momentum strategies. In particular, we highlight the effect of the choice of volatility estimator and trading signal on turnover and strategy performance.

We show that volatility adjustment of the constituents of the time-series momentum is critical for the resulting portfolio turnover. The use of more efficient estimators like the Yang and Zhang (2000) range estimator can substantially reduce the portfolio turnover and consequently the transaction costs for the construction and rebalancing of the portfolio. Momentum trading signals generated by fitting a linear trend on the asset price path maximise the out-of-sample performance while minimizing the portfolio turnover, hence dominating other momentum trading signal commonly used in the literature.

Our results have important implications for portfolio construction and the practical implementation of time-series momentum strategies. Future research on the appropriate sizing of the univariate time-series momentum strategies, instead of ordinary volatility-adjusted aggregation, is potential and promising avenue for future research.

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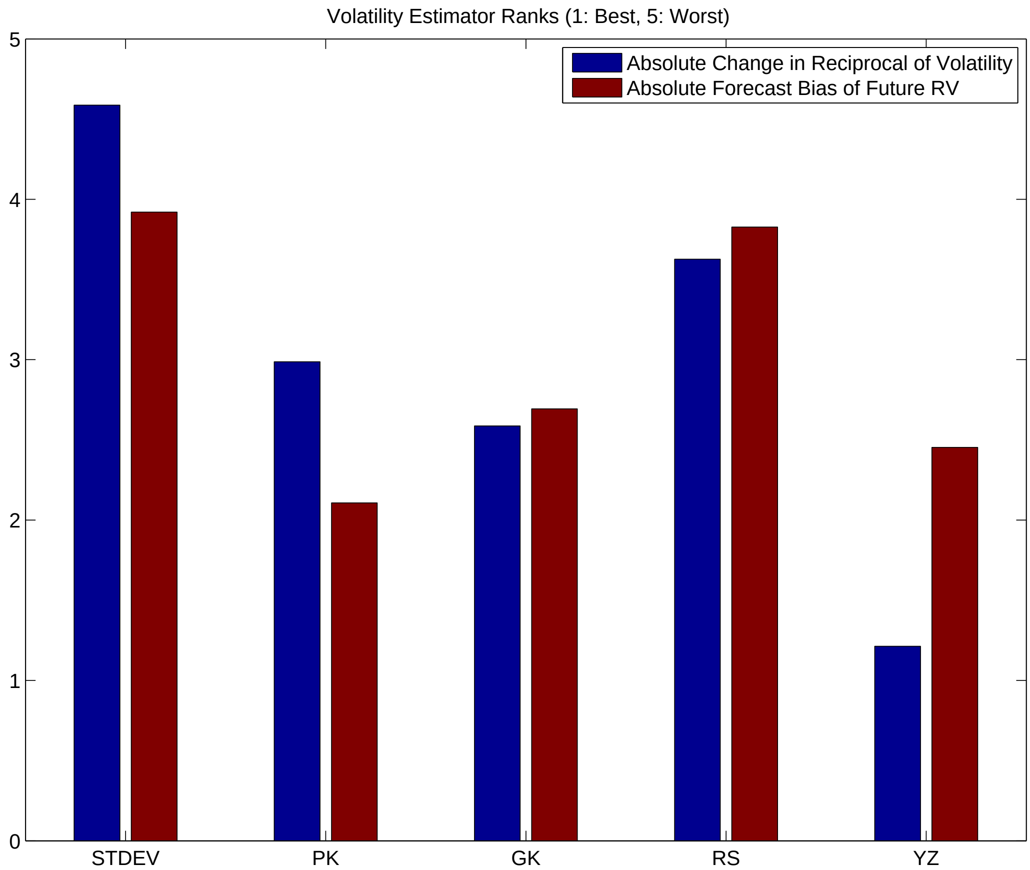

Figure 1: *Volatility Estimator Ranks*

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.

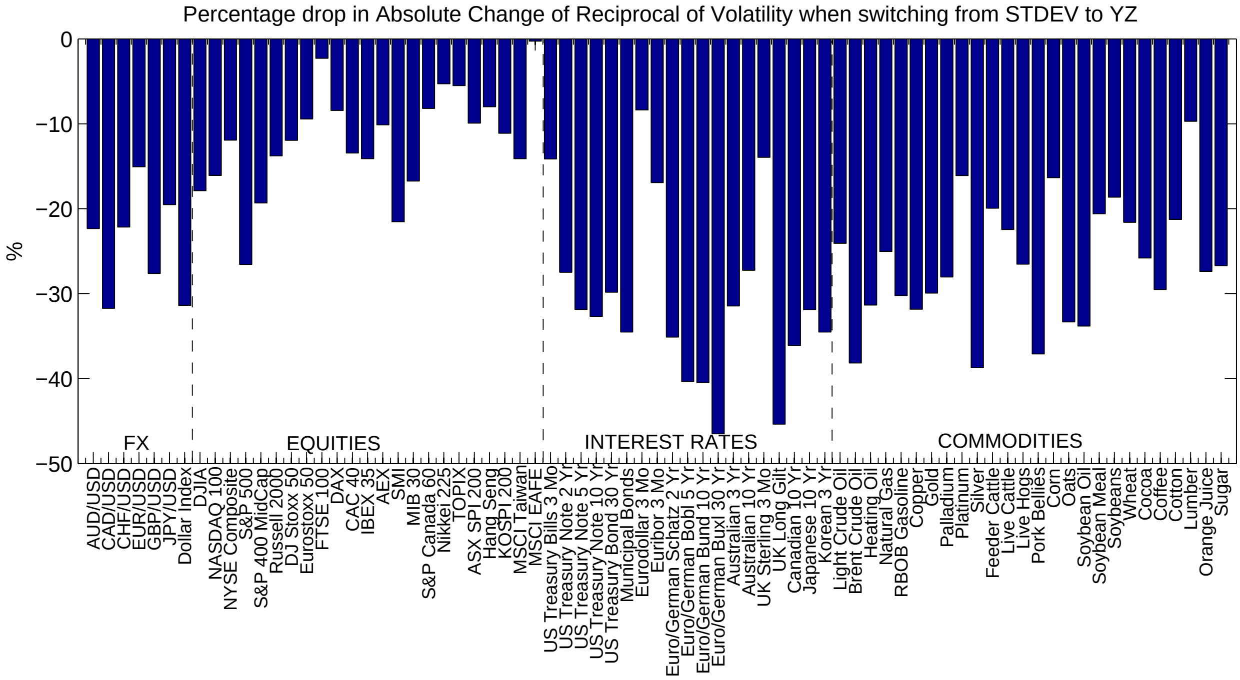

Figure 2: *Effect of Volatility Estimator choice on Reciprocal of Volatility*

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.

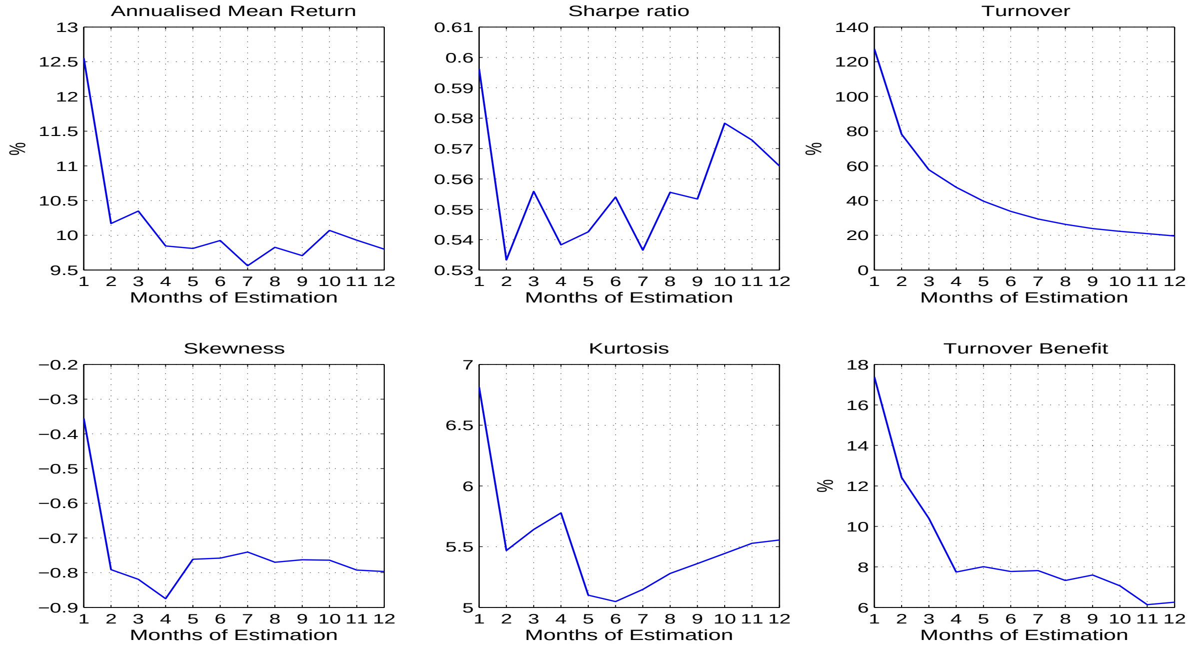

Figure 3: *Long-Only Constant Volatility Statistics for Different Estimation Periods*
The figure presents the annualised mean return, the Sharpe ratio, the annualised turnover, the skewness and the kurtosis of a long-only constant volatility strategy using Yang and Zhang (2000) volatility estimates across 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.

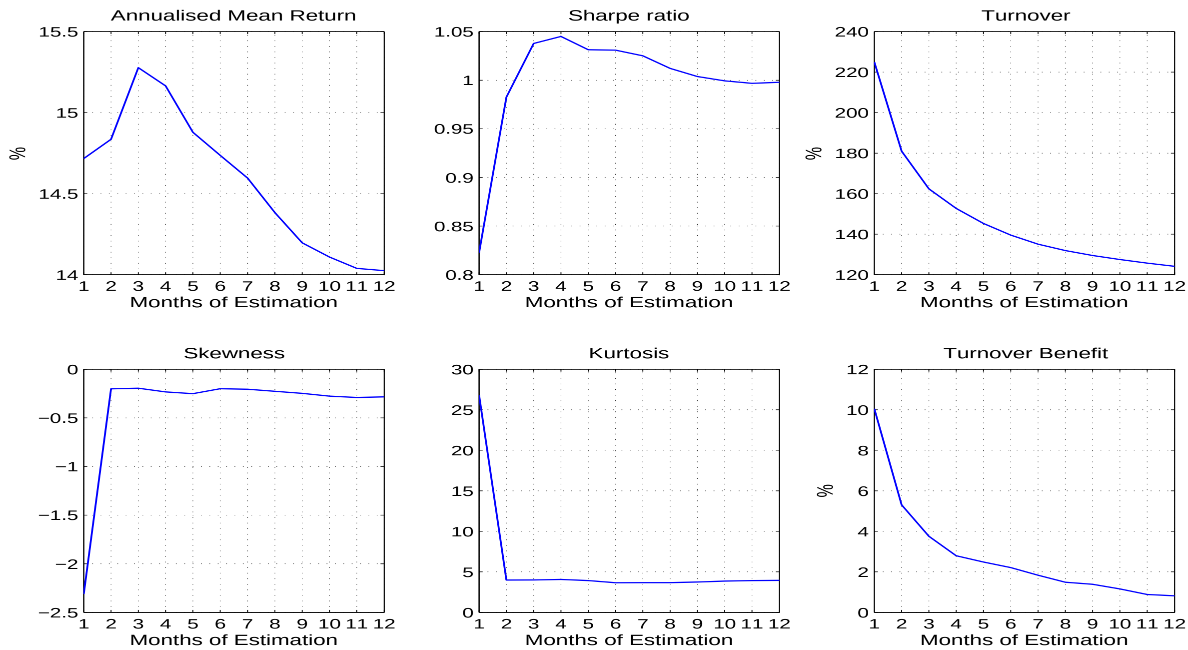

Figure 4: *Time-Series Momentum Statistics for Different Estimation Periods*
The figure presents the annualised mean return, the Sharpe ratio, the annualised turnover, the skewness and the kurtosis of a time-series momentum strategy using Yang and Zhang (2000) volatility estimates across various estimation 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.

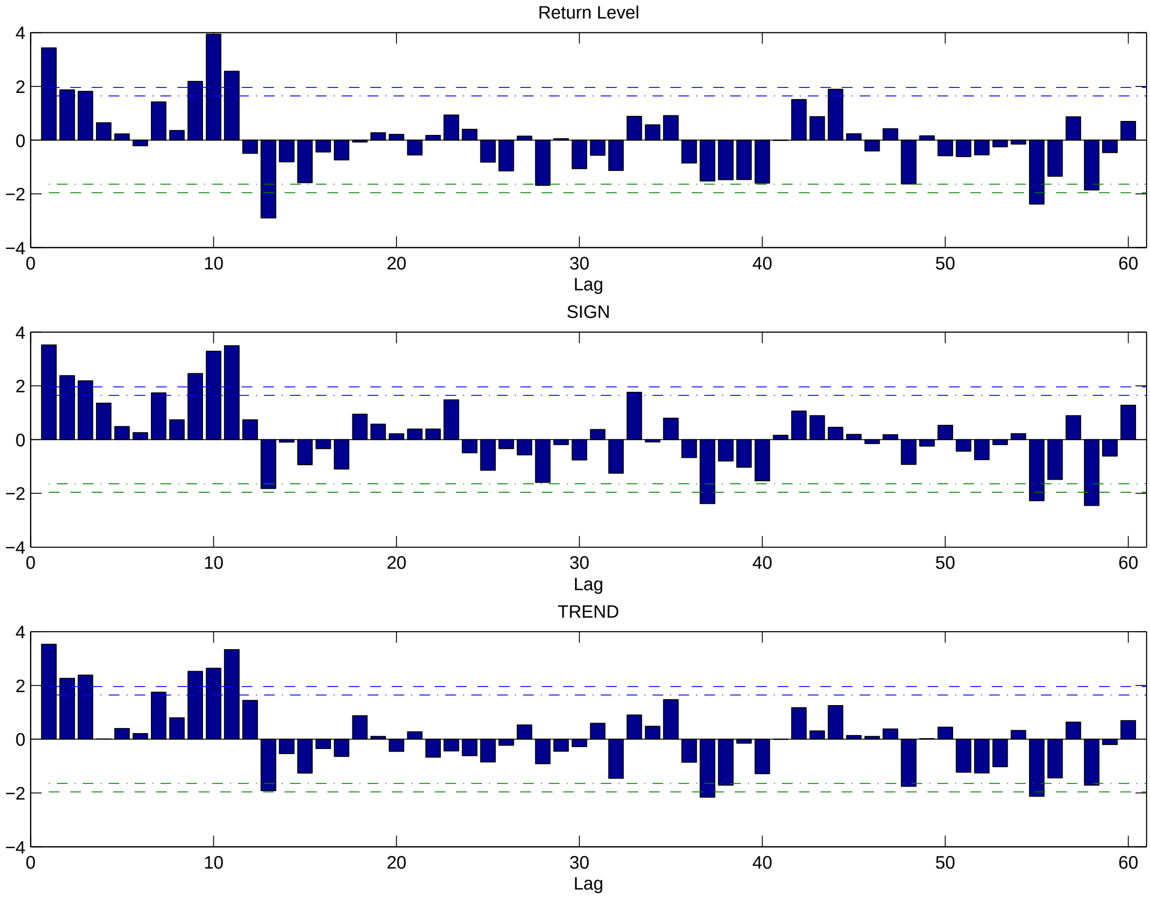

Figure 5: *Time-Series Return Predictability*

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 signals. Panel A presents the results when lagged excess returns are used as the regressor, Panel B when the regressor is the lagged SIGN signal and Panel C when the regressor is the lagged TREND signal. 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% level. The dataset covers the period December 1974 to February 2013.

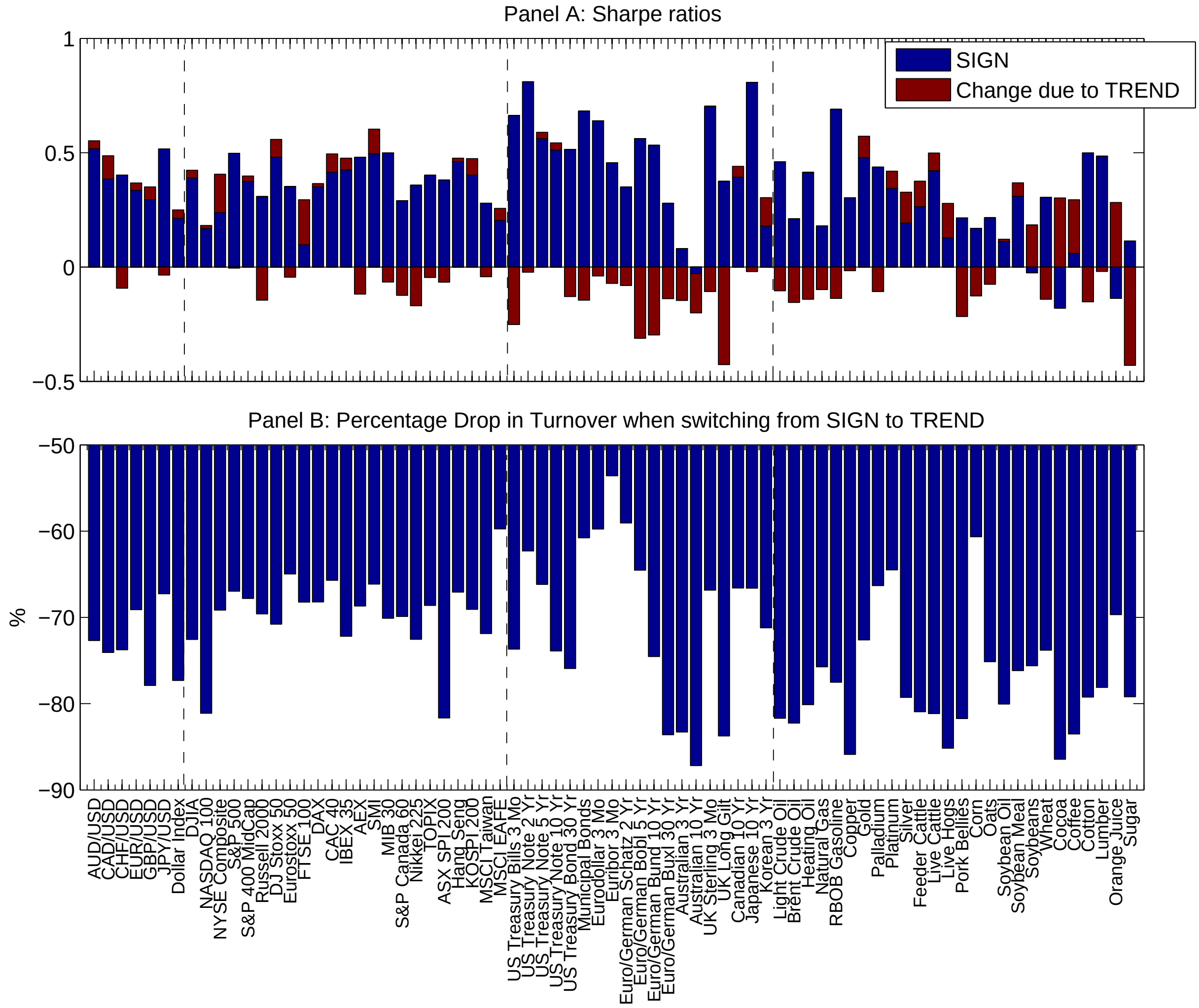

Figure 6: *The Effect of Sparse Trading Signal*

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 signal. Additionally, the change in the Sharpe ratio from applying the TREND sparse trading signal is also presented. Panel B presents the percentage drop in the turnover of each univariate strategy when switching between SIGN and TREND momentum signals. 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.

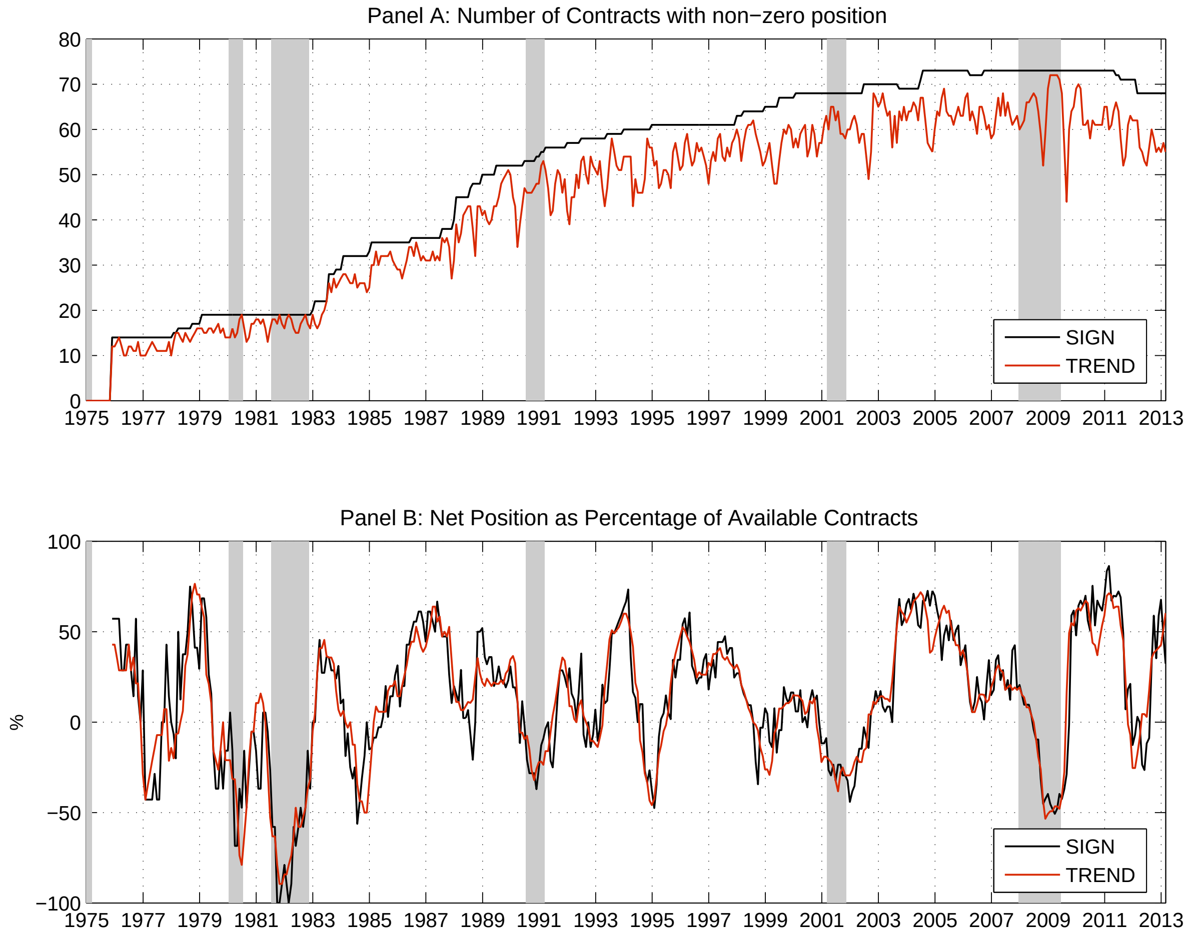

Figure 7: *Number of Contracts Traded and Net Positions*

Panel A presents the number of contracts that are traded at the end of each month for the SIGN and TREND signals. The SIGN signal is always +1 or -1, hence the number of contracts traded for this signal equals the number of available contracts. Panel B presents the net position of the time-series momentum strategy using the SIGN or the TREND signal. 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.

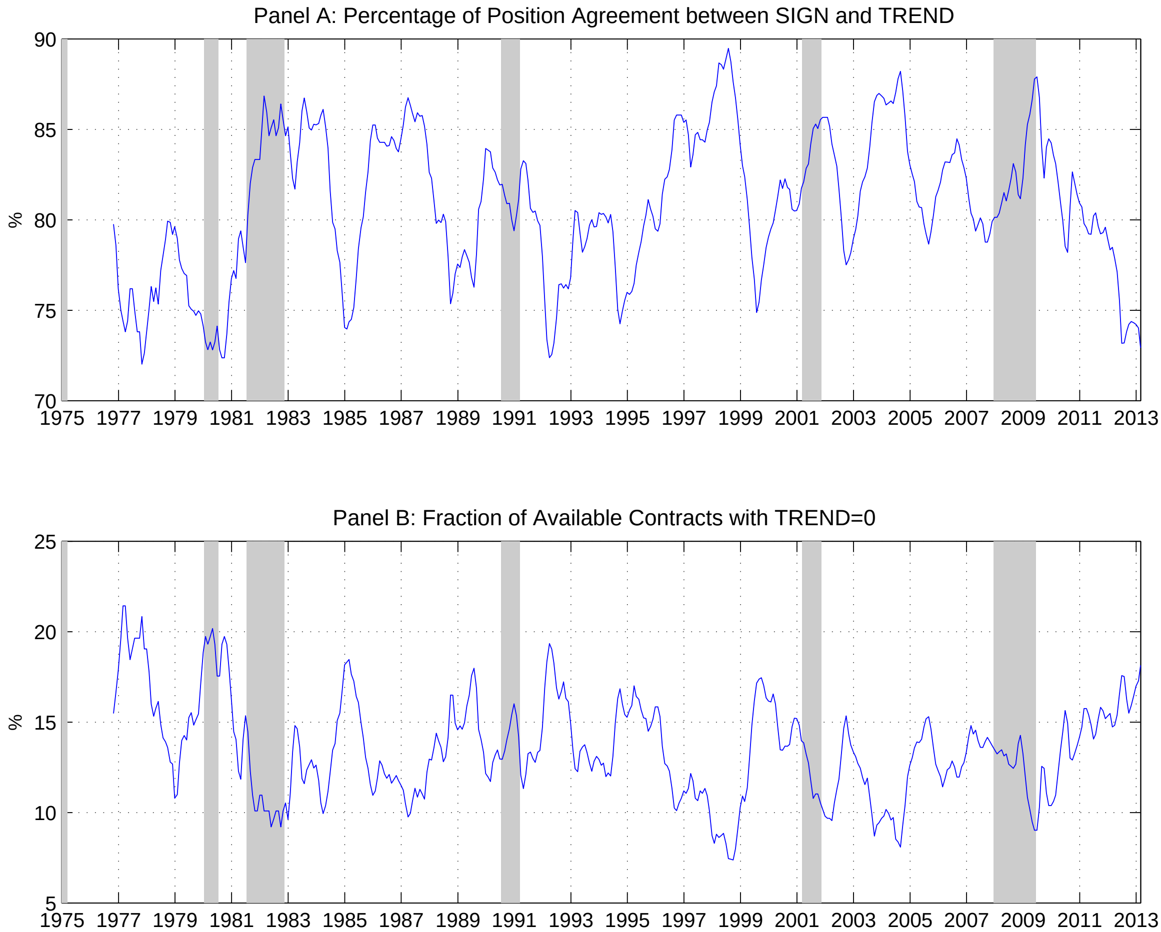

Figure 8: *Comparison between SIGN and TREND Signals*
Panel A presents the 12-month moving average of the percentage of contracts at the end of each month for which SIGN and TREND signals agree (i.e. both long or short for each and every contract). Panel B presents the 12-month moving average of the percentage of available contracts at the end of each month for which the TREND signal does not identify a significant upward or downward trend and is therefore equal to zero. The lookback period for which the signals 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.

	Exchange	From	Mean	t(Mean)	Vol.	Skew	Kurt.	SR
CURRENCIES								
AUD/USD	CME	Feb-1987	5.07	2.11	11.67	-0.40	4.94	0.44
CAD/USD	CME	Feb-1977	0.90	0.79	6.88	-0.31	8.12	0.13
CHF/USD	CME	Dec-1974	0.77	0.36	12.55	0.05	3.81	0.06
EUR/USD	CME	Dec-1974	0.58	0.30	11.37	-0.08	3.55	0.05
GBP/USD	CME	Oct-1977	1.69	0.85	10.70	0.04	4.96	0.16
JPY/USD	CME	Apr-1977	0.69	0.31	11.97	0.49	4.46	0.06
Dollar Index	ICE	Aug-1989	-1.59	-0.84	8.75	0.43	3.83	-0.18
EQUITIES								
DJIA	CBOT	Dec-1974	4.89	1.92	15.22	-0.47	5.37	0.32
NASDAQ 100	CME	Feb-1983	9.29	1.91	25.40	-0.31	4.29	0.37
NYSE Composite	ICE	Dec-1974*	5.19	1.96	15.30	-0.58	5.22	0.34
S&P 500	CME	Dec-1974	5.76	2.20	15.35	-0.48	4.62	0.38
S&P 400 MidCap	CME	Jul-1991	9.59	2.48	17.17	-0.69	5.14	0.56
Russell 2000	ICE	Feb-1988	7.06	1.75	19.17	-0.49	4.01	0.37
DJ Stoxx 50	Eurex	Jan-1987	3.74	1.01	16.49	-0.86	4.98	0.23
Eurostoxx 50	Eurex	Jan-1987	3.88	0.94	18.92	-0.64	4.38	0.21
FTSE 100	NYSE Liffe	Feb-1978	4.41	1.75	16.05	-0.76	5.76	0.28
DAX	Eurex	Dec-1974	4.64	1.33	20.07	-0.48	5.00	0.23
CAC 40	NYSE Liffe	Aug-1987	3.88	0.88	20.64	-0.32	4.12	0.19
IBEX 35	MEFF	Feb-1987	4.92	1.10	22.23	-0.47	4.89	0.22
AEX	NYSE Liffe	Feb-1983	4.81	1.19	20.33	-0.73	5.38	0.24
SMI	Eurex	Aug-1988	6.18	1.66	16.68	-0.56	4.27	0.37
MIB 30	BI	Jan-1998	-0.56	-0.09	22.87	0.00	3.80	-0.02
S&P Canada 60	MX	Feb-1982	4.39	1.38	15.75	-0.68	5.85	0.28
Nikkei 225	CME	Dec-1974	0.60	0.19	19.45	-0.22	4.20	0.03
TOPIX	TSE	Dec-1974	0.37	0.11	17.86	-0.18	4.53	0.02
ASX SPI 200	ASX	Jun-1992*	2.75	0.81	13.58	-0.66	3.70	0.20
Hang Seng	SEHK	Dec-1974	13.01	2.82	28.73	-0.26	5.71	0.45
KOSPI 200	KRX	Feb-1990*	6.51	0.93	31.63	0.86	6.86	0.21
MSCI Taiwan	SGX	Jan-1988	10.28	1.36	34.76	0.43	4.85	0.30
MSCI EAFE	NYSE Liffe	Dec-1974	2.97	1.03	15.90	-0.58	5.32	0.19
INTEREST RATES								
US Treasury Bills 3Mo	CME	Feb-1982*	1.01	2.91	1.44	1.14	8.96	0.70
US Treasury Note 2Yr	CBOT	Feb-1991	1.65	3.73	1.75	0.28	3.44	0.95
US Treasury Note 5Yr	CBOT	Aug-1988	3.23	3.56	4.23	0.05	3.66	0.76
US Treasury Note 10Yr	CBOT	Feb-1983	4.82	3.77	6.90	0.15	3.98	0.70
US Treasury Bond 30Yr	CBOT	Nov-1982	5.93	3.18	10.55	0.25	4.46	0.56
Municipal Bonds	CBOT	Jul-1985*	5.57	3.30	8.04	-0.58	4.62	0.69
Eurodollar 3Mo	CME	Jan-1982	1.19	3.61	1.52	1.09	8.26	0.78
Euribor 3Mo	NYSE Liffe	Feb-1999	0.41	1.56	0.73	1.27	11.72	0.57
Euro/German Schatz 2Yr	Eurex	Apr-1997	1.00	2.43	1.39	0.08	3.59	0.72
Euro/German Bobl 5Yr	Eurex	Feb-1997	2.71	2.94	3.29	-0.02	2.70	0.83
Euro/German Bund 10Yr	Eurex	Feb-1997	4.17	2.98	5.35	0.08	2.88	0.78
Euro/German Buxl 30Yr	Eurex	Oct-2005	5.53	1.28	12.64	1.02	4.83	0.44
Australian 3Yr	ASX	Aug-2001	0.47	1.25	1.08	0.45	2.88	0.43
Australian 10Yr	ASX	Aug-2001	0.36	1.26	0.93	0.27	2.96	0.38
UK Sterling 3Mo	NYSE Liffe	Aug-1998	0.75	2.33	0.92	1.72	12.55	0.82
UK Long Gilt	NYSE Liffe	Aug-1998	2.96	1.82	5.97	0.28	3.59	0.50
Canadian 10Yr	MX	May-1990	4.76	3.88	5.87	-0.04	3.23	0.81
Japanese 10Yr	TSE	Aug-2003	1.75	2.02	2.99	-0.73	4.99	0.59
Korean 3Yr	KRX	Sep-2003*	1.69	1.63	3.08	0.88	6.64	0.55

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	Exchange	From	Mean	t(Mean)	Vol.	Skew	Kurt.	SR
COMMODITIES								
ENERGY								
Light Crude Oil	NYMEX	Feb-1987	13.22	1.71	34.13	0.40	5.46	0.39
Brent Crude Oil	NYMEX	Sep-2003	15.45	1.22	31.37	-0.63	4.81	0.49
Heating Oil	NYMEX	Feb-1984	13.53	2.09	33.75	0.49	4.84	0.40
Natural Gas	NYMEX	Feb-1993	0.01	0.00	61.39	1.03	5.77	0.00
RBOB Gasoline	NYMEX	Oct-1987	22.10	2.99	36.24	0.36	5.45	0.61
METALS								
Copper	COMEX	Jan-1990	9.47	1.48	26.45	-0.05	5.46	0.36
Gold	COMEX	Feb-1984	1.88	0.72	15.42	0.31	4.12	0.12
Palladium	NYMEX	Feb-1994	14.37	1.60	35.29	0.34	5.68	0.41
Platinum	NYMEX	Aug-2003	11.83	1.19	27.03	-0.81	7.33	0.44
Silver	COMEX	Jan-1984	2.71	0.56	27.80	0.26	4.17	0.10
MEAT								
Feeder Cattle	CME	Feb-1978	2.46	1.04	14.52	-0.38	5.20	0.17
Live Cattle	CME	Dec-1974	4.66	1.70	16.51	-0.13	4.39	0.28
Live Hogs	CME	Dec-1974	3.32	0.83	25.57	-0.04	3.31	0.13
Pork Bellies	CME	Dec-1974*	0.80	0.15	36.87	0.44	4.23	0.02
GRAINS								
Corn	CBOT	Aug-1982	-0.92	-0.19	25.95	0.64	6.02	-0.04
Oats	CBOT	Aug-1982	-1.02	-0.16	34.68	2.76	25.57	-0.03
Soybean Oil	CBOT	Aug-1982	2.26	0.48	26.29	0.58	6.13	0.09
Soybean Meal	CBOT	Aug-1982	8.70	1.90	25.19	0.24	3.88	0.35
Soybeans	CBOT	Aug-1982	4.43	1.08	23.53	0.13	4.13	0.19
Wheat	CBOT	Aug-1982	-2.98	-0.68	25.47	0.36	4.92	-0.12
SOFTS								
Cocoa	ICE	Aug-1986	-3.81	-0.76	29.17	0.58	4.14	-0.13
Coffee	ICE	Feb-1987	-2.04	-0.26	37.86	1.00	5.69	-0.05
Cotton	ICE	Feb-1987	1.42	0.24	26.01	0.28	3.78	0.05
Lumber	CME	Dec-1974	-3.43	-0.68	29.17	0.29	3.67	-0.12
Orange Juice	ICE	Aug-1987	2.87	0.47	32.25	0.68	4.57	0.09
Sugar	ICE	Aug-1986	8.77	1.34	33.10	0.33	3.81	0.27

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: Signapore Exchange, NYMEX: New York Mercantile Exchange, COMEX: Commodity Exchange, Inc.

Range Estimator	Drift of diffusion process	Overnight Jump	Efficiency vs. STDEV
Parkinson (1980)	Assumes zero drift	Assumes no jump	5.2x
Garman and Klass (1980)	Assumes zero drift	Assumes no jump	7.4x
Rogers and Satchell (1991)	Allows for non-zero drift	Assumes no jump	6.2x
Yang and Zhang (2000)	Allows for non-zero drift	Allows for jump	8.2x (21-day estimator)

Table II: *Theoretical Features of Range Volatility Estimators*
The table presents the theoretical features for four range volatility estimators: Parkinson (1980) estimator, (b) Garman and Klass (1980) estimator, (c) Rogers and Satchell (1991) estimator and (d) Yang and Zhang (2000) estimator.

Panel A: Performance Statistics						
	STDEV	PK	GK	RS	YZ	PF
Mean (%)	12.69	14.08	14.56	14.60	12.55	14.69
Volatility (%)	20.98	23.44	23.96	24.17	21.08	16.50
Skewness	-0.30	-0.55	-0.56	-0.57	-0.36	-0.41
Kurtosis	6.49	6.05	5.96	5.98	6.81	3.55
CAPM Beta	0.97	1.11	1.14	1.15	0.99	0.80
	(12.36)	(12.46)	(12.44)	(12.42)	(12.55)	(11.93)
Sharpe Ratio	0.61	0.60	0.61	0.60	0.60	0.89
LW p-value(%)						H_0
Turnover (%)	154.20	121.14	119.22	121.27	127.40	148.09
Benefit (%)	0.00	-21.44	-22.68	-21.36	-17.39	-3.97

Panel B: Correlation Matrix						
	STDEV	PK	GK	RS	YZ	PF
STDEV	1					
PK	0.988	1				
GK	0.985	0.999	1			
RS	0.982	0.998	0.999	1		
YZ	0.997	0.991	0.989	0.987	1	
PF	0.873	0.884	0.884	0.882	0.869	1

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

Panel B: Correlation Matrix						
	STDEV	PK	GK	RS	YZ	PF
STDEV	1					
PK	0.990	1				
GK	0.988	0.999	1			
RS	0.986	0.999	1	1		
YZ	0.997	0.992	0.992	0.991	1	
PF	0.833	0.850	0.852	0.853	0.838	1

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.

	SIGN	TREND
Mean (%)	15.28	14.83
Volatility (%)	14.74	14.96
Skewness	-0.20	-0.28
Kurtosis	3.99	3.86
CAPM Beta	0.05	0.08
	(0.45)	(0.79)
Sharpe Ratio	1.04	0.99
LW p-value(%)	53.31	
Turnover (%)	162.38	54.76
Benefit (%)	0.00	-66.2
Correlation	0.92	

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 signal 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 signal and finally the correlation between the two strategies. The dataset covers the period December 1975 to February 2013.