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

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ABSTRACT

Motivated by studies of the impact of frictions on asset prices, we examine the effect of key components of time-series momentum strategies on their turnover and performance from 1984 until 2013. We show that more efficient volatility estimation and price trend detection can significantly reduce portfolio turnover by more than one third, without causing a statistically significant performance penalty. We shed light on the post-2008 underperformance of the strategy by linking it to the increased level of asset co-movement. We propose a novel implementation of the strategy that incorporates the pairwise signed correlations by means of a dynamic leverage mechanism. The correlation-adjusted variant outperforms the naive implementation of the strategy and the outperformance is more pronounced in the post-2008 period. Finally, using a transaction costs model for futures-based strategies that separates costs into roll-over and rebalancing costs, we show that our findings remain robust to the inclusion of transaction costs.

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1. Introduction

Managed futures funds, also known as Commodity Trading Advisors (CTAs), constitute a significant part of the hedge fund industry. Using BarclayHedge estimates at the end of 2014, managed futures funds manage a total of $318bn. of assets, which is about 11% of the $2.8tr. hedge fund industry. These funds typically trade futures contracts on assets in various asset classes (equity indices, commodities, government bonds and FX rates) and profit from systematic price trends[1] by means of time-series momentum strategies; Moskowitz, Ooi and Pedersen (2012) are the first to comprehensively study these strategies in the academic literature, whereas Hurst, Ooi and Pedersen (2013) and Baltas and Kosowski (2013) provide statistical evidence that managed futures and CTA funds do employ such strategies.[2]

Time-series momentum strategies are constructed using long and short positions based on a simple momentum-based trading rule, which is typically the sign of the past 12-month return. The portfolio weights are inversely proportional to realised volatility (Moskowitz et al. 2012), as the correlation structure of the portfolio constituents is not typically incorporated in the weighting scheme. These strategies have recently received considerable investor attention for two reasons. On the one hand, they provided impressive diversification benefits during the recent global financial crisis (GFC) of 2008, but on the other hand, they have exhibited rather poor performance in the subsequent post-crisis period. One of the reasons for this recent underperformance has been claimed to be the recent increase in the level of correlations across markets and asset classes (Baltas and Kosowski 2013, Georgopoulou and Wang 2016).

The objective of this paper is threefold. First, we focus on the portfolio turnover implications of the two key inputs in time-series momentum strategies, namely the volatility estimator that is used to scale the asset positions and the trading rule that is used to identify the price trends. In particular, we explore the turnover reduction benefits from employing more efficient volatility estimates and from identifying more accurately the strength of price trends by means of alternative trading rules. Second, the paper studies the dependence of the performance of time-series momentum strategies on the level of asset

[1] Using BarclayHedge estimates at the end of 2014, systematic traders manage $293bn. of assets, which is about 92% of the $318bn. of assets of the managed futures industry.

[2] Time-series momentum strategies are structurally 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. Cross-sectional momentum effects in futures markets across multiple asset classes have been recently documented by Pirrong (2005), Miffre and Rallis (2007) and Asness, Moskowitz and Pedersen (2013). The time-series momentum strategies rely heavily on serial correlation return patterns, whereas cross-sectional momentum strategies are long-short zero-cost portfolios that aim to capture the return differential between recent winning and losing securities.

pairwise correlations, with special attention paid to their recent underperformance following the GFC. In an attempt to improve the diversification of the strategy and therefore its performance during periods of increased asset co-movement, we introduce a dynamic leverage adjustment at the overall portfolio that reduces the employed leverage in such periods. Finally, we introduce a new transaction costs model for futures-based investment strategies that separates costs into roll-over costs and rebalancing costs. We use this model to evaluate the economic magnitude of the various methodological innovations mentioned in this paragraph. For our empirical analysis, we construct time-series momentum strategies using futures data on 56 assets across four asset classes (commodities, equity indices, currencies and government bonds) for a 30-year period between January 1983 and February 2013.

Starting from the turnover reduction analysis, we first document the economic value of using a volatility estimator with desirable theoretical properties. In the spirit of Fleming, Kirby and Ostdiek (2003), we hypothesise that more efficient and accurate estimators, than those constructed using daily close-to-close returns (standard deviation of past daily returns), can reduce excessive rebalancing and therefore substantially reduce the turnover of a time-series momentum strategy. Using a range-based estimator (constructed using open-high-low-close prices), such as the one proposed by Yang and Zhang (2000), we empirically find that the turnover of the strategy is statistically strongly reduced by 17% (t-statistic of 5.33) without causing any statistically sizeable performance penalty. Importantly, the benefit in the turnover reduction is not due to a small number of portfolio constituents, but instead it is found to be pervasive across all portfolio constituents from all asset classes, without a single exception.

The second part of our turnover reduction analysis focuses on the trading rule of the time-series momentum strategy. The typical momentum trading rule in the literature is binary (-1 or +1), based on the signs of the past 12-month asset returns (Moskowitz et al. 2012). Intuitively, the frequency at which a trading rule switches between long and short positions can dramatically affect the portfolio turnover. Put differently, avoiding the excessive position changes when no significant price trend exists can substantially reduce the turnover. Using a alternative trading rule that takes a continuum of values between -1 and +1 as a function of the statistical strength of daily futures log-returns over the past 12 months, we find that the turnover of the strategy can be reduced by roughly 24% (t-statistic of 8.49) without causing any statistically sizeable performance penalty to the strategy. Importantly, as in the case of the alternative volatility estimator, the benefit is pervasive across all portfolio constituents from all asset classes.

Taken together, we find that these two methodological amendments can lead to statistically strong turnover gains of more than one third (36.23%, t-statistic of 13.19), without having any statistically strong impact on the performance of the strategy. The strategies before and after employing these amendments are statistically indistinguishable. This is an important result as time-series momentum –as any momentum strategy– is a high-turnover strategy[3], and therefore requires frequent rebalancing in order to capture emerging price trends and move away from trends that have already materialised. Put differently, one can only do so much in terms of turnover reduction, before the actual performance of the strategy starts falling significantly. The fact that our results show a turnover reduction of more than one third without a material impact on the actual performance of the strategy is therefore noteworthy. In addition, it is also worth noting that lower turnover generally allows for scalability and capacity in terms of capital invested and is therefore always welcome by investors.

Our second objective is to study the dependence of the performance of the time-series momentum strategy on the level of pairwise correlations of portfolio constituents. This analysis is motivated by the findings in Baltas and Kosowski (2013), who, apart from documenting the business cycle performance of the strategy, also highlight its poor performance after 2008. The authors explain that the underperformance can be due to (i) capacity constraints in the futures markets, (ii) a lack of trends for each asset or (iii) increased correlations across assets, which is, in turn, closely related to a fall in diversification benefits. They find no evidence of capacity constraints based on two different methodologies, but they do show that correlations between futures markets have experienced a significant increase in the period from 2008 to 2013 (also in line with Georgopoulou and Wang 2016).

We show that incorporating the pairwise *signed* correlations of the constituent assets into the weighting scheme of the strategy not only sheds light on its return drivers, but can also significantly improve its performance, especially in periods of increased co-movement. We investigate the interplay between the pairwise signed correlations –hence incorporating the fact that some of the assets command a short position in the portfolio– of portfolio constituents and portfolio volatility and extend the formulation of the standard time-series momentum strategy by introducing a correlation factor in the weighting scheme

[3]The high levels of turnover and therefore the associated costs have been claimed to significantly reduce the profitability of cross-sectional momentum equity strategies; indicatively see Korajczyk and Sadka (2004), Lesmond, Schill and Zhou (2004), Menkhoff, Sarno, Schmeling and Schrimpf (2012) and Novy-Marx and Velikov (2016).

that increases (decreases) the leverage of portfolio constituents in periods of low (high) average pairwise signed correlation. This adjustment improves the risk-adjusted performance of the strategy, both over the entire sample period, but most importantly over the most recent post-crisis period 2009-2013 during which pairwise correlations across assets and asset classes dramatically increased. The improvement is primarily due to the fact that the correlation-adjusted strategy safeguards against downside risk.

Nevertheless, the performance benefit of the correlation adjustment does not come at no cost. The turnover of the strategy increases statistically significantly by about 23% (t-statistic of 3.98), all else being equal. However, when the correlation adjustment is paired with the turnover reduction techniques discussed earlier, the net effect turns positive, as the overall turnover of the strategy compared to its default specification (Moskowitz et al. 2012) falls by 23% (t-statistic of 6.34).

In order to evaluate the economic magnitude of the various methodological amendments suggested in our paper –in particular that of turnover reduction– we introduce a new transaction costs model for futures-based investment strategies that separates the costs into two main distinct sources: (i) roll-over costs of futures contracts and (ii) rebalancing costs. The roll-over costs are incurred when a futures contract approaches maturity and rollovers to the next-to-mature contract and are only related to the gross weight of each asset in the overall portfolio (in line with Barroso and Santa-Clara 2015a). Conversely, the rebalancing costs are incurred when the strategy rebalances and are therefore directly related to the turnover of the strategy and the change in the net weight of each asset at each rebalancing date.

Using our transaction costs model, we estimate annualised trading costs of 163 basis points for the default specification of the time-series momentum strategy (as per Moskowitz et al. 2012), which roughly represent 10% of the strategy's gross annualised performance of 16.12% over our sample period. In line with our earlier findings on turnover reduction, a more efficient volatility estimator and a more robust trading rule can substantially reduce these costs by 13% and 25% respectively, or up to 35% when both are employed (costs fall to 105 basis points without causing a statistically significant fall in the Sharpe ratio of the strategy). Most importantly, the performance benefit of the correlation adjustment –which, when considered in isolation, actually increases the trading costs by about 13% to 185 basis points– can still come with a substantial costs reduction of about 28%, down to 118 basis points, when combined with the turnover reduction techniques discussed above. This translates to better after costs risk-adjusted returns for the strategy, partly due to the performance benefit of the correlation adjustment and partly due to the overall turnover reduction. The impact becomes even more pronounced in the post-GFC period, when the default specification of the strategy exhibits negative after-costs Sharpe ratio.

Our paper is related to and complements several streams of the literature. First, it is related to work on the economic value of volatility-timing and the importance of volatility estimation efficiency on dynamic portfolio construction and turnover. Fleming, Kirby and Ostdiek (2001), Ilmanen and Kizer (2012), Kirby and Ostdiek (2012) and Hallerbach (2012) highlight the benefits of volatility-timing, while Barroso and Santa-Clara (2015b), Daniel and Moskowitz (2016), and Moreira and Muir (2017) examine effect of volatility-scaling on the performance of cross-sectional equity momentum and other factor premia. Fleming et al. (2003) investigate the performance and turnover benefits for a mean-variance portfolio from using more efficient estimates of volatility. Second, our paper is related to recent work by Dudler, Gmür and Malamud (2015) and Levine and Pedersen (2016) on alternative trading rules for time-series momentum strategies and their impact on strategy performance and turnover. Finally, our paper is related to Baltas (2015), who attempts to introduce pairwise correlations in the portfolio construction methodology of the time-series momentum strategy using a long-short risk-parity framework. Although our objective is the same, our methodology differs from Baltas's (2015) methodology in that we introduce a portfolio leverage control mechanism that is driven by the level of the average pairwise signed correlations.

The rest of the paper is organised as follows. Section 2 provides an overview of the dataset. Section 3 describes the construction of the time-series momentum strategy, explores the dependence of the strategy's turnover on the volatility estimator and trading rule and introduces the correlation adjustment. Section 4 presents the empirical results of the effects of the volatility estimator and trading rule on the turnover of time-series momentum strategies. Section 5 discusses the recent underperformance of the time-series momentum strategies and presents our empirical results on the effect of incorporating pairwise signed correlations in the weighting scheme onto the performance of these strategies. Section 6 reports the transaction cost implications of all the methodological alterations that are presented in the paper. Section 7 concludes.

2. Data Description

The dataset that we use is obtained from Tick Data and consists of daily opening, high, low and closing futures prices for 56 assets across all asset classes: 25 commodities, 14 developed country equity indices, 6 currencies and 11 government bonds; see Table I. Since the contracts of different assets are traded on various exchanges each with different trading hours and holidays, the data series are appropriately aligned by filling forward any missing prices. Finally, 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.[4]

The overall sample period of the dataset is from December 1974 to February 2013. However, not all contracts start in December 1974; Table I reports the starting month and year of each contract and Figure 1 presents the number of assets per asset class that are available at the end of each month. At the beginning of the sample period the cross-section is relatively small, containing only nine assets and no government bonds. The composition becomes significantly broader after 1983, when the number of assets increases to 25, including the first government bonds. Because of this, the empirical analysis in this paper focuses on the period that starts in January 1983. As we explain later in the paper, the momentum signals are based on the most recent 12-month returns and, therefore, the first monthly returns of the time-series momentum strategy become available in January 1984.[5]

[Figure 1 about here]

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

[4] 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 and find that our results remain qualitatively unchanged without the equity spot price backfill.

[5] Our results remain qualitatively unchanged if we include the period prior to 1983. These results are available upon request from the authors.

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. The most liquid contract is typically 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 continuous data series.[6]

Second, having obtained single price data series for each asset, we need to calculate 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 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 a 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

[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.

excess of the risk-free rate is:

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

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:

$$r_{t,t+1} = \frac{F_{t+1,T} - F_{t,T}}{F_{t,T}} \tag{2}$$

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.[7] 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 a large cross-sectional variation in the return distributions of the different assets. In total, 49 out of 56 futures contracts have a positive unconditional mean excess return, 21 of which are statistically significant at the 10% level. Currency and commodity futures have insignificant mean returns with only a few exceptions. All but two assets have leptokurtic return distributions (fat tails) and, as expected, 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 the lowest volatilities in the cross-section.

[Table I about here]

3. Methodology

In this section we provide the background in the construction of time-series momentum strategies, which is necessary to understand why their performance is dependent on the efficiency of volatility estimation,

[7] This procedure is fairly standard in the futures literature. Among others, see Bessembinder (1992), Bessembinder (1993), Gorton and Rouwenhorst (2006), Gorton, Hayashi and Rouwenhorst (2007), Miffre and Rallis (2007), Pesaran, Schleicher and Zaffaroni (2009), Fuertes, Miffre and Rallis (2010) and Moskowitz et al. (2012).

the momentum trading rule and the level of average pairwise correlation of the constituents. As we demonstrate, these strategies can be viewed as an extension of constant-volatility (volatility-targeting) strategies, which explains the dependence of their turnover on the efficiency of the volatility estimation and on the nature of the trading rule. At the end of the section we extend the strategy design by explicitly incorporating the pairwise correlations of the constituents.

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

$$r^{lev}_{t,t+1} = \frac{F_{t+1,T} - F_{t,T}}{\sigma_t \cdot F_{t,T}} = \frac{1}{\sigma_t} \cdot r_{t,t+1} \tag{3}$$

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 σ_{tgt} a desired level of target volatility, we can generalise the concept to a single-asset constant-volatility (*cvol*) strategy:

$$r^{cvol}_{t,t+1} = \frac{\sigma_{tgt}}{\sigma_t} \cdot r_{t,t+1} \tag{4}$$

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:

$$r_{t,t+1}^{CVOL} = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{t,t+1}^{i,cvol} \tag{5}$$

$$= \frac{1}{N_t}\sum_{i=1}^{N_t} \frac{\sigma_{tgt}}{\sigma_t^i} \cdot r_{t,t+1}^{i} \tag{6}$$

where N_t is the number of available assets at time t. The target volatility of each asset remains σ_{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 σ_{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:

$$r_{t,t+1}^{TSMOM} = \frac{1}{N_t}\sum_{i=1}^{N_t} X_t^i \cdot r_{t,t+1}^{i,cvol} \tag{7}$$

$$= \frac{1}{N_t}\sum_{i=1}^{N_t} X_t^i \cdot \frac{\sigma_{tgt}}{\sigma_t^i} \cdot r_{t,t+1}^{i} \tag{8}$$

The trading rule is critical for the performance of the strategy. 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 (long or short) for each asset, i.e. $X_t^i = sign\left[r_{t-12,t}^i\right]$:

$$r_{t,t+1}^{TSMOM} = \frac{1}{N_t}\sum_{i=1}^{N_t} sign\left[r_{t-12,t}^i\right] \cdot \frac{\sigma_{tgt}}{\sigma_t^i} \cdot r_{t,t+1}^{i} \tag{9}$$

3.2. Turnover Dynamics

A long-only CVOL strategy involves frequent rebalancing due to the fact that the volatilities of the assets change 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 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 price trends.

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

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 unchanged (either long or short). The turnover of the strategy would then 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:

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

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 it has to be estimated. The objective of the econometrician is to estimate σ_t at every rebalancing date. Realised 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.

We hypothesise that larger in magnitude and time-varying estimation error 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.

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 σ of an asset stays unchanged 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 is illustrated by the following relationship:

$$turnover_{rule}(t-1,t) \propto \left| \frac{X_t}{\sigma} - \frac{X_{t-1}}{\sigma} \right| = \frac{|\Delta X_t|}{\sigma} \tag{11}$$

For a trading rule that takes only two values, such as the sign of the past return that only takes values $+1$ or -1, $|\Delta X_t| = 2$, when the position switches sign from long to short or vice versa. In a more general setup that 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 at 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 (11). This leads to the conjecture that a trading rule, which can avoid frequent swings between long and short positions and smooths out the transition between the two 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 the hypotheses relating to portfolio turnover reduction based on either the volatility estimator or the trading rule in in Section 4.

3.3. Incorporating Pairwise Correlations

The construction of the TSMOM strategy in equations (8) and (9), which follows the standard specification used in the literature (Moskowitz et al. 2012, Hurst et al. 2013, Baltas and Kosowski 2013) does not explicitly model the pairwise correlations between the futures contracts as part of the weighting scheme. This potentially constitutes an important limitation for the strategy, especially in periods of increased asset co-movement, like the post-GFC period. One of the main methodological contributions of this paper is the extension in the formulation of the TSMOM strategy by taking into account the average pairwise correlation of portfolio constituents in an effort to improve the portfolio risk-return characteristics.

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 σ_i for $i = 1, \cdots, N$ respectively. To facilitate the notation, we drop the dependence on time in the following derivations. The portfolio volatility, σ_P, is trivially deduced as follows:

$$\sigma_P = \sqrt{\sum_{i=1}^{N} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} w_i w_j \sigma_i \sigma_j \rho_{i,j}} \tag{12}$$

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 ex-ante volatility equal to a pre-determined target level σ_{tgt}. In particular, each asset has a net leveraged weight equal to $(X_i \cdot \sigma_{tgt}) / (N \cdot \sigma_i)$, where $X_i = \pm 1$. Substituting the portfolio weights in Equation (12) yields:

$$\begin{aligned} \sigma_P &= \sigma_{tgt} \sqrt{\sum_{i=1}^{N} \frac{X_i^2}{N^2} + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} \frac{X_i \cdot X_j}{N^2} \rho_{i,j}} \\ &= \frac{\sigma_{tgt}}{N} \sqrt{N + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} X_i \cdot X_j \cdot \rho_{i,j}} \end{aligned} \tag{13}$$

The derivation above uses the fact that $X_i^2 = (\pm 1)^2 = 1$ for every i, when the trading rule is the sign of the past return.

The *signed* double summation $\sum_{i=1}^{N} \sum_{j=i+1}^{N} X_i \cdot X_j \cdot \rho_{i,j}$ that appears in Equation (13) is effectively the sum of all the elements of the upper right triangle of the correlation matrix of the assets, after taking into account the type of position (long or short) that each asset is going to have over the holding period.[8] 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 in the average pairwise *signed* correlation of the universe, $\bar{\rho}$:

$$\bar{\rho} = 2 \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} X_i \cdot X_j \cdot \rho_{i,j}}{N(N-1)} \tag{14}$$

Solving for the double summation and substituting back into Equation (13) yields:

$$\sigma_P = \sigma_{tgt} \sqrt{\frac{1 + (N-1)\bar{\rho}}{N}} \tag{15}$$

[8] We thank an anonymous referee for suggesting looking at the signed correlation matrix, as opposed to an unsigned one.

The above result lies at the heart of diversification. Given that $\bar{\rho} \leqslant 1$, we deduce that $\sqrt{\frac{1+(N-1)\bar{\rho}}{N}} \leqslant 1$, and therefore that $\sigma_P \leqslant \sigma_{tgt}$. In other words, the fact that correlation –signed or otherwise– 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 (15), we can introduce the average pairwise correlation as a factor that controls the target level of volatility of each asset. When average pairwise signed correlation increases (decreases) we would optimally want to lower (increase) the per asset target level of volatility. Solving Equation (15) for a dynamic level of target volatility for each asset results in:

$$\begin{aligned} \sigma_{tgt}(\bar{\rho}) &= \sigma_P \sqrt{\frac{N}{1+(N-1)\bar{\rho}}} && (16) \\ &= \sigma_P \cdot CF(\bar{\rho}) && (17) \end{aligned}$$

where

$$CF(\bar{\rho}) = \sqrt{\frac{N}{1+(N-1)\bar{\rho}}} \tag{18}$$

denotes a correlation factor (CF) that adjusts the level of leverage applied to each portfolio constituent as a function of the overall average pairwise signed correlation.

Following the above, the generalised TSMOM strategy of Equation (8) can be accordingly adjusted by replacing the volatility target for each asset, σ_{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 signed correlation of the assets. This gives rise to the correlation-adjusted time-series momentum strategy (TSMOM-CF):

$$r_{t,t+1}^{TSMOM-CF} = \frac{1}{N_t} \sum_{i=1}^{N_t} X_t^i \cdot \frac{\sigma_{P,tgt}}{\sigma_t^i} \cdot CF(\bar{\rho}_t) \cdot r_{t,t+1}^i \tag{19}$$

We empirically study the effect of the correlation adjustment in Section 5, with a particular focus on the post-GFC period, when pairwise correlations across assets and asset classes increased significantly, thus diminishing any diversification benefits.

It is important to highlight that, in parallel to our work, a recent paper by Baltas (2015) introduces pairwise correlations between constituents in the portfolio construction methodology of the TSMOM strategy using a long-short risk-parity framework.[9] This is done in an effort to improve the diversification of the strategy and therefore its performance in periods of increased correlation. Although our objective is the same, our methodology differs from Baltas's (2015) methodology in that we introduce a portfolio leverage control mechanism that is driven by the level of the average pairwise signed correlation. We therefore consider our methodology and findings as complementary to those of Baltas (2015).

4. Turnover Reduction

The purpose of this section is to empirically investigate the turnover implications of the two key determinants of a TSMOM strategy, namely the volatility estimator and the trading rule. As motivated in the previous section, more efficient volatility estimators and more robust trading rules can be expected to reduce the turnover of the strategy.

4.1. 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.

The ordinary measure of volatility is the standard deviation of past daily close-to-close returns (SD, hereafter), which, even though an unbiased estimator, it only makes use of daily closing prices and therefore is subject to large estimation error when compared to volatility estimators that make use of intraday information. In the absence of high-frequency data in our dataset, we attempt to improve the estimation efficiency of a close-to-close daily volatility estimator by using intraday open, high, low

[9] For an introduction on risk-parity, see Roncalli (2013). The risk-parity portfolio construction methodology is also referred to in the literature as "equal risk contribution".

and close daily prices. The volatility estimators that make use of open, high, low and close prices are known in the literature as range[10] 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, Brandt and Diebold 2002).

A multitude of range estimators have been suggested in the literature by Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991), and Yang and Zhang (2000), which have been empirically shown (see for example Brandt and Kinlay 2005, Shu and Zhang 2006) to reduce the estimation error of a conventional daily volatility estimator, like the standard deviation of past returns. Out of these estimators, the Yang and Zhang (2000) estimator (YZ, hereafter) is the most efficient and the only to be independent of both the overnight jump (i.e. the price change between the previous day's close and the next day's opening price) and the drift of the price process. For that reason and for the purposes of our analysis we focus solely on the added benefit of more efficient volatility estimates, as these are offered by the the YZ estimator.[11]

The YZ estimator is defined as a linear combination of three volatility estimators: the standard deviation of past close-to-close daily logarithmic returns (i.e. the conventional SD estimator), the standard deviation of past overnight (close-to-open) logarithmic returns and the Rogers and Satchell (1991) (RS, hereafter) range estimator[12]. In particular, the YZ volatility of an asset at the end of month t (assuming

[10]The term "range" refers to the daily high-low price difference and its major advantage is that it can 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. As 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 & 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...*".

[11]In undocumented results, we have additionally evaluated the performance of the less efficient range estimators by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991). These results are available upon request.

[12]Rogers and Satchell (1991) are the first to introduce an unbiased estimator that allows for a non-zero drift in the price process, but their estimator does not account for the overnight jump (see also Rogers, Satchell and Yoon 1994). Their estimator is 6.2 times more efficient than SD. The RS volatility of an asset over the course of a single day τ is given by:

$$\sigma^2_{\mathrm{RS}}(\tau) = h(\tau)\,[h(\tau) - c(\tau)] + l(\tau)\,[l(\tau) - c(\tau)]$$

where $h(\tau)$, $l(\tau)$ and $c(\tau)$ denote the logarithmic difference between the high, low and closing prices respectively and the opening price. The RS volatility of an asset at the end of month t, assuming a certain estimation period is equal to the average daily RS volatility over this period.

some estimation period) is given by:

$$\sigma^2_{\mathrm{YZ}}(t) = \sigma^2_{\mathrm{OJ}}(t) + k \cdot \sigma^2_{\mathrm{SD}}(t) + (1-k) \cdot \sigma^2_{\mathrm{RS}}(t) \tag{20}$$

where $\sigma_{\mathrm{OJ}}(t)$ denotes the overnight jump estimator. The parameter k is chosen so that the variance of the estimator is minimised and is shown by Yang and Zhang (2000) to be a function of the number of days used in the estimation.[13] The YZ estimator is $1+\frac{1}{k}$ times more efficient than SD; this expression is maximised for a 2-day estimator, when YZ is almost 14 times more efficient than SD. For our purposes, a monthly YZ estimator with -on average- 21 daily returns would be 8.2 times more efficient than the monthly SD estimator.

4.1.1. Performance Evaluation

We start our analysis by exploring the effects of a more efficient volatility estimator on the turnover of CVOL and TSMOM portfolios that are constructed as in equations (6) and (9) respectively. In line with Moskowitz et al. (2012) and Baltas and Kosowski (2013) we use a volatility target for each asset (σ_{tgt}) equal to 40%. This choice is motivated in these studies, because it generates ex-post TSMOM portfolio volatilities that are comparable to those of commonly used factors such as those constructed by Fama and French (1993) and Asness et al. (2013).

Table II presents out-of-sample performance statistics for CVOL (Panel A) and TSMOM (Panel B) strategies that employ a different volatility estimator at a time. 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 this reason, we label it as the "perfect forecast" strategy (PF, hereafter).

[Table II about here]

[13]The parameter k is chosen using the following equation:

$$k = \frac{0.34}{1.34 + \frac{N_D+1}{N_D-1}}$$

where N_D denotes the number of days in the estimation period.

At first sight, the two different volatility estimators, SD and YZ, do not have a statistically significantly different economic effect on the performance of the CVOL or TSMOM strategies. The risk-adjusted returns are around 0.76 for the long-only strategies and around 1.15 for the momentum strategies. However, our focus is on the effect of the more efficient volatility estimator on portfolio turnover, given that the level of estimation noise is expected to be relatively lower. We find that the more efficient estimator reduces the turnover by roughly 26% for the CVOL strategy and 17% for the TSMOM strategy, with both estimates being statistically significant at the 1% confidence level. This result is indeed in line with our conjecture; the turnover benefit comes without any significant penalty for the performance of the strategies.

Comparing the results of the implementable strategies to the PF benchmark, it is obvious that the strategy based on perfect forecast delivers larger risk-adjusted performance with a before-transaction cost Sharpe ratios of 1.17 (CVOL) and 1.46 (TSMOM), respectively, which are significantly different from the Sharpe ratios of the rest of the strategies as can be deduced from the very low p-values of the Ledoit and Wolf (2008) statistical test.[14] The rejection of the null of equality in Sharpe ratios shows that there is room for improvement in terms of accurately forecasting increases (decreases) in volatility and therefore better timing the downscaling (upscaling) of positions before an impending drawdown (uptrend). However, this task is beyond the scope 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 volatility-adjusted trading strategy, and not to forecast future realised volatility.

Given the documented turnover benefit for the more efficient volatility estimator, we next investigate whether the turnover reduction is pervasive across all portfolio constituents or whether instead the result is dominated by a few assets. For that reason, we use monthly SD and YZ volatility estimates for all 56 future contracts of our dataset and calculate the time-series average absolute first order 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":

$$\text{Volatility Turnover}\,(i, \text{estimator}) = \frac{1}{\#months} \sum_{\forall m} \left| \frac{1}{\sigma_{i,\text{estimator}}\,(t_m, t_{m+1})} - \frac{1}{\sigma_{i,\text{estimator}}\,(t_{m-1}, t_m)} \right| \qquad (21)$$

[14] In particular, we use the Ledoit and Wolf (2008) bootstrap methodology for time-series data. The optimal block size is estimated to be $b = 10$ and the bootstrap p-values are computed using $M = 4999$ bootstrap samples.

where estimator $= \{\text{SD}, \text{YZ}\}$. In principle, a more efficient volatility estimator should reduce the volatility turnover statistic for each asset. Figure 2 presents the percentage drop in the volatility turnover statistic when switching from the SD estimator to the YZ estimator, i.e. $100 \cdot \left(\frac{\text{Volatility Turnover}(i,\text{YZ})}{\text{Volatility Turnover}(i,\text{SD})} - 1 \right)$ for each asset i.

[Figure 2 about here]

The empirical evidence is very strong. Across all assets, without a single exception, the volatility-induced turnover is reduced when a more efficient volatility estimator is used. The effects are more pronounced for low volatility assets, such as the interest rate contracts, but even for equities 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 SD estimator is the main reason for excess trading in a CVOL or TSMOM strategy.

4.2. The Effect of Trading Rule

The second part of the turnover reduction analysis relates to the trading rule that is employed by the TSMOM strategy. In this section, we explore the mechanics of two different trading rules and investigate how they affect the turnover and the performance of the strategy. In particular, we compare the standard time-series momentum rule (sign of the past return) with a rule that explores the strength of the price trends and accordingly adjusts the allocation.

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:

$$\text{SIGN}_t^{12M} = sign\left[r_{t-12,t}\right] = \begin{cases} +1, & r_{t-12,t} \geqslant 0 \\ -1, & \text{otherwise} \end{cases} \tag{22}$$

Trend Strength (TREND): The SIGN trading rule only maps past performance into ± 1 without considering the statistical properties and strength of the price path. An alternative way to capture the trend of a price series is by looking at the statistical strength of the realised return. In particular, we use the

Newey and West (1987) t-statistic of the daily futures log-returns over the past 12 months to scale the gross exposure to the various assets. In order to safeguard against extreme allocations, the trading rule is capped at ± 1, when the t-statistic exceeds a certain threshold, which for our analysis is set equal to ± 1:

$$\text{TREND}_t^{12M} = \begin{cases} +1, & \text{if } t\left(r_{t-12,t}\right) > +1 \\ t\left(r_{t-12,t}\right), & \text{otherwise} \\ -1, & \text{if } t\left(r_{t-12,t}\right) < -1 \end{cases} \tag{23}$$

Apart from the statistical nature of the t-statistic of past daily log-returns, conveniently, it has an economic interpretation as well, as it coincides with the realised annualised Sharpe ratio of the asset over the past 12 months (adjusted both for heterskedasticity and serial correlation following Newey and West (1987)).

Given the definition of the TREND rule, it is identical to the SIGN rule when the annualised realised Sharpe ratio over the past 12 months –or equivalently the t-statistic of the realised daily log-returns over the same period– is higher than +1, or lower than -1. Otherwise, the gross exposure to the respective asset is less than 100%.

The TREND rule introduces a sigmoid response function that suggests a reduction in the gross exposure for the assets that do not exhibit a certain level of statistical and economic strength in their past realised price path. As price trends switch over time between upward to downward and vice versa, this trading rule is expected to smooth out the transition between 100% long and 100% short and therefore reduce the turnover of the TSMOM strategy. The sigmoid nature of the TREND rule resembles the delta of an option straddle (as shown by Lempérière, Deremble, Seager, Potters and Bouchaud 2014), which, in turn establishes the link between the profitability of TSMOM strategies and that of lookback option straddles (Fung and Hsieh 1997, Fung and Hsieh 2001).

As explained above, the signal strength directly impacts the gross exposure for each asset and therefore the collective signal strength across assets and asset classes determines the leverage that is employed at the overall portfolio level. The portfolio leverage at any point in time (L_t) is defined as the sum of the gross weights of all assets (as in Barroso and Santa-Clara 2015a):

$$L_t = \sum_{i=1}^{N_t} \left|w_t^i\right| \tag{24}$$

$$= \sum_{i=1}^{N_t} \frac{\left|X_t^i\right|}{N_t} \cdot \frac{\sigma_{tgt}}{\sigma_t^i} \tag{25}$$

following from equation (8).

Given the binary nature of the SIGN rule, $\left|X_t^i\right| = 1$ for all assets. Conversely, $\left|X_t^i\right| \leqslant 1$ for the TREND rule and therefore $L_t^{SIGN} \geqslant L_t^{TREND}$ at any point in time; see Figure 3. Put differently, the TREND rule introduces a dynamic leverage reduction mechanism that reduces the overall gross exposure of the TSMOM strategy following periods of collectively weak price trends.

[Figure 3 about here]

Statistically, in the absence of serial correlation and cross-sectional dependence, a t-statistic is larger than +1 or less than -1, which maps into a TREND rule being +1 or -1 respectively, with probability 31.7%. Any empirical deviation from this threshold constitutes evidence of serial correlation (return continuation if the probability is higher than 31.7%, or return reversal –or, equivalently, lack of return continuation– if the probability is lower than 31.7%) and/or evidence of cross-sectional clustering of these serial correlation effects among assets. Figure 4 graphically illustrates this discussion.

[Figure 4 about here]

Panel A in Figure 4 shows the proportion of time for each asset that we document a TREND trading rule being either +1 or -1 (what we call a *strong* trend) and its relationship to asset volatility. The evidence shows that across almost all assets of all asset classes this proportion of time generally exceeds 31.7%. This, in turn, suggests the existence of sizeable return serial correlation (which reduces the standard error, hence inflating the t-statistics). We return to such persistent price trends and the statistical detection of time-series momentum patterns in the next subsection. Most importantly, there does not seem to exist any strong relationship between the underlying volatility of an asset and its respective time-series momentum behaviour. Put differently, the time-series momentum dynamics are neither asset class-specific nor volatility-specific.

Panel B in Figure 4 presents the time-series part of the analysis by showing the proportion of assets that exhibit a strong TREND trading rule at the end of each month. As in Panel A, in the absence of any time-series and cross-sectional dependence, we would expect a flat line at 31.7% across time. Conversely, for the most part of the sample period, a larger proportion of assets exhibit a strong TREND rule, which is again an indication of time-series momentum behaviour. One of the most interesting observations is that the number of assets with a strong TREND trading rule has fallen –more than any other historical period– during and after the GFC. We return to this point at a later stage in our paper, in Section 5.

Parallel to our work, a few other papers have looked at alternative definitions for the TSMOM trading rule, but all of these studies have maintained the rule's binary nature. Dudler et al. (2015) construct a daily rebalanced "risk-adjusted" momentum strategy using the sign of a number of averages of volatility-adjusted daily returns over the lookback period; a similar signal is also used by Lempérière et al. (2014). The risk-adjusted momentum strategy is shown to outperform the typical TSMOM strategy and to reduce portfolio turnover. Levine and Pedersen (2016) focus on the relationship between the basic TSMOM trading rule (SIGN) and moving average cross-over rules.

4.2.1. Return Predictability

As already discussed, the empirical evidence in Figure 4 provides indicative visual evidence of strong time-series momentum behaviour across assets, across asset classes and across time. In this section, we provide strong econometric evidence. Following Moskowitz et al. (2012) and Baltas and Kosowski (2013), we 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:

$$\frac{r_{t-1,t}}{\sigma_{t-1}} = \alpha + \beta_\lambda \cdot \frac{r_{t-\lambda-1,t-\lambda}}{\sigma_{t-\lambda-1}} + \varepsilon_t \qquad (26)$$

and

$$\frac{r_{t-1,t}}{\sigma_{t-1}} = \alpha + \beta_\lambda \cdot X^{1M}_{t-\lambda} + \varepsilon_t \qquad (27)$$

where λ denotes the lag that ranges between 1 and 60 months and the lagged one month rule $X^{1M}_{t-\lambda}$ is either the $\text{SIGN}^{1M}_{t-\lambda}$ or the $\text{TREND}^{1M}_{t-\lambda}$ rule.

The regressions (26) and (27) are estimated for each lag by pooling together all T_i (where $i = 1, \cdots, N$) monthly returns/trading rules for the $N = 56$ assets. We are interested in the t-statistic of the coefficient β_λ 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,[15] 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 (26) and (27) is given by (Cameron, Gelbach and Miller 2011, Thompson 2011):

$$V_{\text{TIME\&ASSET}} = V_{\text{TIME}} + V_{\text{ASSET}} - V_{\text{WHITE}}, \tag{28}$$

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 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 $\bar{T} = \frac{1}{N}\sum_{i=1}^{N} T_i \cong 303$ months of data per asset. We can therefore argue that $\bar{T} > N$ and we document in unreported results (available upon request) 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 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).

Figure 5 presents the two-way clustered t-statistics $t(\beta_\lambda)$ for regressions (26) and (27) and lags $\lambda = 1, 2, \cdots, 60$ months. The t-statistics are almost always positive for the first twelve months for all

[15] 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.

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 drives 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 first year.

[Figure 5 about here]

Even though our focus is on time-series momentum patterns, the results of the above analysis are distantly related to a recent debate on whether cross-sectional momentum in U.S. stocks constitutes an exposition of return continuation or instead an "echo" effect. Cross-sectional momentum describes the empirical pattern that past winner stocks over the past twelve months (excluding the most recent month) outperform past loser stocks over the following month (Jegadeesh and Titman 1993, 2001). However, based on a long sample of US equities, Novy-Marx (2012) argues that cross-sectional equity momentum is, in fact, an "echo" effect, because ranking stocks based on their intermediate past return between 12 and 7 months before the formation date gives rise to a statistically and economically stronger performance compared to ranking by the most recent past return between 6 and 1 month before the formation date. Bearing in mind the difference between time-series and cross-sectional momentum, we note that the autocorrelation patter in Figure 5 is statistically significant for several lags within the immediate and the recent past. Moreover, there is no evidence of a short-term reversal effect at a one month lag as found in cross-sectional momentum strategies. This suggest that time-series momentum may not be an "echo" effect.

Contrary to Novy-Marx (2012), Gong, Liu and Liu (2015) and Goyal and Wahal (2015) use individual stock data from a long list of international countries and show that the "echo" effect is not present in the majority of the countries they study.

4.2.2. Performance Evaluation

Similar to the analysis in Table II, which studies the impact of the volatility estimator choice on portfolio turnover, in Table III we examine the turnover implications from switching the SIGN trading rule for the

TREND rule in a TSMOM strategy.

[Table III about here]

The results show that the SIGN trading rule generates a slightly higher Sharpe ratio than the TREND trading rule; using the SD volatility estimators, the Sharpe ratio of the TSMOM strategy is 1.15 for SIGN and 1.11 for TREND. However, the Ledoit and Wolf (2008) p-value shows that these Sharpe ratios are not statistically indistinguishable from each other.

In order to further study this insignificant change in the Sharpe ratio of the strategy, Figure 6 contains an event study that presents the 12 months prior to portfolio formation and the 36 month post portfolio formation, separately, for assets with a strong TREND rule (± 1) in Panels A and A', and for assets with a weak TREND rule (between -1 and +1) in Panels B and B'. For this analysis, all returns are standardised in order to have a zero mean across time and across the four groups (long or short, strong or not strong) for comparison purposes as in Moskowitz et al. (2012).

[Figure 6 about here]

During the 12 months prior to portfolio formation, the assets with the strong TREND exhibit –by construction– more persistent price trends compared to the assets with weak TREND. However, during the first months after portfolio formation both assets with strong TREND and assets with weak TREND realise their time-series momentum behaviour in equal sizes (Panels A' and B' make this easier to see visually). This is in line with our finding of a statistically insignificant difference in the performance of the TREND rule (which scales down the exposure to assets with weak TREND) versus the SIGN rule (which assumes equal exposure to all the assets of the universe).

Following the first year after portfolio formation, all assets start experiencing reversals. However, the assets with strong TREND experience much stronger reversals both for their long and short positions; in fact, the reversals for the short positions start slightly earlier, at around six months after portfolio formation. This evidence appears complementary to the findings of Lou and Polk (2013), who focus on cross-sectional equity momentum and find that the strategy experiences stronger reversals after periods of increased momentum activity over the portfolio formation period. They measure momentum activity as the average pairwise correlation of stocks in the winner or the loser portfolio, after accounting for the exposure to the Fama and French (1993) model. Hence, high momentum activity implies a stronger co-movement of assets during the portfolio formation period, which, to a certain extent, can be related to having a strong TREND rule across the assets. We therefore consider our analysis in Figure 6 as the multi-asset complement to Lou and Polk's (2013) equity analysis.

Going back to our analysis on the impact of the TREND rule on the properties of the TSMOM strategy in Table III, we note that, contrary to the actual risk-adjusted performance that remains quantitatively almost unchanged when switching the trading rule, the turnover reduction is both sizeable and statistically strong. We report a portfolio turnover reduction of roughly 24% (statistically significant at 1%) when the TREND rule is used. This implies that the TREND rule leads to a similar Sharpe ratio, while requiring one quarter less rebalancing.[16]

As in the case of the volatility estimator, the documented turnover reduction at the strategy level is pervasive across all portfolio constituents. Figure 7 presents the percentage turnover change for univariate TSMOM strategies for each asset of our universe when switching between these rules. Without a single exception, the turnover reduction is pronounced across all assets and asset classes.

[Figure 7 about here]

4.3. The joint benefit and a discussion on the importance of turnover reduction

Taken together, the switch in the volatility estimator and the trading rule can lead to turnover gains of more than one third (36.23%, with a t-statistic of 13.19, as shown in the last rows of Table III), without any significant performance drop in the TSMOM strategy. This is a remarkable result, as without causing any performance penalty, the turnover of the TSMOM strategy has been significantly reduced. In Section 6, we investigate the economic benefit of this turnover reduction in terms of trading cost reduction. It is worth noting the importance of turnover reduction on its own merit.

The TSMOM strategy –as any momentum strategy– is a high-turnover strategy.[17] Using the estimates

[16] Dudler et al. (2015) report a similar turnover reduction for their daily-rebalanced risk-adjusted momentum strategy. For a lookback period of 12 months, the turnover reduction is around 30%.

[17] Academic evidence has even suggested that such high turnover and the associated costs can strongly squeeze the performance of cross-sectional momentum; see Korajczyk and Sadka (2004), Lesmond et al. (2004), Menkhoff et al. (2012) and

from Table III), the default setup of the strategy (using SD volatility estimates and the SIGN trading rule) exhibits a monthly turnover, after leverage, of 170%. The profitability of the strategy is therefore largely dependent on how quickly the portfolio is rebalanced so as to capture the latest emerging price trends and move away from previous trends that have already materialised. This, in turn, means that one can only do so much in terms of turnover reduction, before the actual performance of the strategy starts falling significantly. A momentum strategy cannot just be turned into a low-turnover strategy without an impact on its performance. The fact that our results show a reduction in the turnover of more than one third without a material impact on the actual performance of the strategy is therefore noteworthy.

Looking at the practical implications on the implementation of a trading strategy, a portfolio manager would welcome such a sizeable and statistically strong reduction in the turnover. Investors typically face turnover constraints, either because of mandate and regulation and/or just because they want to avoid having a significant price impact when turning over their portfolios. A lower turnover strategy is therefore more likely to be employed by such investors. Additionally, low turnover allows for scalability and capacity in terms of capital invested.

As we shall show in the next section, the turnover reduction that has been achieved can permit changes in the strategy design that focus on performance improvement, which generally come at the cost of higher turnover.

5. The Recent Underperformance of Time-series Momentum Strategies and the Effect of Pairwise Correlations

The purpose of this section is to investigate the dependence of the performance of the TSMOM strategy on the level of the pairwise signed correlations of portfolio constituents and shed light on the poor performance of the strategy after 2008. Our analysis is motivated by the results of Baltas and Kosowski (2013), who, after finding no significant evidence of capacity constraints in the performance of the strategy, argue that the underperformance can potentially be attributed to the lack of significant price trends or an increased level of correlation across assets of different asset classes in the post-GFC period (also

Novy-Marx and Velikov (2016).

argued by Georgopoulou and Wang 2016).[18] We first empirically document evidence supporting these two claims, namely the relative lack of strong price trends over the most recent period and the increase in the pairwise correlations. Subsequently, we investigate the benefit from incorporating pairwise correlations in the weighting scheme of the TSMOM strategy, as a way to improve its performance in periods of heightened correlations.

5.1. Price Trend Strength and Pairwise Correlations

As already shown in Panel B of Figure 4, the number of assets with a strong TREND rule has fallen significantly during the post-GFC period. This absence of strong momentum patterns could, therefore, be one reason for the recent performance drop of the TSMOM strategy.

In order to shed more light on this, Panel A of Figure 8 presents the average (unsigned) pairwise correlation across all assets over our sample period using a three-month rolling estimation window. In addition to this, Panel B of Figure 8 presents the average signed pairwise correlation across all contracts, as defined in equation (14). The unsigned correlations are useful in identifying periods of regime shifts in the co-movement across assets and asset classes, whereas the signed correlations are useful in identifying periods of systematic clustering of time-series momentum trading rules. During periods of significant signed co-movement between assets, portfolio diversification can be impacted, hence rendering the portfolio construction methodology that is typically employed in TSMOM strategies suboptimal.

[Figure 8 about here]

Looking first at the average unsigned pairwise correlation across all assets in Panel A of Figure 8, it is visually clear that this has increased significantly over the last decade of our sample period, in two distinct phases.

The first shift, which has been the milder to the two, seems to have taken place after 2004 and is more likely to be related to the introduction of the Commodity Futures Modernization Act (CFMA) in 2000. This Act effectively rendered the futures market accessible for investors as a way to hedge

[18]See, for example, "CTA trend-followers suffer in market dominated by intervention" by Emma Cusworth, Hedge Funds Review, 10 October 2013.

commodity price risk. This led to significant capital flows into commodity futures contracts as well as into newly introduced –at the time– exchange traded funds (ETF) tracking the performance of commodity indices, like the Goldman Sachs Commodity Index (GSCI) or the Bloomberg Commodity (BCOM) index (formerly Dow Jones UBS Commodity index). These capital flows gave rise initially, post-2004, to higher levels of correlations within commodities (Tang and Xiong 2012) and subsequently, post-GFC, between commodities and other asset classes (Silvennoinen and Thorp 2013), in what is widely referred as the financialization of commodities. The financialization of commodities has recently been a very active research field (Irwin and Sanders (2011), Singleton (2013), Cheng and Xiong (2014), Büyükşahin and Robe (2014), Henderson, Pearson and Wang (2015), Hamilton and Wu (2015) and Basak and Pavlova (2016)).

The second shift in the average pairwise correlation, which is the more pronounced of the two, seems to have occurred after the GFC. During the post-GFC period assets became more closely related, not only within the same asset class, but most importantly across asset classes; see Silvennoinen and Thorp (2013) for the part of this increase that is due to the already discussed financialization of commodities and Baltas (2015) for a broader analysis across all asset classes. These higher levels of co-movement have substantially reduced the diversification benefits of the investable universe and can explain the common grouping of all tradable assets into "Risk On" and "Risk Off" assets by market participants.

Looking at the signed pairwise correlations in Panel B of Figure 8, the patterns are relatively similar to the unsigned correlations, but generally stronger and larger in magnitude. This effectively means that, in addition to the higher level of asset co-movement, a higher level of clustering of time-series momentum trading rules has recently been exhibited. To give an example of how this can happen, let us consider two assets that are negatively correlated. On an unsigned basis, this negative correlation, in fact, reduces the overall level of the average unsigned correlation. However, if the time-series momentum trading rule suggests taking a short position in one of these two assets then their signed correlation turns positive and therefore contributes positively to the average pairwise signed correlation.

To summarise, during the last decade of our sample period, and most importantly in the post-GFC period, the assets of our universe have exhibited significantly higher levels of correlation compared to the more distant past, and their TSMOM trading rules have exhibited higher levels of clustering. We could therefore hypothesise that this increased level of signed co-movement has reduced the diversification benefits of the multi-asset universe and this could have, in turn, reduced the profitability potential of the TSMOM strategy over that period (as also claimed by Baltas and Kosowski 2013, Georgopoulou and Wang 2016). Put differently, an important research question is whether incorporating information from the signed correlation matrix of the assets into the portfolio construction could render the TSMOM strategy more robust in periods of increased signed co-movement.

As presented in Section 3, this can be achieved by using the level of the average pairwise signed correlation to dynamically adjust the target level of volatility of each asset in the TSMOM strategy. The correlation-adjusted TSMOM strategy of Equation (19) is repeated below for convenience:

$$r_{t,t+1}^{TSMOM-CF} = \frac{1}{N_t} \sum_{i=1}^{N_t} X_t^i \cdot \frac{\sigma_{P,tgt}}{\sigma_t^i} \cdot CF\left(\bar{\rho}_t\right) \cdot r_{t,t+1}^i \tag{29}$$

The correlation factor (CF) depends on the average pairwise signed correlation (see Equation (18)). Incorporating the correlation factor would call for a reduction in the leverage when pairwise signed correlations increase and diversification benefits diminish. We next evaluate the performance of the correlation-adjusted TSMOM strategy.

5.2. Performance Evaluation

Table IV reports performance statistics for the default specification of the TSMOM strategy (using SD volatility estimates and the SIGN trading rule) with a per asset target level of volatility $\sigma_{tgt} = 40\%$ and for various specifications of the correlation-adjusted strategy (using SD or YZ volatility estimates and the SIGN or TREND trading rules) with a portfolio target level of volatility $\sigma_{P,tgt} = 12\%$. These choices of asset and portfolio target volatility are inconsequential and are justified by the arguments of Moskowitz et al. (2012), who similarly choose the asset target level of volatility to be 40%, so that the overall TSMOM strategy exhibits an ex-post portfolio volatility of 12% for their respective sample period (1985-2009), which, in turn, matches roughly the level of volatility of the Fama and French (1993) and Asness et al. (2013) factors. Panel A covers the entire sample period, whereas Panel B focuses on the post-GFC period, which was shown above to have been characterised by elevated levels of co-movement across asset classes and therefore by diminished diversification benefits.

[Table IV about here]

Several interesting insights emerge from the analysis. Over the entire sample period, the correlation adjustment achieves an increase in the Sharpe ratio from 1.15 to 1.19. The performance improvement is much stronger in the post-GFC period with the Sharpe ratio increasing from 0.01 to 0.11 (or even up to 0.17, when all methodological amendments suggested in this paper are incorporated, as seen in the far right column of the Table – YZ estimator, TREND rule and correlation adjustment).

Given the dynamic leverage nature that is introduced by the correlation factor (reducing leverage in times of large asset signed co-movement), the benefit in the performance of the TSMOM strategy becomes much more pronounced when considering crash/downside 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). As an example, the Sortino ratio increases from 2.08 to 2.31 over the entire sample period, and from 0.01 to 0.16 for the post-GFC period. These findings are in line with our hypothesis; that is, taking into account signed pairwise correlations positively affects the diversification benefits of the portfolio and improves the risk-adjusted performance especially in periods of higher asset co-movement, like the post-GFC period. This outcome is in line with Baltas (2015), who, as already discussed earlier, introduces a TSMOM strategy that incorporates pairwise correlations in portfolio construction by means of a long-short risk-parity framework and shows that this strategy performs significantly better in periods of heightened asset co-movement.

As expected, the performance benefit does not come without a cost. The effect of modelling and incorporating correlations in portfolio construction leads to more frequent and larger adjustments in portfolio leverage, which, in turn, increases portfolio turnover; all else being equal, the turnover of the standard TSMOM strategy increases after the correlation adjustment from 170% up to 208.6%, an increase that is statistically significant at 1% level (t-statistic of 3.98).

However, as shown earlier in Section 4, the additional turnover burden could theoretically be alleviated –if not completely contained– by the use of a more efficient volatility estimator and/or trading rule. Applying both (YZ volatility estimates and TREND trading rule), in fact, leads to an overall turnover reduction compared to the original setup of the TSMOM strategy, even after applying the correlation adjustment (130.2% down from 170%; the reduction is statistically significant at 1% level).

In a nutshell, our results highlight the role that the increased pairwise signed correlations have played in the recent performance of simple unadjusted TSMOM strategies. The implication for fund managers and investors is two-fold. First, allowing signed correlations to determine portfolio weights and dynamically adjust the level of leverage that is employed can be beneficial during periods of high co-movement and trading rule clustering. Second, adjusting for correlation can increase turnover and therefore trading costs. However, other methodological adjustments that have been suggested in this paper, such as a more efficient volatility estimator or a trading rule that becomes informed of the statistical strength of the price trends, can counteract and contain this increased turnover. The next section of the paper introduces a new trading costs model for futures-based strategies and provides a set of after-costs results for the variants of the TSMOM strategy.

6. Trading Costs Implications

Our results so far have shown that different volatility estimators, trading rules and correlation adjustments can substantially impact portfolio turnover, which, as a result, can potentially affect the performance of a strategy after accounting for transaction costs. In this section, we present a detailed model for the approximation of transaction costs for futures-based trading strategies and evaluate the after-costs performance of the various variants of the TSMOM strategy.

Transaction costs have several components and these are typically classified into implicit and explicit transaction costs (Harris 2002). Explicit transaction costs include brokerage commissions, market fees, clearing and settlement costs, and taxes/stamp duties. Implicit transaction costs refer to costs that are not explicitly included in the trade price and therefore have to be estimated. They mainly consist of bid-ask spreads, market impact, operational opportunity costs, market timing opportunity costs and missed trade opportunity costs.

Market participants estimate implicit transaction costs using specified price benchmark methods and econometric transaction cost estimation methods (Harris 2002). These costs depend primarily on the characteristics of any given trade relative to prevailing market conditions and include factors such as the order size as well as the asset's daily trading volume and volatility. Several papers focus on estimating transaction costs in cash equities (see for example Jones and Lipson 1999) using institutional equity order data. Frazzini, Israel and Moskowitz (2015) use proprietary data of a large institution on portfolio holdings and execution prices for the construction and rebalancing of various equity factor portfolios (e.g. momentum, value) and estimate the respective average market impact costs. A similar analysis of the costs and therefore of the respective capacity of equity factor portfolios is conducted by Novy-Marx and Velikov (2016).

Our purpose is to study the trading costs of a futures-based strategy, but, unfortunately, we do not have access to datasets similar to those used in the papers discussed above. For that reason, as opposed to looking at the implicit and explicit costs of a TSMOM strategy, we introduce a transaction costs model that separates the costs into two main distinct sources: (i) roll-over costs of futures contracts and (ii) rebalancing costs. We explain in detail the dynamics for both sources below.

6.1. Roll-over Costs

The roll-over costs are incurred when a futures contract approaches maturity and rolls over to the next-to-mature (back) contract. Such costs incur even if there is no change in the notional allocation to an asset; one can think of the roll-over costs as a type of maintenance costs. As an example, if an asset has a 20% weight and a roll-over is imminent because the front contract approaches maturity, there is a cost to pay in order to close down the existing position on the front futures contract and to open a new position of the same notional size on the back contract. One can contrast this against a buy and hold strategy in the spot market, where no additional cost is required to maintain the portfolio.

The roll-over costs are typically quoted in basis points per annum for maintaining a position of 100% gross exposure to an asset. To continue the previous example, if the asset of interest has roll-over costs of 10 basis points per annum, then maintaining a constant 20% weight over a year would incur roll-over costs of $20\% * 10 = 2$ basis points. As it becomes obvious, the roll-over costs are only a function of the gross weight of each asset. Furthermore, roll-over costs are directly impacted by the leverage that is employed at the overall portfolio level. Assuming that the above example relates to an unlevered portfolio (so that the sum of the gross weights equals to 100%), then a leverage of 3x would triple all roll-over costs, as the gross weight of the asset, after leverage, would be 60% and the respective roll-over costs equal to 6 basis points.

Our universe contains a broad list of assets across asset classes with different futures maturity schedules. For our empirical analysis, we assume different levels of roll-over costs for each asset class, which is a rather realistic assumption, as commodity futures are relatively more expensive to roll-over than FX or bond futures.

Denoting by θ_i the roll-over costs for asset i, the roll-over costs of the overall portfolio between rebalancing times t and $t+1$, denoted by $RO_{t,t+1}$, are calculated as follows:

$$RO_{t,t+1} = \sum_{i=1}^{N_t} \left|w_t^i\right| \cdot \theta_i \tag{30}$$

where $w_t^i = \frac{X_t^i}{N_t} \cdot \frac{\sigma_{tgt}}{\sigma_t^i}$ for the TSMOM strategy with no correlation adjustment and $w_t^i = \frac{X_t^i}{N_t} \cdot \frac{\sigma_{P,tgt} \cdot CF(\bar{\rho}_t)}{\sigma_t^i}$ for the correlation-adjusted TSMOM strategy.

6.2. Rebalancing Costs

The other part of the transaction costs, namely the rebalancing costs, relate directly to the turnover of the portfolio. As the TSMOM strategy rebalances on a monthly basis, these costs incur on a monthly basis and describe the costs from changing the net allocation to the various assets due to potential changes in their volatility or trading rule.

Contrary to the roll-over costs, the rebalancing costs are directly related to the net weight of each asset and therefore reflect any position rebalancing between long and short exposure. As an example, if an asset has an unchanged net weight of 20% long over a rebalancing date, it incurs no rebalancing costs (even though it might still incur roll-over costs if a roll-over takes place, as explained earlier). Conversely, if there is a position switch and the net weight shifts from 20% long to 20% short, then there are rebalancing costs relating to $|20\% - (-20\%)| = 40\%$ of gross exposure.

The rebalancing costs are typically quoted in basis points per gross position change of 100% over a rebalancing date. To continue the example used earlier in the last paragraph, if the asset of interest has rebalancing costs of 10 basis points, then the transition from 20% long to 20% short would incur rebalancing costs of $40\% * 10 = 4$ basis points.

For the purposes of our analysis, we assume different levels of rebalancing costs for each asset class. Denoting by η_i the rebalancing costs for asset i, the rebalancing costs of the overall portfolio between rebalancing times t and $t+1$, denoted by $RB_{t,t+1}$, are calculated as follows:

$$RB_{t,t+1} = \sum_{i=1}^{N_t} \left| w_{t+1}^i - w_t^i \right| \cdot \eta_i \tag{31}$$

6.3. Transaction Costs Model

Taken together, both types of costs reduce the profitability of a TSMOM strategy. The after-costs performance of the strategy between rebalancing times t and $t+1$ is therefore given by:

$$\begin{aligned} r_{t,t+1}^{TSMOM,\text{after costs}} &= r_{t,t+1}^{TSMOM} - RO_{t,t+1} - RB_{t,t+1} & (32) \\ &= \sum_{i=1}^{N_t} \left[w_t^i \cdot r_{t,t+1}^i - \left| w_t^i \right| \cdot \theta_i - \left| w_{t+1}^i - w_t^i \right| \cdot \eta_i \right] & (33) \end{aligned}$$

As the rebalancing costs are solely driven by portfolio turnover, they are directly impacted by the choice of the volatility estimator, the choice of the trading rule and the correlation adjustment. Conversely, the roll-over costs are solely related to the gross exposure of the assets and are therefore mostly impacted by the choice of the trading rule (as a reminder, the TREND rule – but not the SIGN rule – scales the exposure to the various assets as a function of their realised Sharpe ratio of daily returns over the past 12 months) and the correlation adjustment (the overall leverage of the strategy is adjusted in response to signed correlation shifts); the choice of the volatility estimator hardly alters the roll-over costs (in the long run), as long as the different volatility estimators are unbiased (for our analysis, both SD and YZ estimators are unbiased).

Before presenting the empirical analysis on transaction costs, it is worth comparing our costs model to the one used by Barroso and Santa-Clara (2015a). The TSMOM strategy (or any other futures-based strategy) incurs, as already explained, two different types of costs that are distinctly different and that are incurred at different times; roll-over costs are incurred when a futures contract rolls-over from the front to the back, whereas rebalancing costs are incurred when the overall portfolio is rebalanced (on a monthly basis in our formulation). Contrary to TSMOM, Barroso and Santa-Clara's (2015a) FX carry strategy is rebalanced on a monthly basis and trades one-month FX forward contracts, which are then settled at next month's spot FX rate before a new set of weights is generated and new positions on one-month FX forward contracts are employed. This means that they only have to consider rebalancing costs.

Following the above discussion, we consider our transaction costs model as an extension of Barroso and Santa-Clara's (2015a) costs model that can be applied to futures-based portfolios whose rebalancing and roll-over schedules do not necessarily coincide.

6.4. Time-Series Momentum and Trading Costs

Using our trading costs model, we next look at the costs estimates of the various TSMOM specifications that have been studied so far in our paper. For this analysis, and based on discussion with market participants, we use realistic levels of roll-over and rebalancing costs for each asset class, reported in Table V.

[Table V about here]

Table VI reports pre-costs performance statistics, annual costs estimates and after-costs performance statistics for all combinations of volatility estimator, trading rule and correlation adjustment, over the entire sample period (Panel A) and over the post-GFC period (Panel B). Our focus is on the marginal relative reduction or increase of trading costs from the various TSMOM methodological amendments suggested in our paper. In order to facilitate these comparisons, the Table contains a three-digit binary code system for every TSMOM specification: the first digit represents the trading rule 0/1: SIGN/TREND, the second digit represents the volatility estimator 0/1: SD/YZ, and the third digit represents the correlation adjustment 0/1: without/with. As an example, the strategy 101 uses the TREND rule, the SD volatility estimator and employs the signed correlation adjustment. The left-most column of the Table contains the default TSMOM specification in the literature (coded as 000), whereas the right-most column of the Table contains the TSMOM specification that incorporates all methodological amendments that have been introduced (coded as 111).

[Table VI about here]

Overall, the results from the costs analysis are very much in line with our earlier findings. The use of the more efficient volatility estimator, YZ, or the more robust TREND trading rule reduces the trading costs of the strategy by about 13% and 25% respectively, whereas taken together these two amendments manage to reduce the trading costs by more than a third (35%), from 163 basis points per annum, down to 105 basis points (comparing codes 000 to 110). This is a sizeable reduction.

Conversely, the correlation adjustment always increases the trading costs due to the higher associated turnover. As an example, the costs of the default TSMOM specification increase by about 13%, from 163 basis points per annum to 185 basis points (comparing codes 000 to 001). Interestingly though, when combined with the more efficient volatility estimator and the trading rule that accounts for price trend strength, the net effect is still a sizeable costs reduction of about 28%, from 163 basis points per annum, down to 118 basis points (comparing codes 000 to 111).

How do these estimates translate into after-costs performance? Comparing pre- and after-costs Sharpe ratios in Panel A of Table VI, one can argue that the benefits in terms of costs reduction are not strongly reflected. This does have an interpretation. Starting from the default TSMOM specification, we find that the estimated trading costs of 163 basis points per annum represent about 10% of the pre-costs average annualised returns of the strategy (16.12%). All else being equal, any turnover and therefore costs reduction, can only impact this 10% of annualised performance, so in total in can only be a small proportion of the overall strategy performance.

However, as already discussed in paragraph 4.3, this should not undermine the importance of our findings. Turnover and costs reduction without any performance drop, especially for a strategy like TSMOM that generally demands high levels of turnover in order to achieve profitability, increases the overall capacity of the strategy in terms of capital invested and therefore improves the potential for scalability.

Focusing in the post-GFC period at Panel B of Table VI, the results relating to the absolute levels of trading costs as well as the relative gains or losses due to the various alternative specifications of the TSMOM strategy are generally similar to those of the full sample analysis. However, it is worth emphasising the importance of incorporating the pairwise signed correlations in the portfolio construction of a TSMOM strategy, especially in this period of increased level of co-movement across asset classes.

When the trading costs are incorporated, the Sharpe ratio of the default setup of the TSMOM strategy turns negative and it is equal to -0.09 (0.01 before costs). After incorporating the various methodological amendments suggested in this paper and most importantly after incorporating the correlation adjustment the Sharpe ratio of the TSMOM strategy remains positive and equal to 0.06 (0.17 before costs).

In absolute terms, these estimates of the Sharpe ratio before and after costs in the post-GFC period are much lower compared to historical standards. However, this highlights two important issues. First, the TSMOM strategy has indeed suffered from significant underperformance in this most recent period as already discussed several times throughout the paper. Second, this underperformance has been partly due to the increased level of co-movement between assets and asset classes over this period, which, however, when taken into account in the design of the strategy by the means of the correlation factor leads to relatively better performance that remains marginally positive even after incorporating the respective trading costs.

7. Concluding Remarks

This paper contributes to the literature on time-series momentum in three ways related to reduction of turnover, improvement of diversification potential, and estimation of trading costs, respectively.

First, we show that the turnover of the strategy can be significantly reduced with the use of more efficient volatility estimates like the ones suggested by Yang and Zhang (2000) or the use of alternative trading rules that depart from the typical binary setup (+1: long, and -1: short). The turnover gains can reach levels of up to approximately 36% (for our sample period and underlying universe), when both methodological amendments are employed, without causing a statistically significant performance penalty.

Second, we provide new empirical evidence to shed light on the post-GFC underperformance of the strategy and the increased level of asset co-movement in this period. This finding subsequently motivates the introduction of a modified implementation of the strategy in a way that incorporates the pairwise signed correlations between portfolio constituents by means of a dynamic leverage mechanism. This mechanism effectively reduces the employed leverage in periods of increased co-movement. We find that the correlation-adjusted variant of the strategy outperforms its naive implementation and the outperformance is more pronounced in the post-GFC period. Importantly, the higher turnover due to dynamic leverage is fully counter-balanced when the earlier turnover reduction techniques are also employed.

Finally, in order to evaluate the economic magnitude of these methodological innovations, we introduce a novel transaction costs model for futures-based investment strategies that separates costs into roll-over costs and rebalancing costs. While roll-over costs are only determined by the gross exposure to the various futures contracts, the rebalancing costs are directly related to the turnover of the strategy. Over our 30-year sample period, we estimate that the trading costs of a time-series momentum strategy roughly represent 10% of its gross return. In line with our earlier findings on turnover reduction, more efficient volatility estimates and more robust trading rules can substantially reduce these costs. In addition, the performance benefit of the correlation adjustment –which, when considered in isolation, actually increases trading costs– can still come with a substantial cost reduction when combined with the turnover reduction techniques discussed above. As a result, the strategy delivers better after costs risk-adjusted returns, benefitting both from the performance benefit of the correlation adjustment and the overall turnover reduction.

Overall, the findings of this paper have important implications for the academic literature on and investors in time-series momentum trading. By shedding light on the drivers of the recent underperformance of CTA funds, we indicate ways to improve the performance of time-series momentum strategies either by estimating volatility and price trends more efficiently or by improving the diversification properties of the portfolio.

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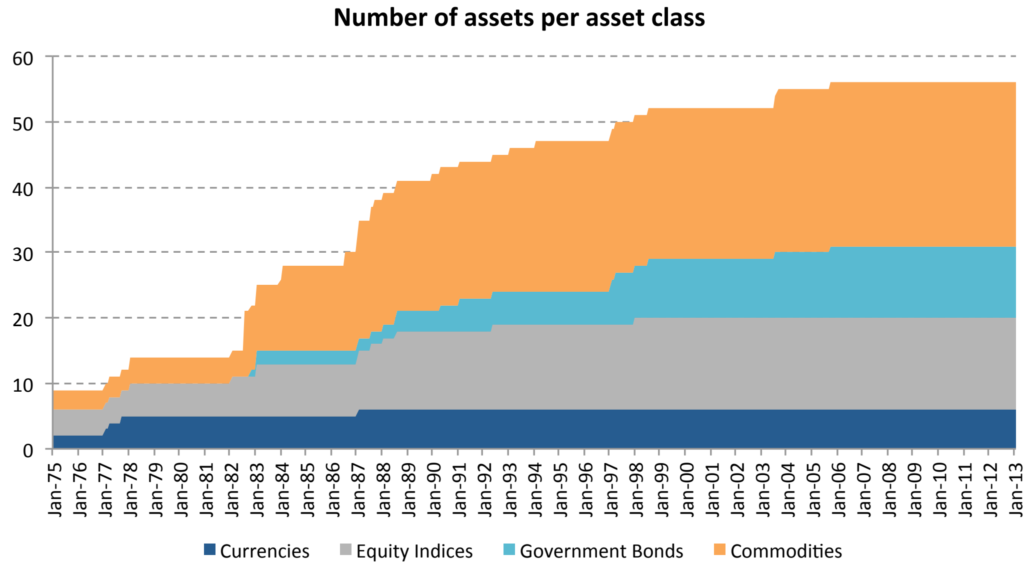


Figure 1: *Number of Assets per Asset Class*
The figure presents the number of assets for each asset class that are available in the dataset at the end of every month. The sample period is from December 1974 to February 2013.

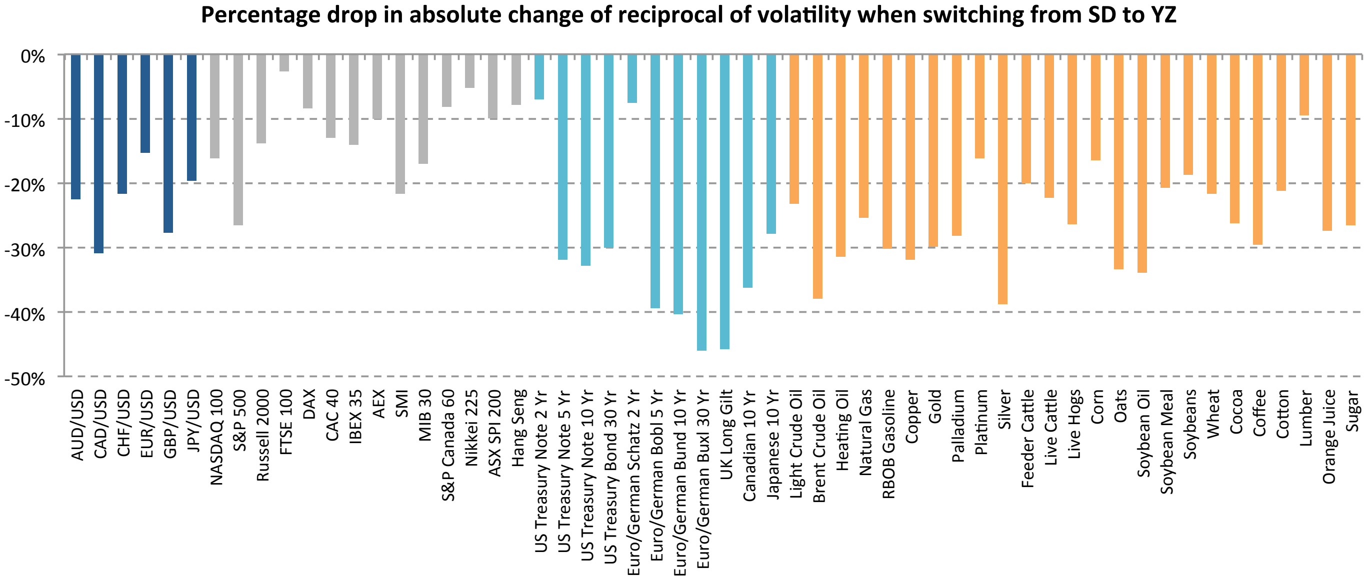


Figure 2: *Effect of Volatility Estimator choice on Reciprocal of Volatility*
The figure presents the percentage drop of the average absolute change in the reciprocal of volatility for each asset of the dataset when switching from the standard deviation of past returns (SD) volatility estimator to the Yang and Zhang (2000) estimator (YZ). The specific sample period of each contract is reported in Table I.

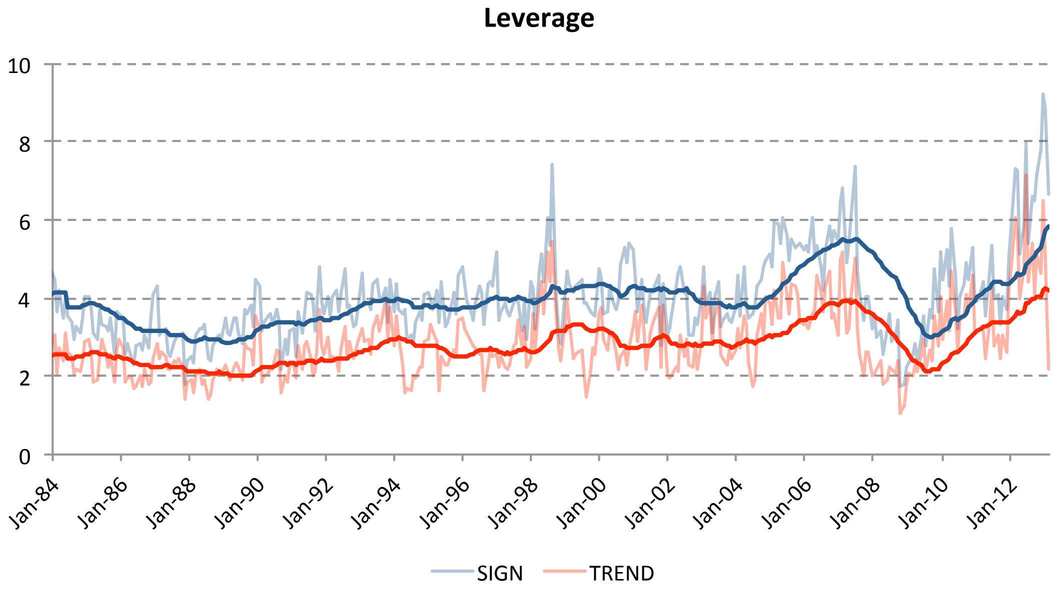


Figure 3: *Leverage of Time-Series Momentum*
The figure presents the leverage that is employed for the two trading rules, SIGN and TREND, across time; 24-month moving averages of the leverage are also superimposed. The lookback period for which the rules are generated is 12 months and the sample period is January 1983 (first observation in January 1984) to February 2013.

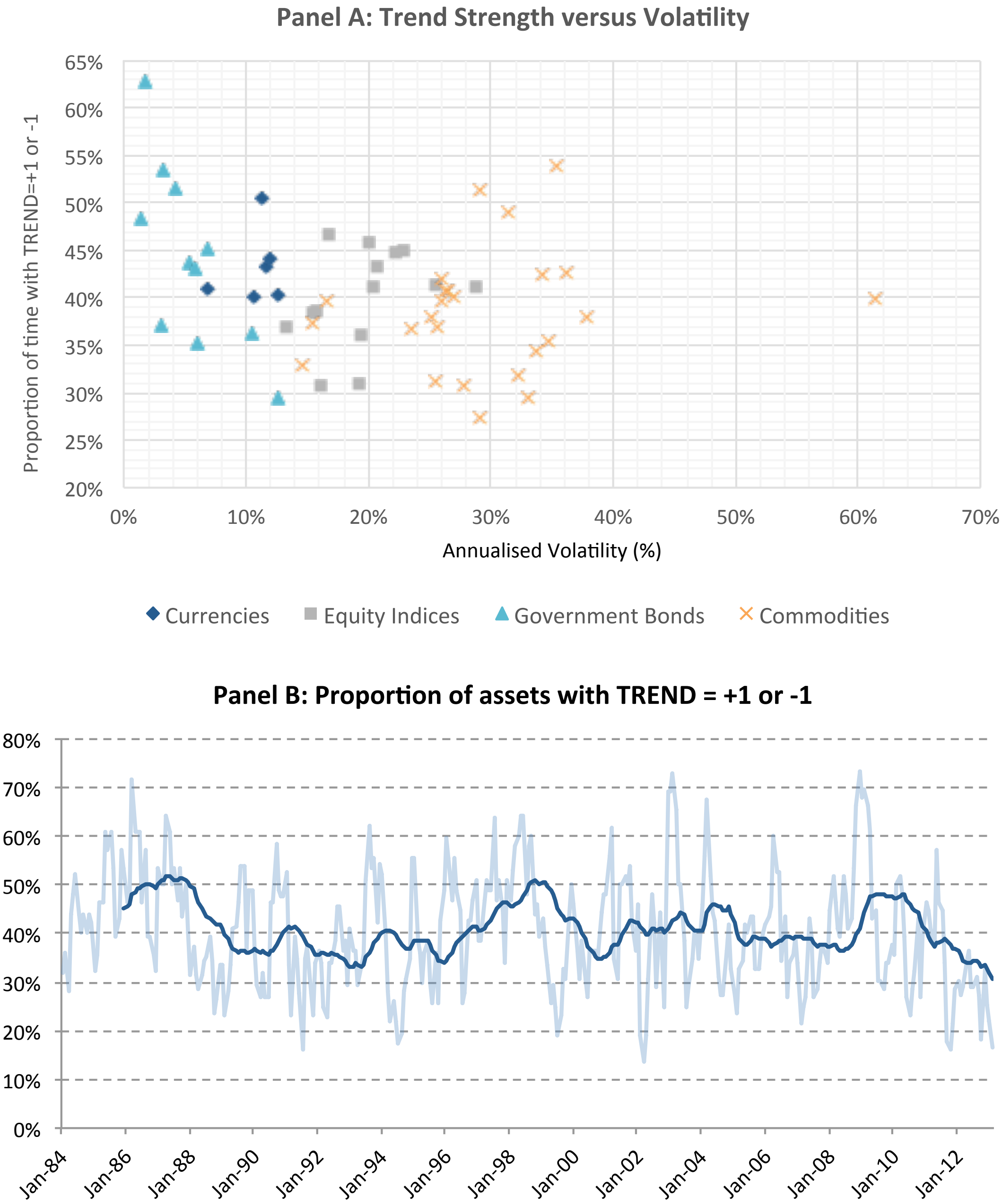


Figure 4: *The statistics of the TREND trading rule*

Panel A presents a scatterplot between the volatility of an asset and the proportion of time that the TREND rule of this asset is either +1 or -1. The specific sample period of each asset of each asset class is reported in Table I. Panel B presents the percentage of available contracts at the end of each month for which the TREND rule is either +1 or -1; the 24-month moving average of this value is also superimposed. The lookback period for which the rules are generated is 12 months and the sample period is January 1983 (first observation in January 1984) to February 2013.

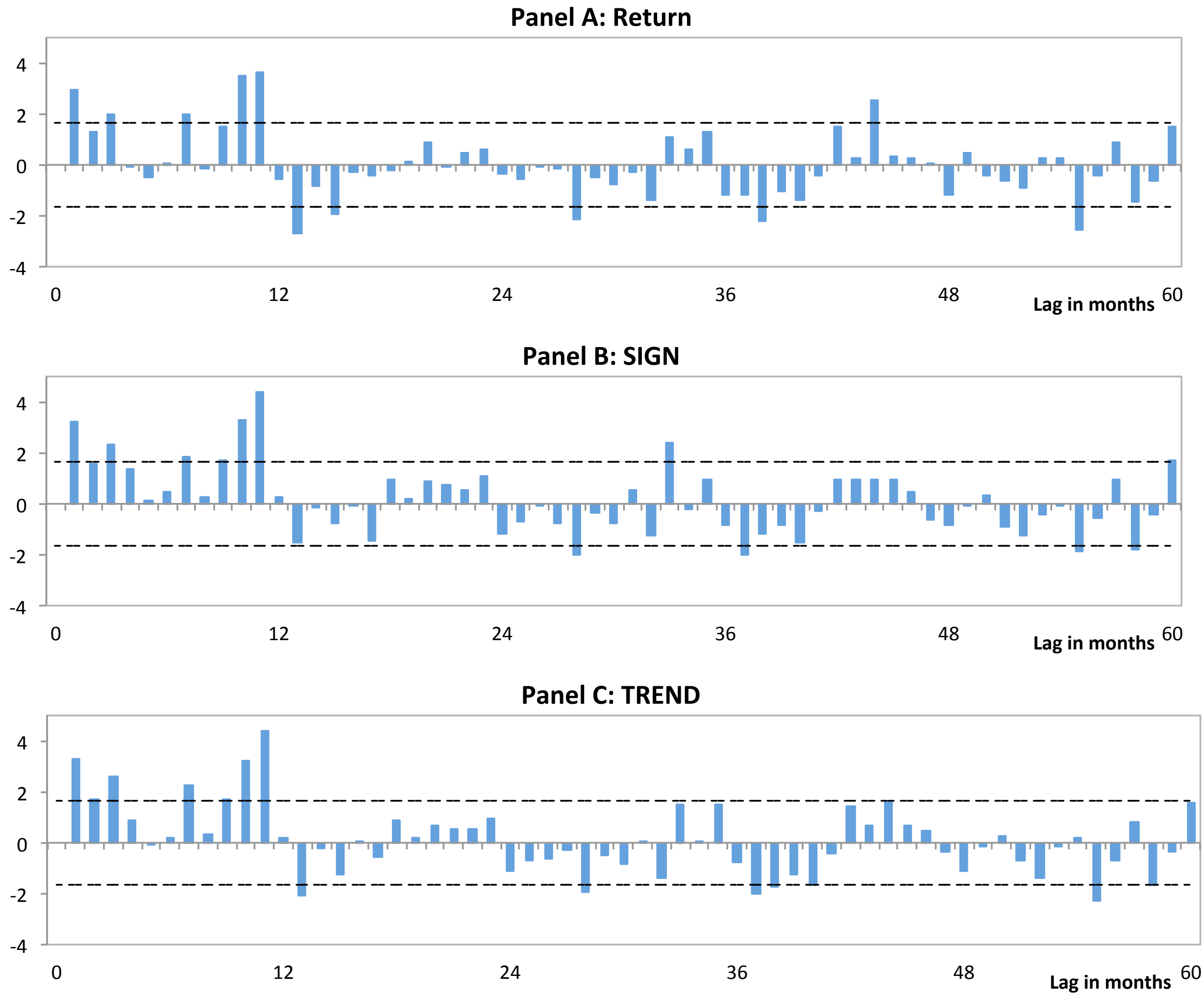


Figure 5: *Time-Series Return Predictability*
The figure presents the t-statistics of the pooled regression coefficient from regressing monthly excess returns of the futures contracts on lagged excess returns or lagged excess momentum trading rules. Panel A presents the results when lagged excess returns 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 SD estimator on a one-month rolling window. The dashed lines represent significance at the 10% level. The dataset covers the period January 1983 to February 2013.

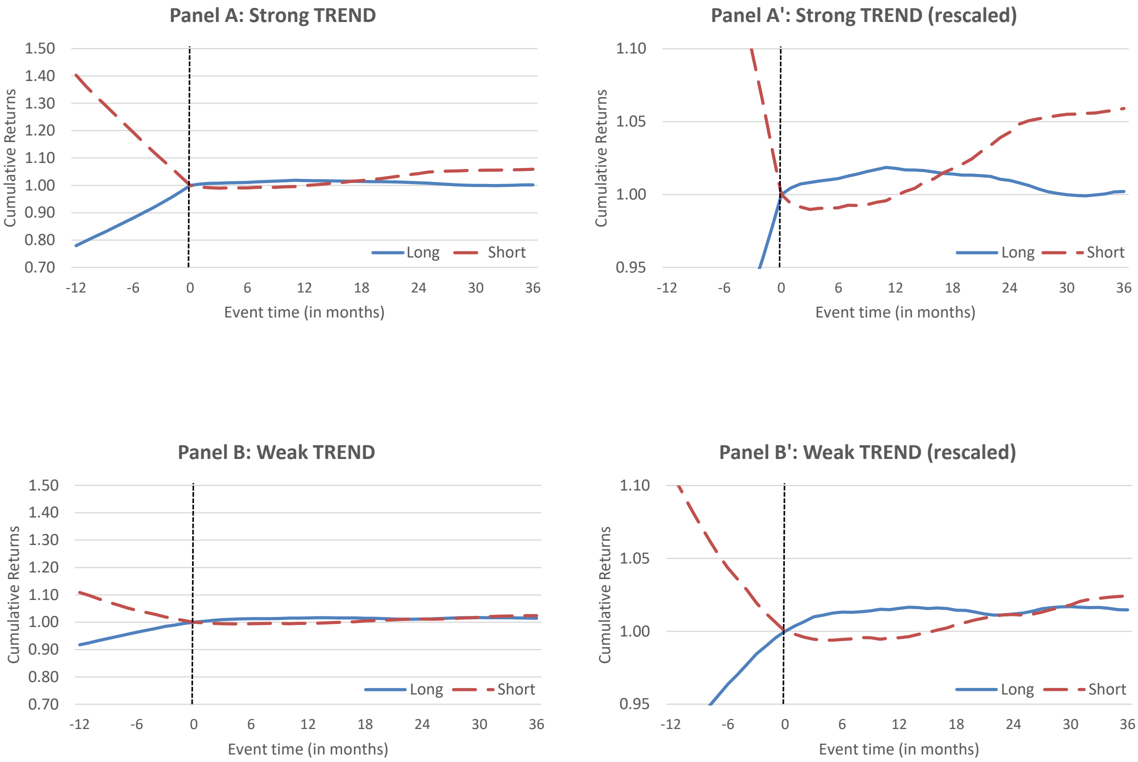


Figure 6: *Event Study of the TREND Trading Rule*
The figure presents an event study across all assets and across time for the period between 12 months before and 36 months after the portfolio formation date (event time ”0”). Panel A contains the cumulative performance of all asset-month pairs with a TREND rule of +1 or -1 (”Strong”), whereas Panel B contains the respective performance of all asset-month pairs with a positive TREND rule strictly less than one or a negative TREND rule strictly larger than -1 (”Weak”). All returns are standardised in order to have zero mean across time and across the four groups (long or short, strong or not strong) for comparison purposes. Panels A’ and B’ present rescaled versions of Panels A and B respectively. The specific sample period of each asset of each asset class that is used in the analysis is reported in Table I.

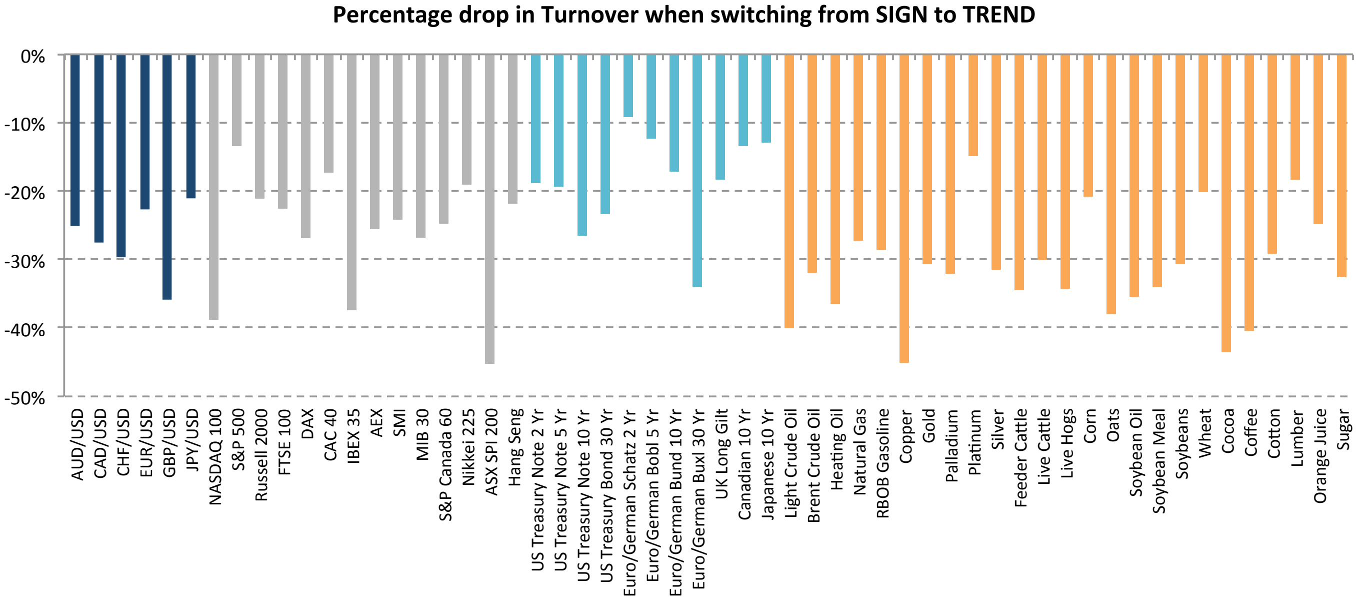
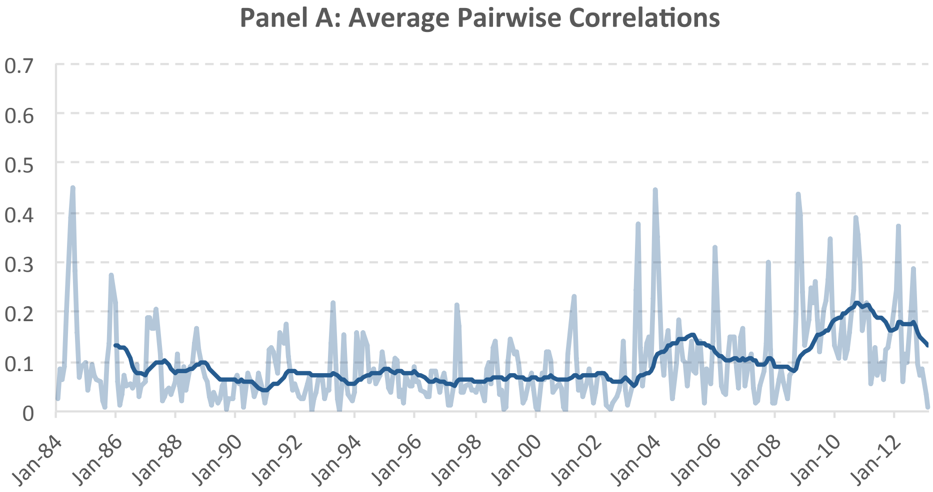


Figure 7: *Effect of Trading Rule choice on Turnover*

The figure presents the percentage drop in the turnover of each univariate time-series momentum strategy when switching between SIGN and TREND trading rules. The one-month SD volatility estimator is used across all strategies. The specific sample period of each contract is reported in Table I.



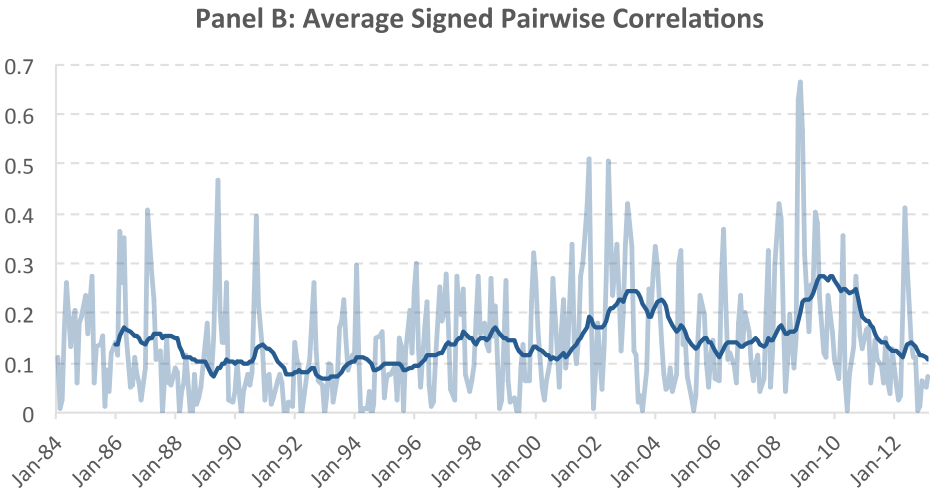


Figure 8: *Average Pairwise Correlations*

The figure presents the three-month raw (Panel A) and signed (Panel B) average pairwise correlation of the available contracts at the end of each month; 24-month moving averages of these estimates are superimposed. The sample period is from January 1984 to February 2013.

	Exchange	From	Mean	t-stat	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
EQUITIES								
NASDAQ 100	CME	Feb-1983	9.29	1.91	25.40	-0.31	4.29	0.37
S&P 500	CME	Dec-1974	5.76	2.20	15.35	-0.48	4.62	0.38
Russell 2000	ICE	Feb-1988	7.06	1.75	19.17	-0.49	4.01	0.37
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
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
INTEREST RATES								
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
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
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

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	Exchange	From	Mean	t-stat	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
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 (February 2013) as well as the starting month and year for each contract. All but 7 contracts have data up until February 2013. The EUR/USD contract is spliced with the DEM/USD (Deutsche 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.

Panel A: Long-Only Constant Volatility Strategies			
	SD	YZ	PF
Average Return (%)	12.64	12.38	17.01
Volatility (%)	16.54	16.37	14.54
Skewness	-0.45	-0.50	-0.24
Kurtosis	3.35	3.62	2.88
Sharpe Ratio	0.76	0.76	1.17
LW Boot-TS p-value	H_0	0.69	0.00
Average Leverage	4.07	3.89	4.06
Monthly Turnover (%)	111.1	81.9	106.6
Relative Turnover change (%)		-26.24	–
(t-stat)		(-9.85)	

Panel B: Time-Series Momentum Strategies			
	SD	YZ	PF
Average Return (%)	16.12	15.70	18.21
Volatility (%)	14.01	13.82	12.46
Skewness	-0.13	-0.21	-0.14
Kurtosis	3.46	3.56	3.40
Sharpe Ratio	1.15	1.14	1.46
LW Boot-TS p-value	H_0	0.53	0.00
Average Leverage	4.02	3.84	4.01
Monthly Turnover (%)	170.0	141.4	164.8
Relative Turnover change (%)		-16.81	–
(t-stat)		(-5.33)	

Table II: *The Effect of the Volatility Estimator*
The table presents performance statistics for long-only constant volatility strategies (Panel A) and time-series momentum strategies (Panel B) that differ between each other in the volatility estimator used: standard deviation of past returns (SD) or the 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 average return in %, annualised volatility in %, skewness, kurtosis, annualised Sharpe ratio, Ledoit and Wolf (2008) bootstrap time-series (Boot-TS) p-value for the null hypothesis of equality of Sharpe ratios between all different strategies against the strategy that uses SD volatility estimates, average leverage, monthly turnover in % and relative turnover change from switching from the SD estimator to the YZ estimator; for the relative turnover change, the table reports the respective two-sample t-statistics for the equality in the turnover of the respective strategies. The dataset covers the period January 1984 to February 2013.

Trading Rule	SIGN		TREND	
Volatility Estimator	SD	YZ	SD	YZ
Average Return (%)	16.12	15.70	13.00	12.72
Volatility (%)	14.01	13.82	11.69	11.60
Skewness	-0.13	-0.21	-0.47	-0.52
Kurtosis	3.46	3.56	3.93	4.37
Sharpe Ratio	1.15	1.14	1.11	1.10
LW Boot-TS p-value	H_0	0.53	0.43	0.37
Average Leverage	4.02	3.84	2.87	2.74
Monthly Turnover (%)	170.0	141.4	128.6	108.4
Relative Turnover change (%)				
- due to volatility		-16.81		-15.67
(t-stat)		(-5.33)		(-5.95)
- due to trading rule			-24.37	-23.34
(t-stat)			(-8.49)	(-8.07)
- joint				-36.23
(t-stat)				(-13.19)

Table III: *Time-series Momentum Strategies and the Effect of the Trading Rule*
The table presents performance statistics for time-series momentum strategies that differ between each other in the momentum trading rule –sign of past return (SIGN) or trend strength (TREND)– and the volatility estimator used –standard deviation of past one-month returns (SD) or the Yang and Zhang (2000) estimator (YZ). The reported statistics are: annualised average return in %, annualised volatility in %, skewness, kurtosis, annualised Sharpe ratio, Ledoit and Wolf (2008) bootstrap time-series (Boot-TS) p-value for the null hypothesis of equality of Sharpe ratios between all different strategies against the strategy that uses the SIGN trading rule and the SD volatility estimator, average leverage, monthly turnover in % and relative turnover change from switching between volatility estimators, trading rules or both ("joint"); for the relative turnover change, the table reports the respective two-sample t-statistics for the equality in the turnover of the respective strategies. The dataset covers the period January 1984 to February 2013.

Trading Rule	SIGN	SIGN		TREND	
Volatility Estimator	SD	SD	YZ	SD	YZ
Correlation Adjustment	No	Yes	Yes	Yes	Yes
Panel A: Full Sample: Jan. 1984 - Feb. 2013					
Average Return (%)	16.12	15.13	14.85	12.20	12.03
Volatility (%)	14.01	12.68	12.60	10.32	10.32
Skewness	-0.13	0.23	0.16	-0.10	-0.13
Kurtosis	3.46	4.36	4.32	3.80	4.01
Sharpe Ratio (Mean/Volatility)	1.15	1.19	1.18	1.18	1.17
LW Boot-TS p-value	H_0	0.56	0.73	0.68	0.85
Sortino Ratio (Mean/Downside Vol.)	2.08	2.31	2.25	2.16	2.11
Calmar Ratio (Mean/Max Drawdown)	0.73	1.03	1.02	0.88	0.80
Average Leverage	4.02	3.72	3.56	2.60	2.48
Monthly Turnover (%)	170.0	208.6	190.1	144.7	130.2
Relative Turnover change (%)		+22.71	+11.82	-14.88	-23.41
(t-stat)		(3.98)	(2.16)	(-3.73)	(-6.34)
Panel B: Post-GFC: Jan. 2009 - Feb. 2013					
Average Return (%)	0.14	1.32	1.32	1.26	1.51
Volatility (%)	15.68	11.57	10.98	9.49	9.00
Skewness	-0.28	-0.28	-0.31	-0.49	-0.53
Kurtosis	3.73	3.52	3.69	3.97	4.14
Sharpe Ratio (Mean/Volatility)	0.01	0.11	0.12	0.13	0.17
LW Boot-TS p-value	H_0	0.56	0.57	0.56	0.55
Sortino Ratio (Mean/Downside Vol.)	0.01	0.16	0.17	0.19	0.24
Calmar Ratio (Mean/Max Drawdown)	0.01	0.09	0.09	0.09	0.13
Average Leverage	5.06	4.73	4.36	3.47	3.17
Monthly Turnover (%)	197.5	230.5	196.7	167.5	137.7
Relative Turnover change (%)		+16.71	-0.41	-15.19	-30.28
(t-stat)		(0.95)	(-0.02)	(-1.18)	(-2.46)

Table IV: *Time-series Momentum Strategies and the Effect of Correlations*
The table presents performance statistics for correlation-adjusted time-series momentum strategies that differ between each other in the momentum trading rule –sign of past return (SIGN) or trend strength (TREND)– and the volatility estimator used –standard deviation of past one-month returns (SD) or the Yang and Zhang (2000) estimator (YZ). The correlation factor is estimated using the average past three-month pairwise signed correlation. For comparison, the first column of the table contains performance statistics for the time-series momentum strategy that uses the SIGN trading rule, the SD volatility estimator and employs no correlation adjustment ("benchmark strategy"). The reported statistics are: annualised average return in %, annualised volatility in %, skewness, kurtosis, annualised Sharpe ratio, Ledoit and Wolf (2008) bootstrap time-series (Boot-TS) p-value for the null hypothesis of equality of Sharpe ratios between all different strategies against the benchmark strategy, Sortino ratio, Calmar ratio, average leverage, monthly turnover in % and relative turnover change from the introduction of the correlation adjustment; for the relative turnover change, the table reports the respective two-sample t-statistics for the equality in the turnover of the respective strategies. Panel A covers the entire sample period from January 1984 to February 2013, whereas Panel B covers the most recent period following the financial crisis, from January 2009 to February 2013.

	Roll-over Costs basis points per annum	Rebalancing Costs basis points per transaction
Currencies	8	3
Equity Indices	10	5
Government Bonds	8	4
Commodities	20	6

Table V: *Levels of Transaction Costs per Asset Class*
The table presents the levels of roll-over costs and rebalancing costs for every asset class. The roll-over costs are measured in basis points per annum for maintaining a position of 100% gross exposure to an asset. The rebalancing costs are measured in basis points per gross position change of 100% over a rebalancing date.

Trading Rule	SIGN		TREND		SIGN		TREND	
Volatility Estimator	SD	YZ	SD	YZ	SD	YZ	SD	YZ
Correlation Adjustment	No	No	No	No	Yes	Yes	Yes	Yes
	(000)	(010)	(100)	(110)	(001)	(011)	(101)	(111)
Panel A: Full Sample (1984-2013)								
Before Costs								
Average Return (%)	16.12	15.70	13.00	12.72	15.13	14.85	12.20	12.03
Volatility (%)	14.01	13.82	11.69	11.60	12.68	12.60	10.32	10.32
Sharpe Ratio	1.15	1.14	1.11	1.10	1.19	1.18	1.18	1.17
Monthly Turnover (%)	170.0	141.4	128.6	108.4	208.6	190.1	144.7	130.2
Annual Costs								
Roll-over (%)	0.45	0.43	0.31	0.30	0.42	0.40	0.29	0.28
Rebalancing (%)	1.18	0.97	0.90	0.75	1.43	1.30	1.01	0.90
Total (%)	1.63	1.41	1.22	1.05	1.85	1.70	1.29	1.18
Relative cost reduction/increase (%)								
due to volatility: (x0x) to (x1x)		-13.77		-13.31		-8.01		-9.14
due to rule: (0xx) to (1xx)			-25.46	-25.06			-30.07	-30.92
due to vol. & rule: (00x) to (11x)				-35.38				-36.46
due to correlation: (xx0) to (xx1)					+13.41	+20.98	+6.39	+11.51
due to all: (000) to (111)								-27.94
After Costs								
Average Return (%)	14.49	14.29	11.78	11.67	13.28	13.15	10.91	10.86
Sharpe Ratio	1.03	1.03	1.01	1.01	1.05	1.04	1.06	1.05
Panel B: Post-GFC (2009-2013)								
Before Costs								
Average Return (%)	0.14	-0.02	-0.66	-0.52	1.32	1.32	1.26	1.51
Volatility (%)	15.68	14.79	12.66	11.91	11.57	10.98	9.49	9.00
Sharpe Ratio	0.01	0.00	-0.05	-0.04	0.11	0.12	0.13	0.17
Monthly Turnover (%)	197.5	145.8	154.5	112.9	230.5	196.7	167.5	137.7
Annual Costs								
Roll-over (%)	0.49	0.45	0.36	0.33	0.45	0.42	0.32	0.29
Rebalancing (%)	1.05	0.78	0.80	0.59	1.21	1.04	0.86	0.71
Total (%)	1.54	1.23	1.16	0.92	1.66	1.46	1.18	1.00
After Costs								
Average Return (%)	-1.39	-1.26	-1.81	-1.44	-0.34	-0.13	0.08	0.51
Sharpe Ratio	-0.09	-0.08	-0.14	-0.12	-0.03	-0.01	0.01	0.06

Table VI: *Transaction Costs Analysis*
The table presents a transaction costs analysis for various specifications of the time-series momentum strategy using (a) two different momentum trading rules –sign of past return (SIGN) or trend strength (TREND), (b) two different volatility estimators –standard deviation of past one-month returns (SD) or the Yang and Zhang (2000) estimator (YZ), and (c) the pairwise signed correlations. To identify each combination of specifications, the fourth row of the table presents a three-digit binary code in the form of (xxx), where the first digit corresponds to the trading rule, the second digit corresponds to the volatility estimator and the third digit corresponds to the correlation adjustment. The reported statistics are: annualised average return in %, annualised volatility in %, annualised Sharpe ratio, monthly turnover in %, roll-over costs, rebalancing costs, total costs (the sum of roll-over and rebalancing costs), and finally annualised average return in % and Sharpe ratio after costs. Panel A covers the entire sample period from January 1984 to February 2013, whereas Panel B covers the most recent period following the financial crisis, from January 2009 to February 2013.