Momentum Strategies in Futures Markets and Trend-following Funds*

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ABSTRACT

In this paper we study time-series momentum strategies in futures markets and their relationship to commodity trading advisors (CTAs). First, we construct one of the most comprehensive sets of time-series momentum portfolios by extending existing studies in three dimensions: time-series (1974-2002), cross-section (71 contracts) and frequency domain (monthly, weekly, daily). Our time-series momentum strategies achieve Sharpe ratios of above 1.20 and provide important diversification benefits due to their counter-cyclical behaviour. We find that monthly, weekly and daily strategies exhibit low cross-correlation, which indicates that they capture distinct return continuation phenomena. Second, we provide evidence that CTAs follow time-series momentum strategies, by showing that time-series momentum strategies have high explanatory power in the time-series of CTA returns. Third, based on this result, we investigate whether there exist capacity constraints in time-series momentum strategies, by running predictive regressions of momentum strategy performance on lagged capital flows into the CTA industry. Consistent with the view that futures markets are relatively liquid, we do not find evidence of capacity constraints and this result is robust to different asset classes. Our results have important implications for hedge fund studies and investors.

JEL CLASSIFICATION CODES: E3, G14.

KEY WORDS: Trend-following; Momentum; Managed Futures; CTA; Capacity Constraints.

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1. Introduction

In this paper we study time-series momentum strategies in futures markets and their relationship to a subgroup of the hedge fund universe which attracted attention during and after the recent financial crisis: commodity trading advisors (CTAs) or managed futures funds. Covel (2009) and Hurst, Ooi and Pedersen (2010) note that the main driver of many managed futures strategies pursued by CTAs is trend-following or momentum investing; that is, buying assets whose price is rising and selling assets whose price is falling. We first extend existing studies of futures time-series momentum strategies (Moskowitz, Ooi and Pedersen 2012) in three dimensions (time-series, cross-section and trading frequency) and do indeed document strong return continuation patterns across different portfolio rebalancing frequencies with the Sharpe ratio of the momentum portfolios exceeding 1.20. These strategies are typically applied to exchange traded futures contracts which are considered relatively liquid compared to cash equity or bond markets. However, a recent Financial Times article[1] observes about CTAs that: "*Capacity constraints have limited these funds in the past. [...] It is a problem for trend-followers: the larger they get, the more difficult it is to maintain the diversity of their trading books. While equity or bond futures markets are deep and liquid, markets for most agricultural contracts -soy or wheat, for example- are less so*".

To our knowledge, the hypothesis of capacity constraints in momentum strategies followed by CTAs has not been examined rigorously in the academic literature using replicating portfolios such as the time-series momentum strategies. We therefore rigorously establish a link between CTAs and momentum strategies by showing that time-series momentum strategies have high explanatory power in the time-series of CTA returns. In fact, our momentum strategies and CTA index estimates confirm media reports that CTAs were one of the few profitable hedge fund styles during the financial crisis of 2008, and, as a result, attracted a lot of attention and inflows in its aftermath[2]. However, in 2009 and 2011, CTA performance was disappointing. Could this be due to capacity constraints despite the fact that futures markets are considered to be relatively liquid? By running predictive regressions of momentum strategy performance on lagged capital flows into the CTA industry we do not find evidence of capacity constraints, consistent with the view that futures markets are relatively liquid. Lagged fund flows into the CTA industry are not statistically significantly related to the future performance of time-series momentum strategies and the relationship exhibits time-variation. Our results have important implications for hedge fund studies and investors.

We next present in more detail the three main contributions in this paper. First, motivated by the fact that managed futures strategies have been pursued by CTAs since at least the 1970s, shortly after futures exchanges increased the number of traded contracts (Hurst et al. 2010) and also by the fact that CTA funds differ in their forecast horizons and trading activity (e.g. long-term vs. short-term) (Hayes 2011), we extend the work of Moskowitz et al. (2012) and evaluate time-series momentum strategies in futures markets over a broad grid of lookback periods, investment horizons and frequencies of portfolio rebalancing. Using daily data on 71 futures contracts across assets classes from December 1974 to January 2012 (Moskowitz et al. (2012) use 58 contracts and their empirical results cover the period January 1985

[1]The Financial Times, November 27, 2011, "*Winton's head is a proud speculator*", by Sam Jones.

[2]The Financial Times, March 13, 2011, "*CTAs: "true diversifiers" with returns to boot*", by Steve Johnson.

to December 2009), we not only document the existence of strong time-series momentum effects across monthly, weekly and daily frequencies[3], but also confirm that strategies at different frequencies have low correlation between each other, hence they appear to capture distinct patterns. The different strategies achieve annualised Sharpe ratios of above 1.20 and appear to take advantage of both up and down markets, therefore exhibiting important diversification benefits in line with Schneeweis and Gupta (2006). We find that time-series momentum profitability is not concentrated on illiquid contracts and that commodity futures strategies have low correlation with other futures strategies, thus providing a diversification benefit despite the fact that they have a relatively low return. We also carry out a sub-sample analysis of Sharpe ratios and alphas and find that the monthly strategies have been more profitable while the weekly and daily strategies have become less profitable during the second sub-sample period (post-1995).

Second, we investigate empirically using time-series analysis whether CTA funds do in practice follow time-series momentum strategies[4]. We document that the regression coefficients of a CTA index on the monthly, weekly and daily time-series momentum strategies are highly statistically significant. This result holds even after controlling for standard asset pricing factors (like Fama and French's (1993) size and value factors and Carhart's (1997) cross-sectional momentum factor) or the Fung and Hsieh (2001) straddle-based primitive trend-following factors. Interestingly, the inclusion of the time-series strategies among the benchmark factors of the Fung and Hsieh (2004) 7-factor model for hedge fund returns dramatically increases its explanatory power, while the statistical significance of some of the straddle factors is driven out.

One explanation for this result may be related to some advantages that our time-series momentum strategy benchmarks exhibit relative to the look-back straddle factors that Fung and Hsieh (2001) introduce in their pioneering work to benchmark trend-following managers. First, our time-series momentum strategies offer a clear decomposition of different frequencies of trading activity. Second, by using futures as opposed to options, our benchmarks represent a more direct simulation of the futures strategies followed by many trend-following funds. Our results represent strong evidence that the historical outperformance of the CTA funds is statistically significantly related to their employment of time-series momentum strategies using futures contracts over multiple frequencies.

Third, given that CTAs are shown to follow time-series momentum strategies, we examine whether there exists any evidence of capacity constraints in these strategies, as the CTA industry has dramatically increased in the recent years. For that purpose, we regress monthly, weekly and daily momentum strategy returns on lagged fund flows into the CTA industry and on a range of additional control variables. Overall, our findings do not support the hypothesis of capacity constraints and the statistically insignificant

[3]One could potentially investigate the quarterly frequency of portfolio rebalancing, however we argue that monthly rebalancing can successfully capture long-term trend-following. Since a quarter is by construction a 3-month period, momentum strategies that use lookback and holding horizons measured in quarters are only a repackaged version of monthly strategies with the respective lookback and holding horizons measured in months and the two groups are expected to exhibit large correlation. In other words, monthly strategies can be seen as quarterly if we translate multiples of 3 months of lookback and holding horizons into quarters. Instead, such equivalence does not exist between monthly and weekly or daily strategies. A month is not a integer multiple of weeks, and not all months include the same number of trading days. In fact, we document that strategies at monthly, weekly and daily frequency have low correlation between each other, hence they capture distinct return patterns.

[4]Our objective is not to provide cross-sectional pricing tests based on CTA returns, but instead to show whether CTA funds do in practice follow time-series momentum strategies.

impact of lagged CTA flows on the performance of time-series momentum strategies holds for all asset classes. In contrast to the quote from the Financial Times that we used as a motivating example, we do not find evidence of capacity constraints when looking at momentum strategies in commodities markets only. This suggests that the futures markets are relatively deep and liquid enough to accommodate the trading activity of the CTA industry in line with Brunetti and Büyükşahin (2009) and Büyükşahin and Harris (2011). The regression coefficient of lagged CTA flows exhibit on average a negative but statistically insignificant value whereas a conditional study, on a rolling window basis, documents that the relationship between CTA flows and time-series momentum performance shows evidence of time-variation including occasional switches in the sign of the relationship. This is in contrast to evidence reported for carry trades (Jylhä and Suominen 2011) or for some investment styles of the hedge fund industry (Naik, Ramadorai and Stromqvist 2007), even if the unconditionally negative (though insignificant) fund flow effect is consistent with Berk and Green (2004), Naik et al. (2007), Aragon (2007) and Ding, Getmansky, Liang and Wermers (2009).

Our paper is related to three main strands of the literature. First, it is related to the literature on futures and time-series momentum strategies. Moskowitz et al. (2012) carry out one of the most comprehensive analyses of "*time-series momentum*" in equity index, currency, commodity and bond futures. We extend their work in several dimensions. Burnside, Eichenbaum and Rebelo (2011) examine the empirical properties of the payoffs of carry trade and time-series momentum strategies. It is important to stress that time-series momentum is distinct from the "*cross-sectional momentum*" effect that was historically documented in equity markets (Jegadeesh and Titman 1993, Jegadeesh and Titman 2001) and subsequently documented in futures markets (Pirrong 2005, Miffre and Rallis 2007), currency markets (Menkhoff, Sarno, Schmeling and Schrimpf 2012) or in fact "everywhere" (Asness, Moskowitz and Pedersen 2009).

Second, our findings of time-series return predictability in a univariate and portfolio setting pose a substantial challenge to the random walk hypothesis and the efficient market hypothesis (Fama 1970, Fama 1991). The objective of this paper is not to explain which mechanism is at work[5], but the fact that the source of this predictability is merely a single firm effect relates the findings to two strands of literature, namely the rational [6] (e.g. Berk et al. 1999, Johnson 2002, Ahn, Conrad and Dittmar 2003, Sagi and Seasholes 2007, Liu and Zhang 2008) and the behavioural[7] explanations (e.g. Barberis et al. 1998, Daniel et al. 1998, Hong and Stein 1999) to serial correlation in a firm's return series. Finally, from a relatively different perspective, Christoffersen and Diebold (2006) and Christoffersen, Diebold, Mariano,

[5]This would require various theoretical economic models with testable implications.

[6]Berk, Green and Naik (1999) argue that a firm's optimal investment choices can change its systematic risk and expected return and consequently allow for return predictability. Based on that, Chordia and Shivakumar (2002) link time-series momentum to time variation in expected returns that is captured by a set of macroeconomic variables, related to the business cycle. Johnson (2002) develops a single-firm partial equilibrium model, under which past performance is correlated with the expected growth rate of the dividend process, which in turn is monotonically related to risk. Sagi and Seasholes (2007) build a model for a single firm that is based on revenues, costs, growth options and shutdown options and show how the return autocorrelation depends on these firm-specific attributes.

[7]Barberis, Shleifer and Vishny (1998) incorporate the representativeness heuristic and the conservatism bias and link return autocorrelation to underreaction effects. Daniel, Hirshleifer and Subrahmanyam (1998) incorporate the overconfidence effect and the biased self-attribution effect of investment outcomes and eventually link momentum to overreaction effects to private information. Finally, Hong and Stein (1999) justify momentum profitability by means of investor underreaction caused by the gradual information diffusion.

Tay and Tse (2007) show that there exists a direct link between volatility predictability and return sign predictability even when there exists no return predictability. Obviously, return sign predictability is enough to generate time-series momentum trading signals.

Third, our paper is related to the literature on capacity constrains in hedge fund strategies and on the flow performance relationship. Jylhä and Suominen (2011) study a two-country general equilibrium model with partially segmented financial markets and an endogenous hedge fund industry. They test implications of the model for the flow-performance relationship between a currency carry trade strategy that they construct and AUM and fund flows into fixed income funds. They find evidence of capacity constraints as lagged AUM are negative related to future carry trade performance. Della Corte, Rime, Sarno and Tsiakas (2011) study the relationship between order flow and currency returns and Koijen and Vrugt (2011) examine carry strategies in different asset classes. Naik et al. (2007) study capacity constraints for various hedge fund strategies and find that for four out of eight hedge fund strategies, capital inflows have statistically preceded negative movements in alpha. Brunetti and Büyükşahin (2009) show that speculative activity is not destabilizing for futures markets, whereas Büyükşahin and Harris (2011) find that hedge funds and other speculator position changes do not Granger-cause changes in the crude oil price.

The rest of the paper is organized as follows. Section 2 provides an overview of our dataset. Section 3 describes the construction of time-series momentum strategies, while section 4 evaluates empirically the time-series momentum strategies. Section 5 links time-series futures momentum strategies to the CTA indices, fund flows and AUM and finally section 6 concludes.

2. Data Description

2.1. Futures Contracts

The dataset that we use consists of daily opening, high, low and closing futures prices for 71 assets in total: 26 commodities, 23 equity indices, 7 currencies and 15 intermediate-term and long-term bonds. The dataset is obtained from Tick Data with the earliest date of available data -for 14 of contracts- being December 1974. The sample goes up to January 2012. Especially for equity indices we also obtain spot (opening, high, low, closing) prices from Datastream, in order to backfill the respective futures series for periods prior to the availability of futures data[8].

Since futures contracts are short-lived contracts and are only active for a few months/years, we first need to construct single data series for each asset, by splicing contracts together in an appropriate way that results in tradable data series. In accordance with Moskowitz et al. (2012) (MOP, henceforth), we use the most liquid futures contract at each point in time, and we roll over contracts so that we always trade on the most liquid contract based on daily tick volume. In practice, almost always the most liquid contract is the nearest-to-delivery ("front") contract up until a few days/weeks before delivery, when the

[8]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 do confirm their arguments.

next nearest-to-delivery ("first-back") contract becomes the most liquid one.

Another issue of concern is the price adjustment at a roll date. Clearly, the two contracts that participate in a rollover should not (and do not in practice) have the same price. If one were to splice these contracts together without any further adjustment, then an artificial non-traded return would appear on that particular day, which would bias the mean return (upwards/downwards for an asset that is on average in contango/backwardation). For that purpose, we ratio-adjust backwards the futures series at each roll date, i.e. we multiply the entire history of the asset by the ratio between the first price of the new contract and the last price of the last contract. Consequently, the entire history of the asset is scaled accordingly so that no artificial return exists in the single data series[9]. Lastly, since the contracts are traded in various exchanges each with different trading hours and holidays, the data series are appropriately aligned in order to avoid potential lead-lag effects by filling forward any missing asset prices, following Pesaran, Schleicher and Zaffaroni (2009).

Having obtained single data series for each of our assets, we form daily *excess* close-to-close returns[10], which are then compounded to generate weekly (Wednesday-to-Wednesday) and monthly returns for the purposes of our empirical results. Table 1 presents summary univariate statistics for all assets in our dataset. The first column presents the starting month for each contract, the following five columns report the first four moments of the raw monthly return distribution along with the Newey and West (1987) t-statistic for the mean return and the last three columns report three investment-related measures (annualised Sharpe ratio, maximum drawdown and dollar growth) for a buy-and-hold or equivalently a long-only univariate strategy.

In agreement with the futures literature (e.g. see de Roon et al. 2000, Pesaran et al. 2009, Moskowitz et al. 2012), there exists large cross-sectional variation in the return distributions of the different contracts in our dataset. In total, 63 out of 71 contracts have a positive unconditional mean monthly return with the equity and bond futures having on average statistically significant estimates (15 out of 23 equity contracts and 11 out of 15 bond contracts have statistically significant positive return at the 10% level). Currency and commodity contracts have insignificant mean returns except for a small number of contracts. All but 2 contracts have leptokurtic return distributions ("fat tails") and as expected all equity contracts (except

[9] Another price adjustment technique is to add/subtract to the entire history the level difference between the 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 updwards/downwards biased for contracts that are on average in backwardation/contango. 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.

[10] The construction of a return data series for a futures contract does not have an objective nature and various methodologies have been used in the literature. As discussed by Miffre and Rallis (2007), the term "return" is imprecise for futures contracts, because the mechanics of opening and maintaining a position on a futures contract involve features like initial margins, potential margin calls, interest accrued on the margin account and if anything, no initial cash payment at the initiation of the contract. Constructing a data series of percentage changes in the asset price level implies that initial cash payment takes places, which, in turn, is practically inaccurate. Following the above discussion, it must be stressed that the use of the term "return" throughout this paper should be interpreted as a holding period return on a fully-collateralized position (in the sense that the initial margin equals the settlement price at the initiation of the contract) without any interest rate accruals, hence leading to a more conservative estimate of the return. Among others, Bessembinder (1992), Bessembinder (1993), Gorton, Hayashi and Rouwenhorst (2007), Pesaran et al. (2009), Fuertes, Miffre and Rallis (2010) and Moskowitz et al. (2012) compute returns as the percentage change in the price level, whereas Pirrong (2005) and Gorton and Rouwenhorst (2006) also take into account interest rate accruals on a fully-collateralized basis. Lastly, Miffre and Rallis (2007) use the change in the logarithms of the price level.

for KOSPI 200 and MSCI Taiwan Index) have negative skewness. The most important feature of the table that is essential for the methodology of our paper is related to the cross-sectional variation of volatility. Commodity and equity contracts exhibit the largest volatilities followed by the currencies and ultimately by the bond contracts, which have very low volatilities in the cross-section. This cross-sectional variation in the volatility profiles is crucial for the contruction of portfolios that include all the available contracts; one should accordingly risk-adjust the position on each individual contract, so to avoid the results being driven by a few dominant assets. As far as the performance of univariate long-only strategies is concerned, almost half of the Sharpe ratios are negative (34 out of 71) and the maximum drawdown reaches extreme levels even for some of the bond futures. RBOB Gasoline contract achieves the largest Sharpe ratio of 0.51, while the S&P500 contract exhibits a mere Sharpe ratio of 0.13 with a maximum drawdown of around 60%.

[Table 1 about here]

2.2. CTA Dataset

For the purposes of Section 5, we collect monthly return and assets-under-management (AUM) data series for all the CTA funds reporting in the BarclayHedge database. There are several reasons why we use the BarclayHedge database for our analysis. A recent comprehensive study of the main commercial hedge fund databases by Joenväärä, Kosowski and Tolonen (2012) compares five databases (the BarclayHedge, TASS, HFR, Eurekahedge and Morningstar databases) and finds that Barclayhedge has the largest number of funds (9719). Moreover, BarclayHedge has the largest percentage of dead/defunct funds (65%), thus making it least likely to suffer from survivorship bias. The BarclayHedge database accounts for the largest contribution to the aggregate database that Joenväärä et al. create. The authors also note that BarclayHedge is superior in the terms of AUM coverage, since it has the longest AUM time-series (57%) suggesting different behavior when aggregate returns are calculated on a value-weighted basis. The amount of missing AUM observations varies significantly across data vendors, being lowest for BarclayHedge (11%) and HFR (19%) and significantly higher for EurekaHedge (37%), TASS (34%), and Morningstar (32%). The authors do find, however, that economic inferences based on the Barclayhedge and TASS databases are similar in a number of dimensions.

The BarclayHedge CTA universe consists of 3834 unique CTA funds between February 1975 and January 2012 with total AUM at the end of this period being about $444 billion (down from its maximum value of $507 billion in August 2011). As a measure of the CTA sector performance, we make use of two indices: the BarclayHedge CTA Index that is part of the above database (BH-CTA, henceforth) with data starting from January 1980 and a custom-built AUM-weighted index of the entire CTA universe (AUMW-BH, henceforth). We additionally estimate the aggregate flow of capital in the CTA industry at the end of each month as the AUM-weighted average of individual fund flows[11]. The individual fund flow of capital, $\mathrm{FuF}_j(t)$, net of fund performance is computed using standard methodologies as in Naik et al. (2007) or

[11]Notice that the order of averaging does not matter. It can be easily mathematically proven that the AUM-weighted average fund flow equals the fund flow computed on the index level using the AUM-weighted index return.

Frazzini and Lamont (2008):

$$\mathrm{FuF}_j(t) = \frac{\mathrm{AUM}_j(t) - \mathrm{AUM}_j(t-1)\cdot(1+R_j(t))}{\mathrm{AUM}_j(t-1)}, \quad j = 1,\cdots,N_t, \tag{1}$$

where N_t is the active number of CTA funds at the end of month t and $R_j(t)$ denotes the net-of-fee return of fund j at the end of month t.

3. Methodology

The ***univariate time-series momentum*** strategy is defined as the trading strategy that takes a long/short position on a single asset based on the sign of the recent asset return over a particular lookback period. Let J denote the lookback period over which the asset's past performance is measured and K denote the holding period. Throughout the paper, both J and K are measured in months, weeks or days depending on the rebalancing frequency of interest. We use the notation M_J^K to denote monthly strategies with a lookback and holding period of J and K months respectively; the notations W_J^K and D_J^K follow similarly for weekly and daily strategies.

Following MOP, we subsequently construct the return series of the (aggregate) ***time-series momentum*** strategy as the inverse-volatility weighted average return of all available individual momentum strategies:

$$R_J^K = \frac{1}{M_t}\sum_{i=1}^{M_t} \mathrm{SIGN}_i\,(t-J,t)\cdot\frac{40\%}{\sigma_i\,(t;D)}\cdot R_i\,(t,t+K)\,, \tag{2}$$

where M_t is the number of available assets at time t, $\sigma_i\,(t;D)$ denotes an estimate at time t of the realized volatility of the i^{th} asset computed using a window of the past $D = 60$ trading days and $\mathrm{SIGN}_i\,(t-J,t)$ denotes the sign of the J-period past return of the i^{th} asset; a positive (negative) past return dictates a long (short) position. The scaling factor 40% is used by MOP in order to achieve an ex-ante volatility equal to 40% for each individual strategy. The argument of MOP for the use of this scaling factor is that it results in an ex-post annualised volatility of 12% for their M_{12}^1 strategy and, in turn, matches roughly the level of volatility of several risk factors for their respective sample period (1985-2009). In comparison to these numbers, for our evaluation sample period January 1978 to January 2012, our chosen monthly, weekly and daily strategies have ex-post annualised volatilities of 14.88%, 12.57% and 15.25% (see Table 4), while the annualised volatilities of the MSCI World index, the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are MSCI: 15.22%, SMB:10.88%, HML: 10.64%, UMD: 16.16%. We therefore consider 40% to be a reasonable choice for the position scaling factor throughout our paper.

Regarding the ex-ante volatility adjustment in equation (2), it must be noted that it is compulsory in order to allow us to combine in a single portfolio various contracts of different asset classes with different volatility profiles (see Table 1). Similar risk-adjustment has also been used by Pirrong (2005), who focuses on futures cross-sectional portfolios. Recently, Barroso and Santa-Clara (2012) revise the equity cross-sectional momentum strategy and scale similarly the winners-minus-losers portfolio in order to form what they call a "risk-managed" momentum strategy. MOP scale their time-series momentum strategies with an exponentially-weighted measure of squared daily past returns, but insist that "*...while all of the results in the paper are robust to more sophisticated volatility models, we chose this model due to its simplicity...*". Since our dataset consists of daily closing, opening, high and low prices, we can use a more efficient *range* estimator. The "range" refers to the daily high-low price difference and its major advantage is that it can even successfully capture the high volatility of an erratically moving price path intra-daily, which happens to exhibit similar opening and closing prices and therefore a low daily return[12]. Alizadeh, Brandt and Diebold (2002) show that the range-based volatility estimates are approximately Gaussian, whereas return-based volatility estimates are far from Gaussian, hence rendering the former estimators more appropriate for the calibration of stochastic volatility models using a Gaussian quasi-maximum likelihood procedure. Shu and Zhang (2006), Baltas (2011) and Baltas and Kosowski (2012) show that the Yang and Zhang (2000) volatility estimator is the most efficient estimator in a pool of range estimators, which for convenience is presented in Appendix A. Throughout the paper, we decide to use 60-day Yang and Zhang (2000) estimates of volatility.

4. Time-Series Momentum Strategies

This section focuses on the evaluation of performance of time-series momentum strategies. This is first achieved by examining the time-series return predictability using a pooled panel regression analysis and consequently by constructing a series of momentum strategies on a grid of lookback and investment horizons on a monthly, weekly and daily frequency of portfolio rebalancing.

4.1. Return Predictability

Before constructing momentum strategies, we first assess the amount of return predictability that is inherent in lagged returns on the monthly, weekly and daily frequencies by running the following pooled time-series cross-sectional regression in line with MOP:

$$\frac{R(t-1,t)}{\sigma_{YZ}(t-1;60)} = \alpha + \beta_\lambda \frac{R(t-h-1,t-h)}{\sigma_{YZ}(t-h-1;60)} + \varepsilon(t), \tag{3}$$

where λ denotes the lag that ranges between 1 and 60 months/weeks/days accordingly.

The regression (3) is estimated for each lag and regressor by pooling all the futures contracts together. The quantity of interest in these regressions is the t-statistic of the coefficient β_λ for each lag. Large and significant t-statistics essentially support the hypothesis of time-series return predictability. Each regression stacks together all T_i (where $i = 1, \cdots, N$) monthly/weekly/daily returns for the $N = 71$ contracts.

[12]As an indicative example, on Tuesday, August 9, 2011, most major exchanges demonstrated a very erratic behaviour, as a result of previous day's aggressive losses, following the downgrade of the US's sovereign debt rating from AAA to AA+ by Standard & Poor's late on Friday, August 6, 2011. On that Tuesday, FTSE100 exhibited intra-daily a 5.48% loss and a 2.10% gain compared to its opening price, before closing 1.89% up. An article in the Financial Times entitled "Investors shaken after rollercoaster ride" on August 12 mentions that "*...the high volatility in asset prices has been striking. On Tuesday, for example, the FTSE100 crossed the zero per cent line between being up or down on that day at least 13 times...*".

The t-statistics $t(\beta_\lambda)$ are computed using standard errors that are clustered by time and asset[13], in order to account for potential cross-sectional dependence (correlation between contemporaneous returns of the contracts) or time-series dependence (serial correlation in the return series of each individual contract). Briefly, the variance-covariance matrix of the regression (3) is given by (see Cameron, Gelbach and Miller 2011, Thompson 2011):

$$V_{\text{TIME\&ASSET}} = V_{\text{TIME}} + V_{\text{ASSET}} - V_{\text{WHITE}}, \tag{4}$$

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. In our dataset, not all assets have the same number of monthly/weekly/daily observations. On average, we have $\bar{T} = \frac{1}{N}\sum_1^N T_i \cong 310$ months of data per asset. We can therefore argue that $\bar{T} > N$ (for the weekly and daily regressions the number of observations per asset is of course much larger than N) and we document that two-way clustering or one-way clustering by time (i.e. estimating T cross-sectional regressions as in Fama and MacBeth (1973)) produces similar results, whereas clustering by asset produces inflated t-statistics that are similar to simple OLS t-statistics. One-way clustering by time is used by MOP in a similar setting of return predictability on the monthly frequency.

Figure 1 presents in panels A, B and C the two-way clustered t-statistics $t(\beta_\lambda)$ for lags $\lambda = 1, 2, \cdots, 60$ months, weeks and days accordingly. For the monthly frequency, the t-statistics are always positive for the first 12 months (statistically significant at the 5% level in 8 of these lags), hence indicating strong momentum patterns. The resemblance of this result to MOP's Figure 1, Panel A is striking. Exactly after the first year there exist relatively weak signs of return reversals and all lags up to 60 months fail to document any other significant effect. Contrary to this last result, MOP document large and significant reversals after the first year of return continuation. This minor difference is due to our larger sample (both in time-series and cross-section); in unreported results we limit our dataset to the cross-section and sample time of MOP and successfully capture the strong reversals.

[Figure 1 about here]

Moving to the weekly frequency and Panel B, we document return predictability clustered around two distinct past periods. First, the t-statistics of the most recent 8-week period are all positive (with 6 of them being statistically significant at the 5% level). This most recent period can also be comfortably extended to the most recent 16-week period. Second, there exists relatively strong return predictability potential for the period between roughly 36 to 52 past weeks (i.e. past 9 to 12 months approximately), which clearly matches to a certain extent the strong yearly effects captured by the monthly frequency results in Panel A.

[13] 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.

However, notice that a 52-week lagged return in the weekly regression is not always aligned with a 12-month lagged return in the monthly regression; the former refers to a Wednesday-to-Wednesday weekly return 52 Wednesdays ago, whereas the latter refers to last year's same-month monthly return.

Lastly, Panel C documents similarly two important regions of past return predictability. The first period extends roughly from the 9$^{\text{th}}$ to the 15$^{\text{th}}$ lagged daily returns (loosely related to the 2-week and 3-week past return) and the second period is located around the 40$^{\text{th}}$ lagged daily return (loosely related to the 8-week lagged return or to the 2-month lagged return). Panel C also reports a relatively large t-statistic for the last day's return, which is in turn directly related to the serial correlation measure. However, as we later see in the subsection 4.3, this effect is largely due to the early sample behaviour and does not represent a stable-over-time significant momentum effect.

Overall, it appears that momentum effects exist in all three frequencies of interest and interesting cross-commonalities arise. If we were to expect time-series momentum effects that are to some extent distinct from each other then the three Panels of Figure 1 would locate them in the most recent 12 months for the monthly frequency, in the most recent 8 (or even 16) weeks for the weekly frequency and in the period between the past 9 to 15 days for the daily frequency.

4.2. Momentum Profitability

Having established the return predicability in futures markets for the daily, weekly and monthly frequencies, we proceed with the construction of time-series momentum strategies for a grid of lookback (J) and investment periods (K). The return of the aggregate time-series momentum strategy over the investment horizon is the volatility-adjusted weighted average of the individual time-series momentum strategies and is computed using equation (2). Instead of forming a new momentum portfolio every K periods, when the previous portfolio is unwound, we follow the overlapping methodology of Jegadeesh and Titman (2001) and perform portfolio rebalancing at the end of each month/week/day. The respective monthly/weekly/daily return is then computed as the equally-weighted average across the K active portfolios during the period of interest. For example, if $K = 3$ and we form monthly-rebalanced portfolios, then at the end of January, the Jan-Feb-Mar portfolio (built at the beginning of January) has been active for one month, the Dec-Jan-Feb portfolio has one more month to be held and the Nov-Dec-Jan portfolio is unwound and its place is taken by the newly constructed Feb-Mar-Apr. Hence, the January return is measured as the equally weighted average of the returns of the three portfolios Jan-Feb-Mar, Dec-Jan-Feb and Nov-Dec-Jan. Based on this technique, $1/K^{\text{th}}$ of the portfolio is only rebalanced every month/week/day.

[Table 2 about here]

Table 2 presents four out-of-sample performance statistics for the (J,K) time-series momentum strategy: the annualised mean return in %, the annualised Sharpe ratio, the annualised alpha for a Carhart (1997)-type four factor model[14] given in equation (5) below and lastly the final dollar value at the end of

[14] A Carhart (1997)-type model might not qualify as the best model to describe non-equity futures return series, but we decide to use it as our benchmark model, following MOP and other studies that similarly use it.

the entire sample period of an initial investment of $1 in each particular strategy. For the mean return and the alpha we indicate statistical significance (*** for 1%, ** for 5%, * for 10% level) based on Newey and West (1987) adjusted standard errors and denote the largest value in bold. For the Sharpe ratio and the dollar growth, we indicate the three largest values by a grey-coloured cell.

The table is split in three Panels, each for a different rebalancing frequency. Panel A presents the results for the monthly strategy and $K,J = \{1,3,6,9,12,24,36\}$ months, Panel B presents the results for the weekly strategy and $K,J = \{1,2,3,4,6,8,12\}$ weeks and lastly Panel C presents the results for the daily strategy and $K,J = \{1,3,5,10,15,30,60\}$ days. Clearly, the three types of strategies have different frequencies of observation. In order to compute the above measures and in order for them to be mutually comparable, we decide to aggregate the daily and weekly returns on a monthly frequency. For the daily frequency, it is straightforward to compound all daily returns of each strategy to a monthly return. For the weekly frequency the case is slightly more complicated as typically weeks do not align with the beginning or the ending of a month. For that purpose, when a week is shared between two neighbouring months, we split the respective weekly return to the two claimant months proportionally to the number of days of that week that belong to each of the two months. Following this procedure, we end up having monthly observed returns out of different frequencies of trading and we can therefore compare them to each other.

Lastly, since the longest lookback period in our empirical study is 36 months and our data sample starts in December 1974, we restrict the return series of all strategies (of any lookback period or trading frequency) to start from January 1978. The last month is of course the last month of the data sample, January 2012. A total of 409 months or equivalently around 34 years.

As mentioned above, one of the reported statistics of Table 2 is the annualised alpha for the Carhart (1997)-type four factor model:

$$R_J^K(t) = \alpha + \beta\,(MSCI(t) - RF(t)) + sSMB(t) + hHML(t) + mUMD(t) + \varepsilon(t) \tag{5}$$

where $MSCI(t)$ is the total return of the World MSCI index in month t, $SMB(t)$ and $HML(t)$ are the monthly returns of Fama and French (1993) size and value risk factors and $UMD(t)$ is the monthly return of the style-attribution Carhart (1997) momentum factor. Notice that the time-series momentum return series $R_J^K(t)$ is by construction in *excess* of the risk-free rate as it has been built using *excess* returns of individual futures contracts. Monthly data for the *MSCI* for the period of interest are retrieved from Datastream, and for the rest of the factors from the website of Kenneth French[15].

It is apparent from Table 2 that the time-series momentum strategy generates a statistically and economically significant mean return and alpha for all three rebalancing frequencies. The significance is very strong at the 1% level for all weekly and daily strategies, while for the monthly strategies, it is only for a few strategies with lookback and holding periods exceeding the 12 months that the average return and alpha become insignificant. The monthly results largely resemble and confirm those by MOP. It is however impressive that the effects hold for higher frequencies of rebalancing, without any drop in the mean return or Sharpe ratio levels. Several (J,K) pairs across all three panels achieve Sharpe ratios larger

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

than 1.20. Following these results, we next aim to investigate the extent to which the different empirical patterns over different trading frequencies are distinct from each other. For that purpose, we first carefully choose the best monthly/weekly/daily strategies and study their intertemporal relationship.

4.3. Benchmark Strategies

In order to choose the best strategies per rebalancing frequency in a more robust way, we augment the evidence from Table 2 with that from Table 3, which reports the Newey and West (1987) t-statistic of the alpha of regression (5) and the Sharpe ratio for each strategy and rebalancing frequency over the two halves of our data sample: January 1978 to December 1994 and January 1995 to January 2012. Similarly to Table 2, we indicate the three largest values in each sub-table by a grey-coloured cell.

[Table 3 about here]

Starting from the monthly strategies, it is clear that the time-series momentum effects are stronger during the second half of the data sample. However, the profitability of the strategies seems to be relatively stable over the grid of lookback and holding horizons. By combining the evidence from Panels A of Tables 2 and 3, we choose the pairs $(12,1)$, $(9,3)$ and $(1,12)$ as the three best monthly strategies. Our choices are to a certain extent subjective and not unanimously the best by every single metric, but we claim that they do capture indeed the greatest amount of potential across the family of monthly strategies. Along these lines, it must be noted that the $(12,1)$ monthly strategy is the single best strategy in agreement to MOP's choice for their benchmark time-series momentum strategy.

Continuing to the weekly strategies and contrary to the monthly frequency, the momentum effects become weaker in the second half of the sample period, without however sacrificing much of their statistical significance; with the exception of the $(1,1)$ strategy, all strategies achieve very large alpha t-statistics that on average exceed the value of 4 for lookback or holding horizons of 8 or 12 weeks. Similarly to the monthly strategies, weekly time-series momentum profitability seems to be relatively stable for the each pair over the two subperiods and in agreement to the overall performance reported in Table 2. Our choice for the best strategy is the pair $(8,1)$, followed by the pairs $(12,2)$ and $(1,8)$.

Arguably, the most interesting patterns that are uncovered in Table 3 are related to the daily frequency of rebalancing. From Table 2 one could argue that the $(1,1)$ is by far the best daily strategy. However, what becomes evident from Table 3 is that this is due to the extreme performance of this strategy during the first half of the data sample up until the end of 1994, with the respective t-statistic being a very large 11.91 and the respective Sharpe ratio reaching the extreme level of 2.63. Moving to the most recent period, the t-statistic drops dramatically to the insignificant value of 1.07 and the Sharpe ratio to the unattractive value of 0.37. What might have caused this significant performance drop? One possibility is that past-1994, financial markets became progressively more computerised and therefore to a certain extent more efficient, hence eliminating any arbitrage opportunities, like the trivial serial day-to-day correlation of the $(1,1)$ strategy. Following the above observation, we refrain from picking the $(1,1)$ strategy as one of the best daily strategies and we focus on choosing carefully such pairs that exhibit relatively stable performance over the two sub-periods. We therefore choose the $(15,1)$ strategy as our best benchmark strategy followed by the pairs $(60,1)$ and $(1,15)$.

Table 4 presents in Panel A several performance statistics for the nine chosen strategies. The commonalities among various sets of strategies are evident. All chosen strategies achieve a very attractive Sharpe ratio of around 1.25 (except for the $(15,1)$ daily strategy that has a Sharpe ratio of almost 1). This value of Sharpe ratio is achieved with a relatively large mean annualised return of about 16-18% and a volatility in the region 13-15% for the six strategies that have an investment horizon of $J = 1$ period (month/week/day). Interestingly, strategies with a lookback horizon of $K = 1$ period achieve the same Sharpe ratio level with around one third of the above mentioned ranges of mean return and volatility. Monthly strategies are essentially zero-beta (market-neutral) investments, while both weekly and daily strategies exhibit negative, statistically significant, but if anything low market exposure with betas ranging from -0.09 down to -0.26.

[Table 4 about here]

From an investor's perspective, volatility *per se* is not a bad feature of a trading strategy. In fact, increases in volatility generated by positive returns are desired. Instead, it is only the part of volatility that is generated by negative returns that is clearly unwanted. Sortino and Van Der Meer (1991), Sortino and Price (1994) and Ziemba (2005) discuss the use of different methodologies in describing what is generally called the "downside risk" of an investment. Sortino and Van Der Meer (1991) suggest the use of "Sortino ratio" as a performance evaluation metric in place of the ordinary Sharpe ratio. The two ratios differ in the risk measurement. The latter is estimated as the ratio between the average excess returns of an investment and the respective volatility (and therefore treats equally positive and negative returns), whereas the former normalises the average excess returns with the square root of the semi-variance of returns (variance generated by negative returns):

$$\text{Sharpe ratio} = \frac{\bar{R}}{\sigma}, \text{ where } \sigma^2 = \frac{1}{N-1}\sum_{j=1}^{N}(R_j - \bar{R})^2 \tag{6}$$

$$\text{Sortino ratio} = \frac{\bar{R}}{\sigma^-}, \text{ where } \left(\sigma^-\right)^2 = \frac{1}{N^- - 1}\sum_{j=1}^{N}\left(R_j \cdot \mathbf{1}_{\{R_j<0\}}\right)^2, \tag{7}$$

where N denotes the number of trading periods, N^- denotes the number of periods with a negative return and $\bar{R} = \frac{1}{N}\sum_{j=1}^{N} R$ is the average excess return over all N periods.

It is therefore expected that the Sortino will be relatively larger than the ordinary Sharpe ratio for positively skewed distributions. Panel A reports these statistics for the nine time-series momentum strategies. On the one hand, the monthly strategies exhibit small and insignificant negative skewness and as a consequence the Sortino ratio is very close to -but still larger than- to the ordinary Sharpe ratio. On the other hand, weekly and daily strategies exhibit large and positive skewness and the respective Sortino ratio reaches relatively larger values in comparison to the monthly ones. If anything, the above results indicate that trend-following strategies manage to capture existing trends in the futures price series and offer an attractive risk-return profile to an investor in all three different frequencies of portfolio rebalancing.

Panel B of Table 4 reports the unconditional correlation matrix between the nine chosen strategies. Strategies of the same rebalancing frequency tend to be largely correlated, with the effects becoming weaker as we move from monthly to daily rebalancing frequency. Most importantly however, strategies of different rebalancing frequencies are not strongly correlated with each other, which means that they capture different empirical features of the dataset. For instance, the correlation coefficient between the daily $(15,1)$ strategy and the monthly $(12,1)$ strategy is just 22%. It is crucial to remember that all strategies constitute risk-adjusted portfolios of the same 71 futures contracts and they only differ from each other in terms of the lookback period, investment horizon and frequency of rebalancing. Clearly, both short-term and long-term momentum features exist in the time-series of the dataset, but these phenomena appear to be distinct from each other, as they do not tend to exist simultaneously.

4.3.1. The "MWD" Strategies

In order to investigate the relationship between the trading activity of CTA funds and time-series momentum strategies in the next section, we decide and focus on the best strategy per trading frequency. Following the above discussion and evidence from Tables 2, 3 and 4, we decide to work with the strategies M_{12}^{1}, W_{8}^{1} and D_{15}^{1} for the remaining of the paper (we henceforth denote this triplet as "MWD" strategies). The chosen triplet is characterised by some of the lowest cross-correlations as reported in Panel B of Table 4 (the respective correlations are indicated in bold).

Table 5 reports the results from regressing the return series of the three strategies on three different specifications: (a) a Carhart (1997)-type model that uses as the market proxy the excess return of the MSCI World index and is augmented by the excess return of the S&P GSCI Commodity Index and the excess return of the Barclays Aggregate BOND Index[16], (b) the hedge-fund return benchmark 7-factor model by Fung and Hsieh (2004) (FH7, henceforth), which incorporates three primitive trend-following (PTF) factors for bonds, foreign-exchange and commodity asset classes[17] and (c) an extended Fung and Hsieh (2004) 9-factor model (FH9, henceforth) that incorporates the remaining two PTF Fung and Hsieh (2001) factors for interest rates and stocks, since our strategies tend to capture return continuation in all asset classes. The data period for model (a) is December 1989 to November 2011 (264 data points) and for models (b) and (c) is January 1994 to December 2010 (204 data points).

[Table 5 about here]

The strongest conclusion from these regressions is the very significant and economically important alpha of all strategies. No factor specification can successfully capture the profitability of our trend-

[16] This 6-factor model is also used by MOP. Data for MSCI, GSCI and BOND indices are obtained from Datastream.

[17] In detail, the seven factors of the FH7 model are: the excess return of the S&P500 index; the spread return between small-cap and large-cap stock returns (SCMLC) constructed using the spread between Russell 2000 index and S&P500 index; the excess returns of three Fung and Hsieh (2001) primitive trend-following (PTF) factors that constitute portfolios of lookback straddle options on bonds, commodities and foreign exchange; the excess return of the US 10-year constant maturity treasury bond (TCM 10Y); the spread return of Moody's BAA corporate bond returns index and the US 10-year constant maturity treasury bond. Data for the PTF factors are downloaded from the website of David Hsieh: `http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm`. Return data for the remaining factors are retrieved from Datastream using instructions from the afore-mentioned website.

following strategies, which achieve annualised alphas in the region 13% to 20% all significant at the 1% level (all Newey and West (1987) t-statistics are very big and larger than 4.77). The only factors that succeed in capturing part of variability of the return series are momentum-related (cross-sectional momentum factor and trend-following factors). The cross-sectional momentum factor (UMD) is largely and positively related to the monthly strategy, as also documented by MOP. The two types of monthly momentum, time-series and cross-sectional, appear to be related but the latter does not entirely capture the former. The UMD factor is also positively but weakly (significant at the 10% level) related to the weekly time-series strategy and it has no significant relationship with the daily time-series strategy.

As far as the trend-following factors are concerned, the commodity factor is the strongest determinant of the profitability of the MWD strategies. The factor coefficient is positive and statistically significant at the 1% level for all specifications and rebalancing frequencies (5% for the monthly strategy and specification (b)). Similarly important is the trend-following factor for stocks, which is only marginally significant (at 10% level; t-statistic of 1.67) for the monthly strategy. For the remaining trend-following factors, the coefficient of the bond factor is negative and significant at the 5% level for the monthly strategy and positive and significant at the 5% level for the daily strategy. The FX factor is only significant at the 5% or 10% level for the weekly strategy. Lastly, the interest rate trend-following factor is only significant at the 10% level for the monthly strategy with a negative coefficient.

The above results indicate that different rebalancing frequencies of time-series momentum strategies capture various and distinct empirical features. Additionally, there is a great amount of return variability of these strategies that cannot be captured by traditional asset pricing risk factors, hedge-fund return related factors or even trend-following factors.

Figure 2 presents in Panel A the growth of an initial investment of $100 in each of the MWD strategies, as well as in the MSCI World Index for the entire sample period January 1978 to January 2012. The superiority of the momentum strategies over a long-only strategy on a proxy for the world market is evident. Interestingly, during all five NBER recession periods in our sample period (as indicated by grey bands), when MSCI Index suffers dramatic losses, the time-series momentum strategies enjoy positive growth. In order to corroborate these findings, Figure 3 presents scatterplots of the returns of the MWD strategies against the returns of the MSCI World index along with the least-squares quadratic fit. Clearly, the returns of MWD are larger during extreme market movement of either direction[18]; this is what MOP call the "time-series momentum smile".

Additionally, Panel B of Figure 2 presents a 12-month running Sharpe ratio for the MWD strategies. All strategies achieve at most times a very attractive and positive Sharpe ratio. Interestingly, there exist periods during which two or even all three of the strategies co-move, but there also exist various periods of decoupling amongst them, which in turn indicates that time-series momentum strategies of different rebalancing frequencies attribute their profitability to empirical patterns that are distinct from each other.

[Figure 2 about here]

[18] An article in the Financial Times FTfm by Eric Uhlfelder entitled "*Tool toughened in testing times*" on June 11, 2011, states that "*The strategy excels when trends are clear - especially during protracted downturns.*".

[Figure 3 about here]

Having studied the MWD strategies at the portfolio level, we now turn to the asset level. Figure 4 demonstrates the annualised Sharpe ratio of the univariate time-series momentum strategies that comprise our aggregate MWD strategies. Additionally, the figure indicates the unconditional correlation between each univariate strategy and the respective aggregate strategy. Most individual strategies exhibit positive ex-post Sharpe ratio in all rebalancing frequencies, hence they all contribute to the portfolio's overall performance. Bond futures appear to have the best cross-sectional performance followed by currency futures and equity index futures. Time-series momentum strategies in commodity markets exhibit the lowest Sharpe ratios cross-sectionally, but at the same time appear to act as diversifiers, as they tend to have little -if not insignificant- correlation with the aggregate strategies. Instead, equity strategies exhibit an average correlation of about 50%, whereas currency and interest rate strategies exhibit an average correlation of around 30% with the aggregate strategies.

[Figure 4 about here]

In order to exclude the possibility that the profitability of the MWD strategies is more pronounced for the more illiquid contracts, we present in Figure 5 a measure of illiquidity for all futures contracts of the dataset. Following MOP, the contracts within each asset class are ranked (from the largest to the smallest) based on their daily volume at the end of the sample period, January 31, 2012. Subsequently, the rank of each contract is normalised by subtracting the average rank across the asset class and dividing by the respective standard deviation rank. Positive normalised rank corresponds to larger illiquidity than the average contract within the respective asset class. Respectively, contracts with negative normalised ranks are the most liquid contracts of each asset class. Expectedly, the futures contracts of EUR/USD, CAD/USD, Dow Jones Industrial Average, S&P500, 10Y US Treasury Note, 10Y German Bund, Light/Brent Crude Oil, Natural Gas and Gold are the most liquid contracts within the respective asset classes in line with the the patterns identified by MOP.

The correlation of the illiquidity ranks of Figure 5 and the univariate Sharpe ratios of Figure 4 are indeed negligible[19]: -0.01 with respect to the monthly strategies, -0.04 with respect to the weekly strategies and -0.05 with respect to the daily strategies. These correlation estimates remain fairly stable whether we use ranks based on the January 2012 monthly volume (-0.09, -0.17 and -0.20 respectively) or the time-average of daily liquidity ranks across the entire sample period for each contract (-0.08, -0.12 and -0.10 respectively). These results confirm that momentum patterns are not related to illiquidity effects; in fact, the negative correlation can be interpreted as more pronounced time-series momentum effects among the most liquid contracts.

[Figure 5 about here]

[19] Moskowitz et al. (2012) report a correlation of -0.16 between their illiquidity rank measures as of June 2010 and the univariate Sharpe ratios of their monthly $(12, 1)$ strategy.

5. Evidence from the CTA Industry

Trend-following strategies in the futures markets are in practice employed by Commodity Trading Advisors (CTA) (Covel 2009, Hurst et al. 2010). This section provides a formal investigation of the performance of CTAs and, using time-series analysis, establishes links between CTA performance and the performance of our time-series momentum strategies. First, we show that the MWD strategies have high explanatory power in the time series for CTA returns. Next, we investigate whether there exist capacity constraints in time-series momentum strategies, by running predictive regressions of momentum strategy performance on lagged capital flows into the CTA industry.

5.1. Trend-Following and CTAs

CTA funds have historically profited from trends in the prices of futures contracts. Panel A of Table 6 presents the yearly return between the years 1978 and 2001 for five different strategies: our best MWD time-series momentum strategies (M^1_{12}, W^1_8 and D^1_{15} respectively), the assets-under-management weighted CTA Index using the BarclayHedge database (AUMW-CTA) and finally the official BarclayHedge CTA Index (BH-CTA). It is evident that trend-following strategies have enjoyed multi-year superior performance, with only a few years with negative returns such as 2009 and 2011. Both up and down trends offer a profitable opportunity for such strategies. As a result, they are profitable in both up and down markets and this renders them good diversifiers and hedges in bear markets[20] as already shown in Figure 3. Our results complement the literature on the relationship between hedge fund returns and macroeconomic conditions (Avramov, Kosowski, Naik and Teo 2011).

Panel B of Table 6 reports the average return, volatility and Sharpe ratio during the NBER recessionary and expansionary months for the entire sample period. Not only do all five indices exhibit positive and statistically significant returns during recessionary periods, but also four out of five of them clearly generate larger returns during recessionary periods than during expansionary periods (for the monthly time-series momentum strategy the average returns between the two types of periods are very close to each other). Returns appear less significant (however remain significant) during recessionary periods, which could be due to the small number of recessionary months (relative to the number of expansionary months) in the sample period and due to the overall larger volatility during such periods. Panel B of Table 6 also reports unconditional correlation estimates between the five indices. As we would expect the two CTA indices (AUMW-BH and BH-CTA) are highly correlated (with a correlation coefficient of 90%). The positive correlation of the CTA indices with the MWD strategies suggests that CTAs follow strategies that are similar to the MWD strategies. We test this hypothesis rigorously below by means of a regression analysis that includes several control variables.

[Table 6 about here]

[20]Kazemi and Li (2009) present an elaborate study on the market-timing ability of CTA and find that systematic CTAs are generally more skilled at market timing than discretionary CTAs.

CTAs are known to following trend-following strategies (see for example Covel 2009) and to test this statement we use time-series analysis. Table 7 presents regression coefficients obtained from regressing the net-of-fee monthly returns of the AUM-CTA Index on various combinations of factors. Columns (a) and (b) report the results for the FH7 and the extended FH9 models. These two models achieve adjusted R^2 of 23.57% and 27.24% respectively, with all PTF factors and the slope of the term structure of interest rates being largely significant with the smallest Newey and West (1987) t-statistic in absolute value being 2.31. However, based on these two benchmarks, the CTA index still exhibits an economically relatively large alpha which is significant at the 1% level.

The explanatory power of the regressions and the alpha change dramatically when we examine univariate regression results (c), (d) and (e), which are based on regressing the CTA index returns independently on the best monthly, weekly and daily time-series strategies. In these specifications, the alpha becomes insignificant and the adjusted R^2 ranges from around 14% for the daily strategy to 31% for the weekly strategy. We note that the dependent variables in these regressions are after fee (and transaction costs) returns while the independent variables (such as the Fama-French, Fung-Hsieh or our MWD factors) do not include transaction costs. This has to be borne in mind when interpreting the sign of the alphas in the regressions.

The increase in the model's explanatory power continues to be impressive when regressing the CTA index on all three time-series momentum strategies (the MWD model) labeled as specification (f). The annualised alpha of the strategy remains insignificant and even turns negative, with the R^2 exceeding 37%. Importantly, all three MWD factors remain significant at the 1% level, hence demonstrating that CTAs are likely to follow momentum strategies at different frequencies and that these patterns at different frequencies are also distinct from each other in line with the arguments of Hayes (2011). The additional explanatory power of the MWD factors is not surprising since CTAs are known to be active in futures markets. The Fung and Hsieh (2004) model helps to explain the time-series behaviour of CTA strategies by using option based factors to proxy trend following behaviour. It is likely that by directly replicating CTA strategies using futures momentum strategies, the MWD factors closely match the underlying instruments used by CTA funds in practice.

It is important to note that to establish a link between time-series momentum strategies and CTA returns a time-series analysis, as carried out here, is most appropriate. Our objective is not to carry out a cross-sectional analysis of fund returns similar to that used in the literature on cross-sectional differences in hedge fund returns (Bali, Brown and Caglayan 2011, Buraschi, Kosowski and Trojani 2012). Instead, we document a relationship between between CTA returns and time-series momentum strategies to support the use of flows into CTA funds, when examining capacity constrains in momentum strategies.

[Table 7 about here]

5.1.1. Robustness Tests

To test the robustness of our results, the remaining three regressions of Table 6 report results from combining the MWD factors with subsets of the FH9 factors: regression (g) involves the non-trend-following Fung and Hsieh (2004) factors, regression (h) involves instead only the five PTF Fung and Hsieh (2001) factors and lastly regression (i) puts all factors together as part of a 12-factor model that is denoted as FH9+MWD. The adjusted R^2 progressively increases and exceeds 50% for the last specification. Thus, compared to the standard Fung and Hsieh (2004) model, the R^2 pretty much doubles.

What is more important is that all three MWD remain largely significant at 1%, except for the daily strategy that is significant at 5% for the last two specifications. Contrary to FH7 and FH9 specifications, not all PTF factors remain significant after incorporating the time-series momentum strategies. The factors that survive are those capturing the trend-following features in bonds, foreign exchange and interest rates. Our results show that when tested side by side, the MWD strategies appear to be better at explaining CTA strategy returns than the PTF factors, or in other words that CTAs do largely follow time-series momentum strategies using liquid futures contracts.

As an additional test of robustness, Table B.1 in Appendix B presents the FT9, MWD and FT9+MWD decompositions for the return series of another three CTA indices: (1) the BH-CTA Index, (2) the Newedge CTA Index and (3) the Newedge CTA Trend Sub-Index[21]. The Newedge CTA Trend Sub-Index is constructed with a subset of CTAs that are originally included in the Newedge CTA Index and are widely recognised as trend followers. The results show that our findings are robust to the choice of CTA index as dependent variable. The MWD factors are highly significant for all three indices and the R^2 of the FH9 increases by a factor of two to three when the MWD factors are added in.

The above results show that the MWD factors play an important role in explaining CTA index returns, independent of the choice of CTA index. So far we have examined unconditional regression results based on CTA returns. In order to shed further light on this relationship we examine whether there is time-variation in the R^2. In order to assess the robustness of the results in Table 7 over our sample period, we present in Figure 6 the 60-month rolling adjusted R^2 for the FH7 benchmark model, MWD and FH9+MWD specifications (regressions (a), (f) and (i) of Table 7). The results are striking, as the explanatory power of the FH7 is almost always lower than that of the MWD model except during the late 2002 and early 2003 period. It is also interesting to note that the performance of the FH7 becomes significantly worse after 2007 when the adjusted R^2 drops below 10% , while that of MWD model remains close to 40%. Finally, the figure shows that the 12-factor FH9+MWD model achieves very large levels of adjusted R^2 (even exceeding 60% at times) over the entire sample period.

[Figure 6 about here]

Overall, our results in Tables 6 and 7 show that the time-series MWD momentum strategies have highly significant explanatory power for the CTA index returns even after accounting for the Fung and

[21]Documentation for the Newedge indices can be found in `http://www.newedge.com/feeds/Two_Benchmarks_for_Momentum_Trading.pdf`.

Hsieh (2004) factors. Accounting for the MWD strategies leads to statistically insignificant alpha for the CTA index returns. This suggest that on one hand that CTAs do heavily follow time-series momentum strategies with different trading frequencies and on the other hand that it is important to use the MWD strategies as benchmark returns when evaluating the intertemporal performance of CTAs.

5.2. Capital Flows and CTA Performance

Futures markets are viewed as relatively liquid markets compared to other financial markets such as cash equities or bonds. Since CTA funds do follow time-series momentum strategies in futures markets, the question arises whether the growing CTA industry has imposed any capacity constraint in the time-series momentum strategies. Previous studies of hedge fund returns have examined capacity constraints for different aggregate hedge fund categories (e.g. Naik et al. 2007). One limitation that applies to these studies and many other papers in the hedge fund literature is that the self-reported nature of hedge fund investment objectives implies that it is not possible to know for sure whether certain funds labeled as “directional traders”, “managed futures” or “CTAs” indeed follow CTA strategies. Examining time-series momentum strategies that are constructed bottom up from futures data in order to study capacity constraints is one solution to this limitation.

Jylhä and Suominen (2011) examine the relationship between fund flows and AUM in fixed income arbitrage funds and a carry trade strategy that they construct by forming long and short currency portfolios. For that purpose, they regress the returns from the currency carry trade strategy on the previous month’s hedge fund AUM and the current month’s hedge fund flow. They report that increased lagged hedge fund AUM and positive contemporaneous inflows of funds (which they interpret as a proxy for the number of speculators) into hedge funds decrease the expected returns from carry trade strategies.

Figure 7 presents the time evolution of the number of CTA funds, the total AUM of the CTA industry and the annual net flow of funds into these funds from January 1978 to January 2012 (the dataset is collected from BarclayHedge database). Evidently, the CTA industry has increased massively during the last decade, with more than 1000 funds being active at the end of the period and close to half-a-trillion dollars invested in these funds. Given the increasing size of the industry over the years, it is interesting to investigate whether the inflow of capital has had an statistically significant effect on the performance of the time-series momentum strategies. For example and in agreement with the annual performance of CTA indices of Table 6, the CTA industry appears in Panel A of Figure 7 to have experienced significant AUM drawdowns during the recent years 2009 and 2011. At the same time, Panel B of Figure 7 documents a large inflow of capital into CTAs (15.6%) during 2009[22], which raises the question of the existence of capacity constraints. We therefore test this hypothesis rigorously.

[Figure 7 about here]

[22] An article in the Financial Times FTfm by Eric Uhlfelder entitled “*Tool toughened in testing times*” on June 11, 2011, states that “*Despite relative underperformance to equities since markets turned in March 2009, managed futures continued to enjoy net inflows as investors increasingly recognised the benefits of this asset class.*”.

Table 8 reports the results from regressing separately the return series of the best monthly, weekly and daily time-series momentum strategies on lagged CTA fund flows and a range of control variables, in order to decompose the performance-flow relationship at different portfolio rebalancing frequencies[23]. The fund flow regressor is constructed similarly to Naik et al. (2007) by summing up the fund flows from the $t-12$ month up to the past $t-1$ month. One of the motivating examples that we provided in the introduction was based on a quote from the Financial Times, which stated that capacity constraints may differ by asset class. Therefore, in Table 8 we report results for (i) all futures contracts as well as (ii) all contracts excluding commodities, (iii) commodities only, (iv) currencies only, (v) equities only and (vi) interest rates only. The t-statistics that are reported are calculated using Newey and West (1987) robust standard errors with 11 lags, in order to account for the serial correlation inherent in the construction of the fund flow regressor and also to adjust for potential heteroscedasticity.

[Table 8 about here]

Whether we look at the monthly, weekly or daily frequency, the evidence shows that, unconditionally, lagged fund flows have indeed a negative but however statistically insignificant impact on future performance. The statistically insignificant impact of lagged CTA flows on momentum strategy performance holds for all asset classes. These results suggest that capacity constraints in time-series momentum strategies do not differ significantly between asset classes which is consistent with the view that futures markets are relatively deep and liquid markets. The findings are also in line with the small and negative (positive) relationship between the Sharpe ratios of univariate momentum strategies and the illiquidity (liquidity) of the respective futures contracts as documented in the previous section in Figures 4 and 5.

Our results are also consistent with the recent literature on futures markets and CFTC data on commitment of traders, including hedge funds and CTAs. Brunetti and Büyükşahin (2009) show that, in a forecasting sense, speculators do not cause price movements and volatility in futures markets and that speculative activity is not destabilizing. Our finding that there is no statistically significant evidence of capacity constraints in commodity futures markets is also consistent with a recent study by Büyükşahin and Harris (2011). The authors employ Granger causality tests to analyze lead and lag relations between crude oil price and CFTC position data at daily and multiple day intervals. They do not find significant evidence that hedge funds and other non-commercial (speculator) position changes Granger-cause crude oil price changes. Instead, they report that their results suggest that price changes precede their position changes.

In sum, we interpret the above results as evidence of lack of statistically significant capacity constraints in time-series momentum strategies followed by CTAs. The, on average, unconditionally negative fund flow effect in fourteen out of the eighteen regressions is consistent with Berk and Green (2004), Naik et al. (2007), Aragon (2007) and Ding et al. (2009). The only regression coefficient related to lagged flows that is close to being statistically significant is the one associated with a weekly momentum strategy

[23] In unreported results, available upon request, we found that (i) adding contemporaneous flows, (ii) splitting lagged flows into past month and past year excluding past month, (iii) adding lagged logarithmic AUM level or (iv) adding lagged returns of the respective independent variable to the regressions does not change the statistical significance or economic interpretation of our results. For brevity we therefore do not report these in the paper.

in currency futures. Interestingly, the adjusted R^2 of the regressions is relatively small and at time negative, except for monthly strategies that include equities (groups (i), (ii), (v)), where the cross-sectional momentum factor (UMD) captures some large portion of the return variability.

To further investigate the performance-flow relationship, we present conditional results of the regressions of Table 8 for all futures contracts excluding commodities and for commodity contracts only. Using a rolling window of 60 months, Figure 8 presents the time evolution of the t-statistic of the lagged CTA flow of funds variable. Across all portfolio rebalancing frequencies, the relationship of interest exhibits a large degree of time-variation and there isn't strong evidence in favour of capacity constraints in the momentum strategies followed by CTAs. However, the evidence shows that during some periods and most importantly during the recent financial crisis, past year's flows are negatively and statistically significantly correlated with future performance of all momentum strategies.

[Figure 8 about here]

Overall, our findings suggest the absence of a statistically significant performance-flow relationship for the time-series momentum strategies that are followed by CTA funds. In fact, our results suggest that the CTA industry is large enough so that the employment of time-series momentum strategies by CTA investments have not considerably affected market prices in the futures markets during the last 30 years.

6. Concluding Remarks

Motivated by the fact that CTA funds differ in their forecast horizons and trading activity (e.g. Hayes 2011) we extend the work of Moskowitz et al. (2012) and evaluate time-series momentum strategies in futures markets over a broad grid of lookback periods, investment horizons and frequencies of portfolio rebalancing. We find strong time-series momentum patterns in monthly, weekly and daily frequencies across 71 futures contracts over a 35-year period (January 1978 - January 2012). The different strategies achieve annualised Sharpe ratios of above 1.20 and appear to take advantage of both up and down markets, hence exhibiting important diversification benefits. Additionally, not only do we confirm that strategies at monthly, weekly and daily frequency have low correlation between each other, hence they capture distinct phenomena of return continuation, but we also find, using time-series analysis, that CTA funds do in practice employ time-series momentum strategies using futures contracts over multiple frequencies. Interestingly, the inclusion of the time-series strategies among the benchmark factors of the Fung and Hsieh (2004) 7-factor model for hedge fund returns dramatically increases its explanatory power, while the statistical significance of some of the straddle-based trend-following factors is driven out.

The above findings along with the fact that the CTA industry has dramatically increased during the last 30 years raise concerns about the existence of capacity constraints in the time-series momentum strategies that are followed by CTAs. Using predictive regressions of momentum strategy performance on lagged capital flows into the CTA industry, we show that futures markets are indeed relatively liquid and we do not find evidence of capacity constraints, except for some very short period, like the most recent financial crisis. Lagged fund flows into the CTA industry are not statistically significantly related to the future performance of the time-series momentum strategies and the relationship even exhibits time-variation. This is in contrast to evidence reported for carry trades (Jylhä and Suominen 2011) or for some investment styles of the hedge fund industry (Naik et al. 2007), even if the unconditionally negative (though insignificant) fund flow effect is consistent with Berk and Green (2004), Naik et al. (2007), Aragon (2007) and Ding et al. (2009).

Our results have important implications for hedge fund studies and investors. From a theoretical perspective, the strong evidence of time-series momentum profitability implies strong autocorrelation in the individual return series of the contracts and therefore poses a substantial challenge to the random walk hypothesis and the market efficiency. Given the existence of a broad range of rational (e.g. Berk et al. 1999, Chordia and Shivakumar 2002, Johnson 2002) and behavioural (e.g Barberis et al. 1998, Daniel et al. 1998, Hong and Stein 1999) attempts to explain the momentum patterns, the need for a unified theoretical explanation remains a fertile ground for future research. From an investment perspective, the findings of this paper suggest the use of time-series momentum strategies over different frequencies when evaluating the risk-return profile of CTA and managed futures funds.

Appendix

A. Yang-Zhang Volatility Estimator

Let D denote the number of past trading days that are used to estimate the volatility of an asset. Denote the opening, high, low and closing daily log-prices of day t by $O(t)$, $H(t)$, $L(t)$, $C(t)$ and define:

$$\text{Normalised Opening price ("overnight jump"): } o(t) = O(t) - C(t-1) \tag{8}$$

$$\text{Normalised Closing price: } c(t) = C(t) - O(t) \tag{9}$$

$$\text{Normalised High price: } h(t) = H(t) - O(t) \tag{10}$$

$$\text{Normalised Low price: } l(t) = L(t) - O(t) \tag{11}$$

$$\text{Daily Close-to-Close return: } r(t) = C(t) - C(t-1) \tag{12}$$

The Yang and Zhang (2000) estimator (YZ, henceforth) is the first-in-literature unbiased volatility estimator that is independent of both the opening jump and the drift of the underlying price process. This estimator practically improves the Rogers and Satchell (1991) estimator (RS, henceforth), which might be an unbiased estimator that allows for a non-zero drift in the price process, but it does not account for the opening (overnight) jump. The YZ estimator is a linear combination of the RS estimator, the ordinary "standard deviation of past daily log-returns" estimator (STDEV, henceforth) and an estimator in the nature of STDEV that uses the normalised opening prices (overnight log-returns) instead of the close-to-close log-returns:

$$\sigma^2_{\text{YZ}}(t;D) = \sigma^2_{\text{OPEN}}(t;D) + k\sigma^2_{\text{STDEV}}(t;D) + (1-k)\,\sigma^2_{\text{RS}}(t;D) \tag{13}$$

where k is chosen so that the variance of the estimator is minimised (Yang and Zhang (2000) show that this is in practice achieved for $k = \frac{0.34}{1.34+(D+1)/(D-1)}$) and

$$\sigma^2_{\text{STDEV}}(t;D) = \frac{261}{D}\sum_{i=0}^{D-1}\left[r(t-i) - \bar{r}(t)\right]^2 \tag{14}$$

$$\sigma^2_{\text{OPEN}}(t;D) = \frac{261}{D}\sum_{i=0}^{D-1}\left[o(t-i) - \bar{o}(t)\right]^2 \tag{15}$$

$$\sigma^2_{\text{RS}}(t;D) = \frac{261}{D}\sum_{i=0}^{D-1}\left[h(t)\left[h(t)-c(t)\right] + l(t)\left[l(t)-c(t)\right]\right] \tag{16}$$

where $\bar{r}(t) = \frac{1}{D}\sum_{i=0}^{D-1} r(t-i)$, $\bar{o}(t) = \frac{1}{D}\sum_{i=0}^{D-1} o(t-i)$ and 261 is the number of trading days per year. Yang and Zhang (2000) show that their estimator is $1+\frac{1}{k}$ times more efficient than the ordinary STDEV estimator. Throughout the paper we use $D = 60$, hence the YZ estimator is almost 8 times more efficient than the STDEV estimator.

B. Decomposing CTA Indices Returns

The Appendix section presents in Table B.1 the FT9, MWD and FT9+MWD decompositions for the return series of three CTA indices: the BarclayHedge CTA Index, the Newedge CTA Index and the Newedge CTA Trend Sub-Index.

[Table B.1 about here]

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	From	Mean	t(Mean)	Vol.	Skew	Kurt	SR	MDD	DG
CURRENCIES									
AUD/USD	Feb-1987	5.28	2.11	11.75	-0.41	4.94	0.13	41.18	3.14
CAD/USD	Feb-1977	0.98	0.84	6.89	-0.30	8.23	-0.62	28.32	1.30
CHF/USD	Dec-1974	0.84	0.38	12.65	0.06	3.77	-0.35	67.74	1.02
EUR/USD	Dec-1974	0.60	0.30	11.42	-0.07	3.55	-0.41	61.53	0.98
GBP/USD	Oct-1977	1.84	0.90	10.77	0.05	4.95	-0.31	57.79	1.54
JPY/USD	Apr-1977	1.26	0.56	11.99	0.49	4.49	-0.33	58.47	1.21
Dollar Index	Aug-1989	-1.77	-0.90	8.82	0.41	3.80	-0.60	44.92	0.62
EQUITIES									
DJIA	Dec-1974	9.01	3.43	15.38	-0.46	5.37	0.25	49.71	18.06
NASDAQ 100	Feb-1983	12.06	2.39	25.76	-0.33	4.23	0.30	82.99	12.32
NYSE Composite	Dec-1974	7.74	2.94	15.30	-0.59	5.32	0.16	55.23	11.35
S&P 500	Dec-1974	7.16	2.71	15.44	-0.47	4.66	0.13	58.73	9.10
S&P 400 MidCap	Jul-1991	9.51	2.36	17.44	-0.67	5.06	0.37	52.90	5.12
Russell 2000	Feb-1988	7.99	1.91	19.42	-0.48	3.96	0.22	54.97	4.28
DJ Stoxx 50	Jan-1987	6.64	1.70	16.80	-0.82	4.78	0.17	63.24	3.67
Eurostoxx 50	Jan-1987	6.04	1.40	19.19	-0.65	4.30	0.12	64.04	2.83
FTSE 100	Feb-1978	8.47	3.19	16.30	-0.71	5.58	0.20	53.01	11.17
DAX	Dec-1974	8.52	2.39	20.29	-0.51	5.00	0.16	71.68	10.81
CAC 40	Aug-1987	6.04	1.30	21.06	-0.27	4.02	0.10	64.90	2.53
IBEX 35	Feb-1987	8.08	1.78	22.06	-0.52	4.99	0.20	56.84	4.04
AEX	Feb-1983	8.72	2.05	20.69	-0.74	5.31	0.21	68.53	6.58
SMI	Aug-1988	7.64	1.96	16.97	-0.49	4.12	0.23	53.18	4.26
MIB 30	Jan-1998	0.61	0.09	22.87	0.03	3.99	-0.09	67.42	0.75
S&P Canada 60	Feb-1982	8.01	2.44	15.98	-0.66	5.80	0.22	51.72	7.44
Nikkei 225	Dec-1974	3.26	0.97	19.42	-0.29	4.28	-0.10	85.40	1.65
TOPIX	Dec-1974	4.51	1.37	17.77	-0.21	4.71	-0.04	72.65	2.96
ASX SPI 200	Jun-1992	5.09	1.49	13.59	-0.66	3.75	0.15	52.33	2.26
Hang Seng	Dec-1974	17.79	3.72	29.15	-0.23	5.60	0.43	59.41	145.46
KOSPI 200	Feb-1990	9.29	1.34	31.65	0.90	7.03	0.19	72.74	2.68
MSCI Taiwan Index	Jan-1988	12.35	1.56	35.52	0.46	4.72	0.24	77.03	4.42
MSCI EAFE	Dec-1974	7.79	2.62	15.98	-0.61	5.38	0.16	58.96	11.09
INTEREST RATES									
US Treasury Note 2 Yr	Feb-1991	1.74	3.75	1.79	0.24	3.30	-0.83	3.79	1.43
US Treasury Note 5 Yr	Aug-1988	3.34	3.53	4.31	0.03	3.56	-0.08	8.47	2.14
US Treasury Note 10 Yr	Feb-1983	4.91	3.72	6.99	0.14	3.91	0.08	14.32	3.86
US Treasury Bond 30 Yr	Nov-1982	6.08	3.17	10.62	0.23	4.47	0.16	21.09	5.00
Municipal Bonds	Jul-1985*	5.57	3.30	8.04	-0.58	4.62	0.13	17.89	2.95
Euro/German Schatz 2 Yr	Apr-1997	1.04	2.37	1.42	0.07	3.51	-1.20	4.45	1.17
Euro/German Bobl 5 Yr	Feb-1997	2.69	2.74	3.28	0.01	2.73	-0.02	7.83	1.48
Euro/German Bund 10 Yr	Feb-1997	4.09	2.77	5.28	0.11	2.92	0.25	9.81	1.81
Euro/German Buxl 30 Yr	Oct-2005	5.31	1.09	12.14	1.19	4.86	0.28	17.63	1.34
Australian 3 Yr	Aug-2001	0.49	1.24	1.07	0.36	2.73	-1.22	2.11	1.05
Australian 10 Yr	Aug-2001	0.34	1.14	0.93	0.12	2.72	-1.58	1.63	1.04
UK Long Gilt	Aug-1998	2.90	1.69	5.94	0.19	3.51	0.07	12.15	1.44
Canadian 10 Yr	May-1990	4.91	3.83	5.95	-0.06	3.18	0.26	14.72	2.80
Japanese 10 Yr	Aug-2003	1.67	1.72	3.15	-0.68	4.52	-0.05	4.74	1.15
Korean 3 Yr	Sep-2003*	1.69	1.63	3.08	0.88	6.64	-0.09	5.00	1.14

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	From	Mean	t(Mean)	Vol.	Skew	Kurt	SR	MDD	DG
COMMODITIES									
ENERGY									
Light Crude Oil	Feb-1987	14.15	1.76	34.46	0.40	5.42	0.30	78.21	7.96
Brent Crude Oil	Sep-2003	15.98	1.13	32.25	-0.64	4.78	0.44	74.24	2.43
Heating Oil	Feb-1984	13.80	2.06	34.18	0.50	4.75	0.28	69.30	9.63
Natural Gas	Feb-1993	-0.11	-0.01	62.55	1.03	5.65	-0.05	99.25	0.03
RBOB Gasoline	Oct-1987	22.27	2.89	36.71	0.37	5.39	0.51	70.73	44.23
METALS									
Copper	Jan-1990	10.22	1.53	26.79	-0.06	5.41	0.25	64.16	4.29
Gold	Feb-1984	2.31	0.86	15.55	0.30	4.10	-0.12	74.30	1.36
Palladium	Feb-1994	14.83	1.57	35.95	0.33	5.57	0.33	86.28	4.56
Platinum	Aug-2003	11.04	1.03	26.90	-0.98	8.10	0.34	64.03	1.84
Silver	Jan-1984	3.27	0.66	27.87	0.26	4.23	-0.03	86.82	0.85
MEAT									
Feeder Cattle	Feb-1978	3.07	1.25	14.53	-0.39	5.30	-0.15	60.97	1.98
Live Cattle	Dec-1974	5.06	1.80	16.65	-0.14	4.34	-0.01	44.45	3.90
Live Hogs	Dec-1974	3.67	0.89	25.77	-0.05	3.30	-0.06	89.03	1.13
Pork Bellies	Dec-1974*	0.80	0.15	36.87	0.44	4.23	-0.12	97.49	0.12
GRAINS									
Corn	Aug-1982	-1.98	-0.41	25.24	0.48	5.83	-0.25	90.21	0.22
Oats	Aug-1982	-2.50	-0.39	34.33	2.88	27.32	-0.20	96.53	0.10
Soybean Oil	Aug-1982	2.55	0.52	26.49	0.58	6.14	-0.07	83.90	0.77
Soybean Meal	Aug-1982	7.63	1.67	24.94	0.24	3.99	0.13	63.55	3.82
Soybeans	Aug-1982	3.64	0.88	23.36	0.14	4.28	-0.03	70.01	1.31
Wheat	Aug-1982	-3.17	-0.72	25.44	0.33	4.97	-0.30	91.53	0.15
SOFTS									
Cocoa	Aug-1986	-3.75	-0.72	29.46	0.57	4.12	-0.26	94.54	0.13
Coffee	Feb-1987	-0.25	-0.03	38.38	0.97	5.56	-0.11	91.66	0.16
Cotton	Feb-1987	1.33	0.22	25.98	0.35	3.76	-0.10	93.21	0.61
Lumber	Dec-1974	-4.59	-0.89	29.34	0.31	3.68	-0.34	98.23	0.04
Orange Juice	Aug-1987	3.73	0.60	31.58	0.70	4.77	-0.00	89.27	0.77
Sugar	Aug-1986	9.73	1.43	33.38	0.32	3.81	0.18	63.75	2.95

Table 1: *Summary Statistics for Futures Contracts*

The table presents summary statistics for the 71 futures contracts of the dataset using monthly return series. The statistics are: annualised mean return in %, Newey-West t-statistic, annualised volatility in %, skewness, kurtosis, annualised Sharpe ratio (SR), maximum drawdown (MDD) in % and dollar growth (DG). The table also indicates the starting month and year for each contract. All but 3 contracts have data up until January 2012. The remaining 3 contracts are indicated by an asterisk (*) next to the starting date and their sample ends prior to January 2012: Municipal Bonds up to March 2006, Korean 3 Yr up to June 2011 and Pork Bellies up to April 2011. The EUR/USD contract is spliced with the DEM/USD (Deutche Mark) contract for dates prior to January 1999 and the RBOB Gasoline contract is spliced with the Unleaded Gasoline contract for dates prior to January 2007 following Moskowitz, Ooi and Pedersen (2012).

Panel A: Monthly Frequency

K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualised Mean (%)							Sharpe ratio						
1	11.85***	9.37***	7.13***	7.08***	7.44***	4.55***	3.23***	0.92	1.04	1.04	1.11	1.27	0.94	0.75
3	14.00***	10.59***	8.73***	10.26***	9.37***	6.20***	4.47***	0.97	0.83	0.83	1.05	1.05	0.84	0.66
6	13.30***	11.11***	12.12***	11.63***	9.87***	6.45***	4.24***	0.89	0.82	0.99	1.00	0.92	0.74	0.51
9	16.56***	16.77***	15.15***	13.33***	11.48***	7.28***	5.03***	1.13	1.23	1.16	1.07	0.98	0.74	0.57
12	**18.54*****	16.27***	13.59***	12.13***	10.51***	6.76***	4.67**	1.25	1.15	1.01	0.95	0.87	0.65	0.51
24	11.45***	10.58***	9.14***	8.08***	7.01***	4.38*	3.18	0.78	0.73	0.66	0.61	0.55	0.38	0.30
36	8.36***	7.52***	6.58**	5.47**	4.39*	2.92	2.63	0.60	0.55	0.50	0.42	0.35	0.24	0.22
J	Annualised Alpha (%)							Dollar Growth						
1	13.19***	8.85***	6.17***	5.85***	6.35***	3.68***	2.61***	42.2	21.0	10.4	10.3	11.8	4.5	2.9
3	11.75***	8.36***	6.33***	7.98***	7.34***	4.70***	3.19**	80.3	27.5	16.0	27.7	21.0	7.5	4.2
6	11.19***	8.04***	9.32***	9.09***	7.64***	4.71***	2.71	62.2	31.5	47.3	40.9	23.5	7.9	3.8
9	13.24***	13.58***	12.49***	10.82***	9.26***	5.56***	3.55**	189.3	213.2	126.9	70.5	38.9	10.1	4.8
12	**15.74*****	13.63***	11.36***	10.17***	8.80***	5.30***	3.53*	365.0	176.7	73.6	46.4	27.6	8.3	4.2
24	9.55***	8.86***	7.95***	7.06***	6.15**	3.74	2.68	33.8	25.5	16.1	11.5	8.2	3.5	2.4
36	7.67***	6.80**	6.02**	4.94*	4.02	2.68	2.18	12.3	9.4	7.0	4.8	3.4	2.1	1.9

Panel B: Weekly Frequency

K	1	2	3	4	6	8	12	1	2	3	4	6	8	12
J	Annualised Mean (%)							Sharpe ratio						
1	8.64***	10.79***	10.44***	9.03***	6.89***	6.95***	5.98***	0.65	0.99	1.15	1.13	1.07	1.24	1.20
2	13.11***	12.38***	11.42***	9.48***	7.52***	8.08***	7.13***	0.95	1.02	1.08	1.01	0.98	1.15	1.15
3	15.66***	13.69***	11.85***	9.95***	8.84***	9.14***	8.36***	1.20	1.14	1.09	0.99	1.02	1.12	1.18
4	15.68***	13.73***	11.82***	10.61***	9.76***	9.73***	8.99***	1.20	1.13	1.04	0.99	1.00	1.07	1.12
6	14.91***	13.13***	12.20***	11.25***	10.99***	10.65***	9.67***	1.14	1.06	1.03	0.98	1.02	1.05	1.05
8	15.72***	15.09***	13.86***	12.77***	11.84***	11.64***	10.52***	1.25	1.22	1.14	1.08	1.04	1.05	1.04
12	**16.63*****	16.61***	15.41***	14.25***	13.15***	12.48***	11.15***	1.25	1.28	1.21	1.13	1.06	1.03	0.98
J	Annualised Alpha (%)							Dollar Growth						
1	10.10***	11.97***	11.46***	9.56***	7.31***	7.12***	5.96***	13.9	31.8	30.1	19.2	9.7	10.0	7.3
2	14.50***	13.39***	12.04***	9.86***	7.74***	8.01***	6.89***	62.0	52.2	39.7	21.4	11.6	14.2	10.5
3	**17.10*****	14.53***	12.44***	10.34***	9.02***	9.03***	8.03***	151.0	81.0	45.5	24.6	17.6	19.8	15.6
4	16.55***	14.36***	12.26***	10.96***	9.81***	9.42***	8.41***	151.7	81.5	44.2	30.0	23.3	23.5	18.8
6	15.49***	13.42***	12.23***	11.11***	10.63***	10.01***	8.80***	116.9	66.1	49.4	36.2	34.0	31.1	22.9
8	16.10***	15.15***	13.57***	12.24***	11.08***	10.72***	9.35***	156.2	127.5	85.1	59.7	44.4	42.0	29.7
12	15.88***	15.70***	14.37***	13.03***	11.76***	10.98***	9.51***	205.0	207.3	139.9	94.9	66.2	53.3	35.1

Panel C: Daily Frequency

K	1	3	5	10	15	30	60	1	3	5	10	15	30	60
J	Annualised Mean (%)							Sharpe ratio						
1	**18.58*****	5.66***	5.11***	4.39***	4.75***	3.04***	2.59***	1.51	0.69	0.81	0.80	0.99	0.86	0.89
3	15.94***	6.05***	4.07***	5.36***	6.16***	4.28***	3.68***	1.22	0.61	0.49	0.74	0.97	0.93	1.01
5	17.56***	7.99***	5.17***	7.46***	8.06***	5.69***	5.18***	1.24	0.65	0.46	0.78	0.98	0.98	1.11
10	15.55***	10.06***	9.32***	10.39***	9.60***	6.74***	6.49***	1.06	0.73	0.71	0.89	0.95	0.91	1.07
15	18.44***	14.51***	12.88***	12.35***	10.44***	8.01***	7.85***	1.21	1.02	0.96	1.02	0.96	0.92	1.08
30	16.97***	14.29***	13.21***	12.15***	11.34***	10.20***	9.49***	1.24	1.07	1.02	0.98	0.95	0.93	1.00
60	18.08***	17.06***	16.38***	16.02***	14.99***	13.11***	11.24***	1.26	1.23	1.20	1.19	1.13	1.02	0.96
J	Annualised Alpha (%)							Dollar Growth						
1	19.79***	6.82***	6.12***	5.30***	5.46***	3.49***	2.73***	412.0	6.1	5.3	4.2	4.8	2.7	2.4
3	17.59***	7.52***	5.32***	6.41***	7.06***	4.78***	3.77***	164.7	6.6	3.6	5.7	7.6	4.1	3.4
5	19.72***	10.08***	7.05***	8.85***	9.17***	6.20***	5.22***	271.9	11.7	4.7	10.8	13.7	6.5	5.6
10	17.71***	11.81***	11.01***	11.49***	10.14***	6.90***	6.15***	135.4	22.1	17.7	27.1	21.9	9.0	8.5
15	**20.61*****	16.49***	14.63***	13.30***	10.93***	8.08***	7.34***	348.6	97.4	58.5	51.6	28.2	13.3	13.1
30	18.12***	15.10***	13.76***	12.22***	11.13***	9.55***	8.44***	227.2	93.5	65.9	47.4	36.7	25.9	21.4
60	17.67***	16.48***	15.73***	15.06***	13.72***	11.50***	9.38***	319.8	231.4	185.7	166.7	118.7	64.0	35.7

Table 2: *Time-Series Momentum*
The table presents the annualised mean return, the annualised Sharpe ratio, the annualised Carhart (1997) 4-factor alpha and the dollar growth for monthly (Panel A), weekly (Panel B) and daily (Panel C) time-series momentum strategies. The dataset covers the period January 1978 to January 2012.

Panel A: Monthly Frequency

K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Alpha t-stat: 1978-1994							Alpha t-stat: 1995-2012						
1	4.00	2.54	2.40	2.45	2.94	2.24	2.06	4.07	4.78	4.95	4.98	5.78	3.69	2.60
3	1.54	0.99	0.91	1.89	2.00	1.70	1.35	5.09	4.42	4.25	4.68	4.66	3.55	2.17
6	1.68	0.99	1.85	1.90	1.86	1.50	0.93	4.23	3.75	3.95	4.03	3.73	2.80	1.38
9	2.39	2.58	2.90	2.59	2.36	1.96	1.47	4.56	4.83	4.41	4.06	3.90	2.48	1.47
12	3.49	3.16	2.82	2.47	2.20	1.99	1.57	5.09	4.49	3.96	3.84	3.71	1.90	1.13
24	1.40	1.35	1.53	1.53	1.46	0.82	0.86	4.17	3.76	2.99	2.45	2.02	1.20	0.69
36	1.29	1.07	1.08	0.86	0.78	0.88	0.80	2.79	2.54	2.04	1.67	1.27	0.46	0.25
J	Sharpe Ratio: 1978-1994							Sharpe Ratio: 1995-2012						
1	0.97	0.86	0.86	0.95	1.10	0.85	0.71	0.88	1.25	1.27	1.35	1.49	1.04	0.80
3	0.72	0.59	0.60	0.90	0.91	0.73	0.62	1.27	1.15	1.17	1.28	1.26	0.98	0.70
6	0.76	0.64	0.88	0.88	0.80	0.69	0.51	1.07	1.07	1.14	1.16	1.07	0.80	0.51
9	1.04	1.12	1.07	0.99	0.87	0.76	0.63	1.26	1.38	1.27	1.16	1.10	0.72	0.51
12	1.20	1.10	0.95	0.86	0.75	0.73	0.61	1.32	1.24	1.10	1.06	1.01	0.58	0.41
24	0.64	0.61	0.59	0.58	0.54	0.39	0.36	0.96	0.90	0.75	0.64	0.55	0.38	0.25
36	0.53	0.48	0.46	0.40	0.33	0.33	0.34	0.69	0.64	0.54	0.46	0.37	0.15	0.10

Panel B: Weekly Frequency

K	1	2	3	4	6	8	12	1	2	3	4	6	8	12
J	Alpha t-stat: 1978-1994							Alpha t-stat: 1995-2012						
1	4.22	5.04	4.90	5.25	5.65	5.94	4.47	0.63	2.51	4.62	4.09	3.48	4.55	4.42
2	4.70	4.46	4.20	4.33	5.30	5.37	4.07	2.65	3.50	4.05	3.42	2.95	4.19	4.76
3	5.52	5.01	4.78	4.84	5.50	5.62	4.21	4.54	4.16	3.83	3.25	3.34	3.90	4.70
4	5.55	5.46	5.34	5.71	5.30	4.75	3.65	3.85	3.41	3.07	2.83	3.09	3.73	4.34
6	5.38	5.56	5.29	5.07	4.44	4.07	2.83	3.71	3.29	3.54	3.34	3.70	4.05	4.67
8	6.12	6.37	6.16	5.11	4.04	3.37	2.40	4.84	4.55	4.10	4.01	4.01	4.41	4.75
12	6.35	5.99	4.95	3.95	2.84	2.38	1.91	4.11	4.40	4.52	4.46	4.57	4.55	4.26
J	Sharpe Ratio: 1978-1994							Sharpe Ratio: 1995-2012						
1	1.10	1.30	1.28	1.26	1.19	1.29	1.22	0.13	0.61	1.06	1.01	0.96	1.21	1.20
2	1.21	1.19	1.17	1.14	1.14	1.20	1.10	0.65	0.84	0.98	0.87	0.81	1.10	1.20
3	1.38	1.27	1.25	1.16	1.18	1.26	1.16	1.00	0.99	0.94	0.83	0.88	1.00	1.19
4	1.46	1.40	1.30	1.26	1.20	1.22	1.12	0.92	0.86	0.81	0.75	0.83	0.96	1.13
6	1.41	1.32	1.19	1.13	1.13	1.12	0.94	0.90	0.83	0.90	0.85	0.92	1.00	1.16
8	1.43	1.38	1.30	1.19	1.11	1.03	0.88	1.10	1.07	1.00	0.99	0.98	1.09	1.19
12	1.51	1.48	1.31	1.14	0.98	0.89	0.81	1.01	1.10	1.12	1.12	1.14	1.17	1.18

Panel C: Daily Frequency

K	1	3	5	10	15	30	60	1	3	5	10	15	30	60
J	Alpha t-stat: 1978-1994							Alpha t-stat: 1995-2012						
1	11.91	7.88	7.66	6.39	6.29	5.36	4.05	1.07	-0.85	0.51	1.51	3.06	3.21	3.77
3	10.16	6.45	5.38	5.25	5.01	5.44	4.23	1.11	0.33	-0.29	1.50	3.58	3.31	3.91
5	9.14	5.88	4.50	4.61	4.33	5.36	4.59	2.74	0.40	-0.16	1.66	3.61	3.07	4.00
10	6.46	4.58	4.41	4.13	3.75	5.50	3.98	2.60	1.35	1.17	2.40	3.13	2.34	4.12
15	6.85	5.57	5.02	4.47	4.07	5.31	3.69	3.87	3.52	3.37	3.62	3.27	2.80	4.37
30	6.94	5.77	5.76	5.79	5.22	4.16	2.70	3.65	3.05	2.62	2.52	2.80	3.01	4.43
60	6.01	6.03	5.90	5.42	4.46	2.70	1.88	4.50	4.27	4.04	4.23	4.29	4.51	4.31
J	Sharpe Ratio: 1978-1994							Sharpe Ratio: 1995-2012						
1	2.63	1.36	1.37	1.14	1.26	0.91	0.82	0.37	-0.18	0.07	0.33	0.67	0.86	1.08
3	2.16	1.13	0.97	1.05	1.17	1.01	0.97	0.29	0.02	-0.10	0.33	0.76	0.89	1.10
5	1.90	1.17	0.87	1.09	1.14	1.12	1.14	0.49	0.00	-0.09	0.35	0.81	0.83	1.09
10	1.57	1.11	1.09	1.16	1.12	1.13	1.06	0.45	0.22	0.20	0.56	0.76	0.67	1.08
15	1.55	1.28	1.20	1.20	1.12	1.10	1.06	0.81	0.70	0.68	0.83	0.78	0.74	1.10
30	1.62	1.38	1.36	1.30	1.17	1.09	0.89	0.81	0.72	0.64	0.65	0.72	0.78	1.11
60	1.46	1.43	1.41	1.36	1.21	0.92	0.77	1.06	1.02	0.97	1.02	1.04	1.11	1.16

Table 3: *Time-Series Momentum in 2 Subperiods*
The table presents the Newey and West (1987) t-statistic of the 4-factor alpha and the annualised Sharpe ratio for monthly (Panel A), weekly (Panel B) and daily (Panel C) time-series momentum strategies over two periods; January 1978 to December 1994 and January 1995 to January 2012.

Panel A: Performance Statistics									
	M^1_{12}	M^3_9	M^{12}_1	W^1_8	W^2_{12}	W^8_1	D^1_{15}	D^1_{60}	D^{15}_1
Ann. Mean Return (%)	18.54	16.77	7.44	15.72	16.61	6.95	18.44	18.08	4.75
Ann. Volatility (%)	14.88	13.66	5.88	12.57	13.00	5.61	15.25	14.34	4.79
Skewness	-0.34	-0.46	-0.30	0.73	0.54	0.97	1.61	0.47	2.54
Kurtosis	4.75	5.35	5.40	4.93	4.51	5.76	10.75	3.60	18.15
CAPM Beta	0.00	0.02	0.01	-0.15	-0.12	-0.06	-0.26	-0.16	-0.09
	(-0.05)	(0.22)	(0.13)	(-2.41)	(-1.82)	(-2.32)	(-3.29)	(-2.25)	(-3.63)
Sharpe ratio	1.25	1.23	1.27	1.26	1.29	1.23	1.21	1.27	0.99
Sortino Ratio	1.32	1.28	1.30	1.66	1.65	1.81	1.74	1.70	1.64
Maximum Drawdown (%)	22.12	25.10	9.18	12.03	15.63	6.86	15.65	17.68	7.18
MDD Period	2	6	2	16	8	7	16	10	25
Dollar Growth	365.0	213.2	11.8	156.2	207.3	10.0	348.6	319.8	4.8

Panel B: Correlation Matrix									
	M^1_{12}	M^3_9	M^{12}_1	W^1_8	W^2_{12}	W^8_1	D^1_{15}	D^1_{60}	D^{15}_1
M^1_{12}	1.00								
M^3_9	0.89	1.00							
M^{12}_1	0.84	0.88	1.00						
W^1_8	**0.41**	0.38	0.38	1.00					
W^2_{12}	0.52	0.50	0.50	0.80	1.00				
W^8_1	0.43	0.41	0.44	0.84	0.74	1.00			
D^1_{15}	**0.22**	0.20	0.20	**0.52**	0.43	0.55	1.00		
D^1_{60}	0.51	0.47	0.48	0.78	0.89	0.72	0.52	1.00	
D^{15}_1	0.33	0.30	0.31	0.52	0.46	0.57	0.84	0.56	1.00

Table 4: *Time-Series Momentum Best Strategies*
The table presents in Panel A various performance statistics for nine time-series momentum strategies: the monthly $(12,1)$, $(9,3)$, $(1,12)$ strategies, the weekly $(8,1)$, $(12,2)$, $(1,8)$ strategies and the daily $(15,1)$, $(60,1)$, $(1,15)$ strategies. The reported statistics are: annualised mean return in %, annualised volatility in %, skewness, kurtosis, CAPM beta with the respective Newey and West (1987) t-statistic, Sharpe ratio, Sortino ratio, maximum drawdown in % and the respective period that this is observed (the period is measured in months/weeks/days respectively according to the rebalancing frequency) and the dollar growth. Weekly and daily strategies are appropriately compounded on a monthly frequency, before the above statistics are calculated. Panel B reports the unconditional correlation matrix of the above nine strategies. Correlations of the best three MWD strategies are indicated in bold. The dataset covers the period January 1978 to January 2012.

	M^1_{12}			W^1_8			D^1_{15}		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
alpha	13.81	17.33	20.26	13.69	15.19	20.05	13.12	12.91	18.67
	(4.77)	(5.51)	(5.72)	(5.36)	(6.29)	(6.58)	(5.21)	(5.38)	(7.18)
MSCI	0.05			-0.14			-0.15		
	(0.49)			(-1.90)			(-1.93)		
S&P500		0.01	0.01		-0.03	-0.02		-0.07	-0.05
		(0.07)	(0.06)		(-0.46)	(-0.30)		(-1.09)	(-0.92)
SMB	-0.01			-0.11			-0.06		
	(-0.22)			(-1.62)			(-0.71)		
SCMLC		0.06	0.06		-0.00	0.00		0.01	0.02
		(0.80)	(0.78)		(-0.07)	(0.05)		(0.19)	(0.40)
HML	0.01			-0.04			-0.02		
	(0.18)			(-0.67)			(-0.19)		
GSCI	0.01			0.01			-0.02		
	(0.16)			(0.19)			(-0.38)		
BOND	-0.05			-0.08			-0.16		
	(-0.19)			(-0.39)			(-0.68)		
UMD	0.32			0.09			-0.02		
	(5.67)			(1.93)			(-0.51)		
PTF Bonds		-0.05	-0.05		0.01	0.00		0.04	0.03
		(-2.39)	(-2.27)		(0.43)	(0.10)		(2.20)	(2.24)
PTF FX		0.00	0.00		0.03	0.02		0.02	0.01
		(0.30)	(0.26)		(2.11)	(1.79)		(1.20)	(0.46)
PTF Com		0.06	0.07		0.07	0.07		0.07	0.07
		(2.54)	(2.72)		(4.07)	(4.62)		(2.80)	(3.05)
PTF IR			-0.01			-0.00			0.01
			(-1.90)			(-0.52)			(0.76)
PTF Stock			0.04			0.08			0.10
			(1.67)			(3.91)			(6.19)
TCM 10Y		0.17	0.14		-0.01	-0.06		-0.05	-0.11
		(1.16)	(0.99)		(-0.14)	(-0.66)		(-0.52)	(-1.21)
BAA Spread		-0.21	-0.23		-0.29	-0.20		-0.08	0.07
		(-1.27)	(-1.23)		(-1.42)	(-1.13)		(-0.48)	(0.63)
adj. R^2 (%)	14.89	6.65	7.56	5.88	19.06	26.43	1.95	15.40	28.87
N	264	204	204	264	204	204	264	204	204

Table 5: *Return Decomposition of the Best Monthly, Weekly, Daily Strategies*
The table reports the regression coefficients (alpha is in % and it is annualised) and the respective Newey and West (1987) t-statistics from regressing the returns of the best monthly, weekly and daily time-series momentum strategies (M^1_{12}, W^1_8 and D^1_{15} respectively) on three model specifications: (a) a version of Carhart's (1997) model that uses as the market proxy the excess return of the MSCI World index and is augmented by the excess return of the S&P GSCI Commodity Index and the excess return of the Barclays Aggregate BOND Index, (b) the Fung and Hsieh (2004) hedge-fund return benchmark 7-factor model, (c) an extended Fung and Hsieh (2004) 9-factor model that incorporates the remaining two Fung and Hsieh (2001) trend-following factors for interest rates and stocks. The regressions are conducted on a monthly frequency (weekly and daily strategies are appropriately compounded on a monthly frequency before conducting the regressions) and the data period for model is (a) December 1989 to November 2011 (264 data points) and for models (b) and (c) January 1994 to December 2010 (204 data points).

Panel A: Yearly Performance

	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
M^1_{12}	10.34	15.33	19.41	37.19	28.20	36.65	37.32	44.26	27.11	8.84	10.39	24.18
W^1_8	21.82	-2.45	32.69	31.70	37.52	17.69	43.16	21.64	11.51	37.30	2.36	9.80
D^1_{15}	36.92	17.23	38.02	28.95	20.64	36.41	50.40	48.05	32.01	65.31	21.28	19.46
AUMW-CTA	58.43	46.24	65.22	8.37	13.40	-7.56	16.22	19.05	-3.80	39.06	0.64	-1.40
BH-CTA	-	-	47.48	8.09	5.58	13.84	-1.04	16.61	-2.21	49.34	14.54	-6.11

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
M^1_{12}	18.52	-5.69	14.06	21.24	3.49	9.07	24.21	27.48	24.02	34.92	13.19	24.68
W^1_8	37.51	0.36	11.54	19.01	3.04	11.81	9.80	17.71	25.73	7.70	6.26	21.79
D^1_{15}	37.66	3.50	18.07	18.88	11.83	9.11	11.27	27.18	32.83	5.57	-6.25	15.11
AUMW-CTA	12.22	4.39	-1.25	9.54	-5.93	6.68	9.57	5.30	8.59	-1.70	3.62	4.41
BH-CTA	12.31	-1.80	-4.29	7.28	-4.40	7.65	3.74	5.38	2.06	-5.63	1.88	-2.91

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
M^1_{12}	26.35	15.87	13.22	19.75	38.56	24.12	26.35	-9.37	7.26	-2.33
W^1_8	14.08	12.88	9.15	20.31	21.90	5.32	49.76	-8.79	14.52	-1.11
D^1_{15}	8.23	3.17	-4.34	12.42	10.81	19.56	28.76	-12.25	18.50	-3.71
AUMW-CTA	12.47	18.58	3.87	2.33	-0.38	6.73	12.13	-4.33	18.75	1.37
BH-CTA	10.57	7.60	2.10	-1.23	-1.22	2.85	12.26	-0.15	6.96	-3.10

Panel B: Correlation Matrix & Recession/Expansion Perforamce

	M^1_{12}	W^1_8	D^1_{15}	AUMW CTA	BH CTA	Return REC	Return EXP	Volatility REC	Volatility EXP	Sharpe ratio REC	Sharpe ratio EXP
M^1_{12}	1.00					18.11**	18.61***	17.81	14.33	1.03	1.30
W^1_8	0.43	1.00				28.07***	13.61***	17.49	11.41	1.62	1.19
D^1_{15}	0.22	0.55	1.00			25.14***	17.29***	23.56	13.29	1.08	1.30
AUMW-CTA	0.38	0.51	0.42	1.00		13.34*	10.25***	16.63	14.63	0.81	0.70
BH-CTA	0.31	0.45	0.36	0.90	1.00	12.58*	5.52**	17.73	14.39	0.72	0.38

Table 6: *Time-Series Momentum Strategies and CTA Indices*
The table reports in Panel A the yearly performance for the years 1978 to 2011 of five indices: the best monthly, weekly and daily time-series momentum strategies (M^1_{12}, W^1_8 and D^1_{15} respectively), the AUM-weighted CTA Index and the BarclayHedge CTA Index. Panel B presents the correlation matrix between the five indices for the period that they overlap (January 1980 to January 2012; 385 months) and the respective annualised mean returns, annualised volatilities and annualised Sharpe ratios during the NBER recessionary (REC) and expansionary (EXP) periods. All five indices have data for 61 recessionary months. The time-series momentum strategies and the AUM-weighted Index have data for 348 expansionary months and the BarclayHedge CTA Index for 324 months. Statistical significance of the mean returns at 1%, 5% and 10% level is denoted by ***, ** and * respectively using Newey and West (1987) t-statistics.

Dependent Variable: AUM-Weighted CTA Index									
	(a) FH7	(b) FH9	(c)	(d)	(e)	(f) MWD	(g)	(h)	(i) FH9+ MWD
alpha	5.87	8.88	0.41	0.05	2.83	-2.38	-3.55	-0.01	-1.65
	(3.33)	(4.61)	(0.20)	(0.03)	(1.41)	(-1.36)	(-2.07)	(-0.00)	(-0.83)
S&P500	0.00	0.00					-0.00		0.01
	(0.08)	(0.02)					(-0.09)		(0.27)
SCMLC	0.02	0.02					0.01		0.01
	(0.53)	(0.50)					(0.30)		(0.15)
PTF Bonds	0.03	0.03						0.04	0.03
	(2.47)	(2.85)						(3.88)	(3.37)
PTF FX	0.04	0.04						0.03	0.03
	(3.86)	(4.40)						(4.21)	(4.19)
PTF Com	0.03	0.04						0.01	0.00
	(2.31)	(2.82)						(0.64)	(0.44)
PTF IR		-0.02						-0.02	-0.01
		(-2.63)						(-2.70)	(-2.70)
PTF Stock		0.04						0.00	-0.00
		(3.04)						(0.36)	(-0.01)
TCM 10Y	0.27	0.23					0.30		0.23
	(3.13)	(2.80)					(4.19)		(3.20)
BAA Spread	0.08	0.05					0.15		0.14
	(1.08)	(0.70)					(1.74)		(2.20)
M_{12}^1			0.31			0.18	0.16	0.20	0.19
			(6.26)			(3.57)	(3.58)	(4.99)	(5.02)
W_8^1				0.44		0.28	0.29	0.22	0.24
				(8.52)		(4.95)	(6.65)	(4.33)	(4.87)
D_{15}^1					0.29	0.13	0.13	0.09	0.10
					(6.22)	(3.06)	(3.30)	(2.15)	(2.31)
adj. R^2 (%)	23.57	27.24	20.20	31.09	13.98	37.28	42.24	47.33	50.12

Table 7: *Return Decomposition of the AUM-Weighted CTA Index*
The table reports the regression coefficients (alpha is in % and it is annualised) and the respective Newey and West (1987) t-statistics from regressing the net-of-fee monthly returns of the AUM-Weighted CTA Index (constructed from the BarclayHedge database) on various combinations of factors: the excess return of the S&P500 index; the spread return between small-cap and large-cap stock returns (SCMLC) constructed using the spread between Russell 2000 index and S&P500 index; the excess returns of the five Fung and Hsieh (2001) primitive trend-following (PTF) factors that constitute portfolios of lookback straddle options on bonds, commodities, foreign exchange, interest rates and stocks; the excess return of the US 10-year constant maturity treasury bond (TCM 10Y); the spread return of Moody's BAA corporate bond returns index and the US 10-year constant maturity treasury bond, and finally the best monthly, weekly and daily time-series momentum strategies (M_{12}^1, W_8^1 and D_{15}^1 respectively). The first regression (Column 2) replicates the Fung and Hsieh (2004) hedge-fund return benchmark 7-factor model. The data period for the regressions is restricted by the availability of the five Fung and Hsieh (2001) PTF factors: January 1994 to December 2010 (204 data points).

	(i) All Contracts			(ii) All excl. Commodities			(iii) Commodities		
	M_{12}^1	W_8^1	D_{15}^1	M_{12}^1	W_8^1	D_{15}^1	M_{12}^1	W_8^1	D_{15}^1
Const.	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.01	0.01
	(6.65)	(7.35)	(5.33)	(4.93)	(5.92)	(4.96)	(3.54)	(4.12)	(3.83)
FuF$(t-12 \rightarrow t-1)$	-0.07	-0.11	-0.02	-0.16	-0.20	0.04	0.08	-0.04	-0.12
	(-0.62)	(-1.02)	(-0.14)	(-0.79)	(-1.21)	(0.17)	(0.48)	(-0.26)	(-0.77)
MSCI	0.06	-0.15	-0.24	0.15	-0.16	-0.30	-0.04	-0.13	-0.12
	(0.55)	(-2.04)	(-2.54)	(0.83)	(-1.50)	(-2.29)	(-0.59)	(-2.15)	(-1.90)
SMB	0.03	-0.14	-0.13	-0.02	-0.18	-0.21	0.10	-0.10	-0.02
	(0.38)	(-2.04)	(-1.25)	(-0.18)	(-2.03)	(-1.48)	(1.26)	(-1.12)	(-0.27)
HML	0.07	-0.04	-0.03	0.09	-0.05	-0.07	0.04	-0.04	0.04
	(0.81)	(-0.67)	(-0.25)	(0.85)	(-0.55)	(-0.55)	(0.50)	(-0.53)	(0.48)
GSCI	-0.06	-0.02	-0.04	-0.06	0.02	-0.01	-0.06	-0.10	-0.08
	(-0.93)	(-0.47)	(-0.98)	(-0.76)	(0.23)	(-0.18)	(-0.74)	(-1.81)	(-1.75)
UMD	0.33	0.07	-0.09	0.47	0.08	-0.14	0.08	0.03	-0.01
	(5.60)	(1.64)	(-1.55)	(5.83)	(1.39)	(-1.94)	(1.43)	(0.64)	(-0.24)
adj. R^2 (%)	10.91	5.73	7.00	11.67	3.01	5.65	0.16	3.17	2.13

	(iv) Currencies			(v) Equities			(vi) Interest Rates		
	M_{12}^1	W_8^1	D_{15}^1	M_{12}^1	W_8^1	D_{15}^1	M_{12}^1	W_8^1	D_{15}^1
Const.	0.03	0.03	0.02	0.01	0.01	0.02	0.03	0.02	0.02
	(3.70)	(4.17)	(3.25)	(1.22)	(2.50)	(3.68)	(4.10)	(4.51)	(3.17)
FuF$(t-12 \rightarrow t-1)$	-0.53	-0.57	-0.42	0.02	-0.11	0.33	-0.04	-0.12	-0.03
	(-1.41)	(-1.82)	(-1.21)	(0.08)	(-0.50)	(1.09)	(-0.10)	(-0.40)	(-0.08)
MSCI	-0.17	-0.20	-0.13	0.31	-0.16	-0.36	0.10	-0.04	-0.21
	(-1.37)	(-1.84)	(-1.22)	(1.21)	(-0.96)	(-1.91)	(0.51)	(-0.30)	(-1.40)
SMB	-0.06	-0.14	-0.02	0.08	-0.10	-0.25	-0.19	-0.41	-0.13
	(-0.51)	(-1.08)	(-0.14)	(0.51)	(-0.85)	(-1.13)	(-1.14)	(-3.34)	(-1.05)
HML	0.12	0.07	0.10	0.12	-0.02	-0.07	-0.01	-0.19	-0.10
	(0.88)	(0.55)	(0.81)	(0.78)	(-0.14)	(-0.36)	(-0.07)	(-1.38)	(-0.65)
GSCI	-0.10	-0.11	-0.11	-0.09	0.04	-0.01	0.09	0.07	0.07
	(-1.50)	(-1.37)	(-1.70)	(-0.70)	(0.37)	(-0.05)	(1.00)	(0.80)	(0.82)
UMD	0.14	0.05	0.02	0.74	0.12	-0.17	0.19	0.08	-0.15
	(1.46)	(0.51)	(0.23)	(6.73)	(1.18)	(-1.46)	(1.82)	(1.08)	(-1.58)
adj. R^2 (%)	2.12	2.47	0.55	16.53	0.79	4.20	0.18	0.60	-0.37

Table 8: *Time-Series Momentum Profitability across Asset Classes and CTA Fund Flows*
The table reports the regression coefficients and the respective Newey and West (1987) t-statistics (using 11 lags) from regressing the monthly returns of the best monthly, weekly and daily time-series momentum strategies formed using (i) all futures contracts, (ii) all contracts excluding commodities, (iii) commodities only, (iv) currencies only, (v) equities only and (vi) interest rates only, on the sum of past year's CTA fund flows, FuF$(t-12 \rightarrow t-1)$, and a number of control variables (the MSCI World Index, the Fama and French (1993) size (SMB) and value (HML) risk factors, the S&P GSCI Commodity Index and the Carhart (1997) momentum factor (UMD)). The sample period is January 1979 to January 2012 (397 data points).

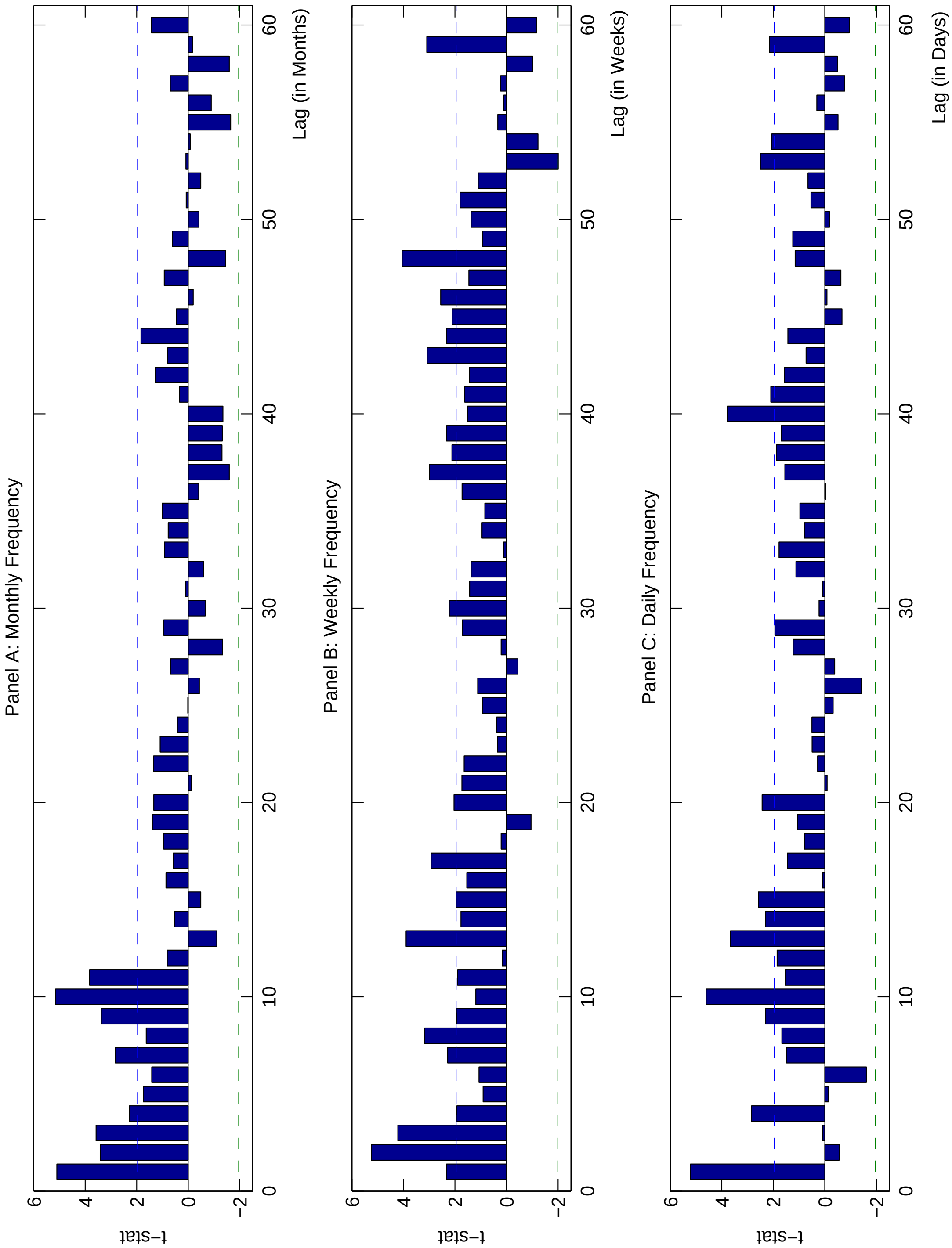

Figure 1: *Return Predictability*

The figure presents the t-statistics of the β_λ coefficient for the pooled panel linear regression $\frac{R(t-1,t)}{\sigma_{YZ}(t-1;D)} = \alpha + \beta_\lambda \frac{R(t-1-\lambda,t-\lambda)}{\sigma_{YZ}(t-1-\lambda;D)} + \varepsilon(t)$ for lags $\lambda = 1, 2, \cdots, 60$ on a monthly, weekly and daily frequencies (Panels A, B and C respectively). The t-statistics are computed using standard errors clustered by asset and time (Cameron, Gelbach and Miller 2011, Thompson 2011). The volatility estimates are computed using the Yang and Zhang (2000) estimator on a $D = 60$ day rolling window. The dashed lines represent significance at the 5% level. The dataset covers the period December, 1974 to January, 2012.

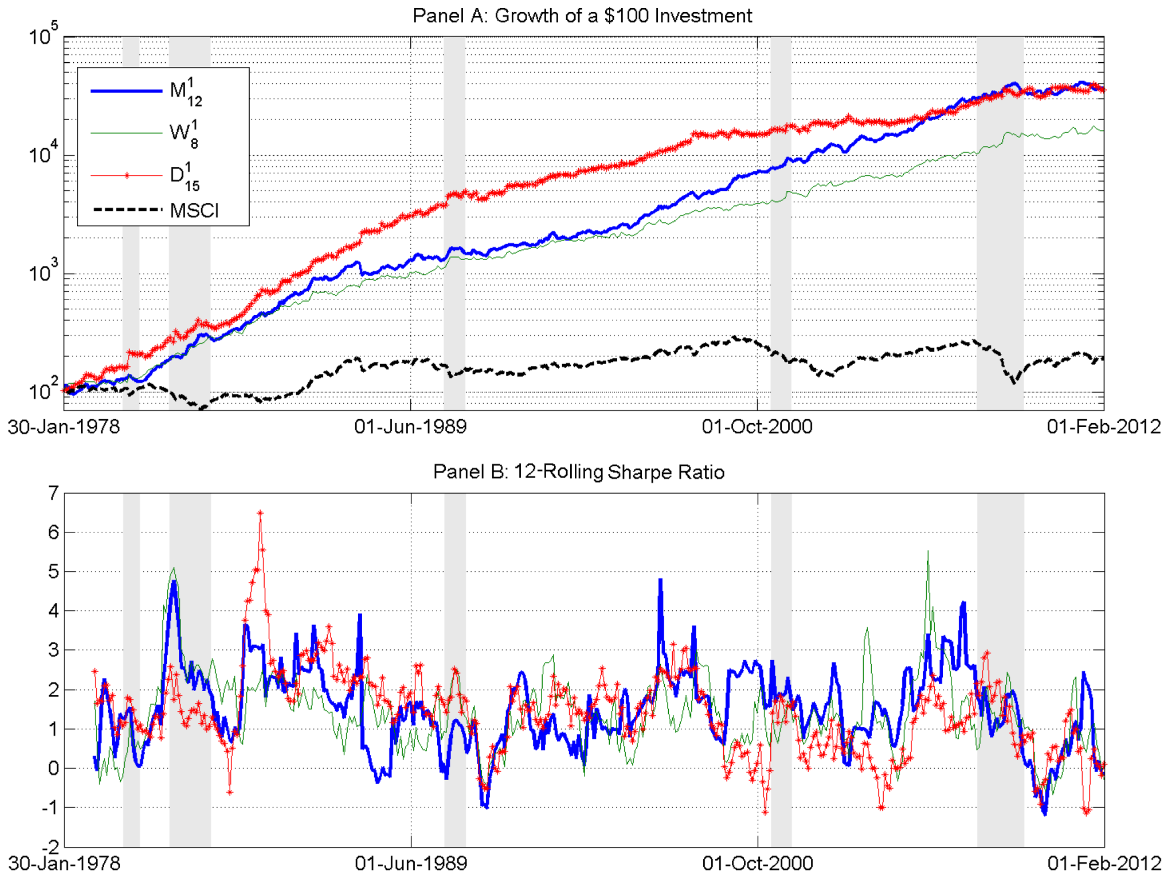

Figure 2: *Historical Performance of Time-Series Momentum Strategies*
The figure presents in Panel A the growth of an investment of $100 in the best monthly, weekly and daily time-series momentum strategies (M^1_{12}, W^1_8 and D^1_{15} respectively) and in the MSCI World Index for the period January 1978 to January 2012. All return series are excess returns. Panel B presents the 12-month rolling Sharpe ratio of the time-series momentum strategies for the same period. The grey bands in both panels indicate the NBER recessionary periods.

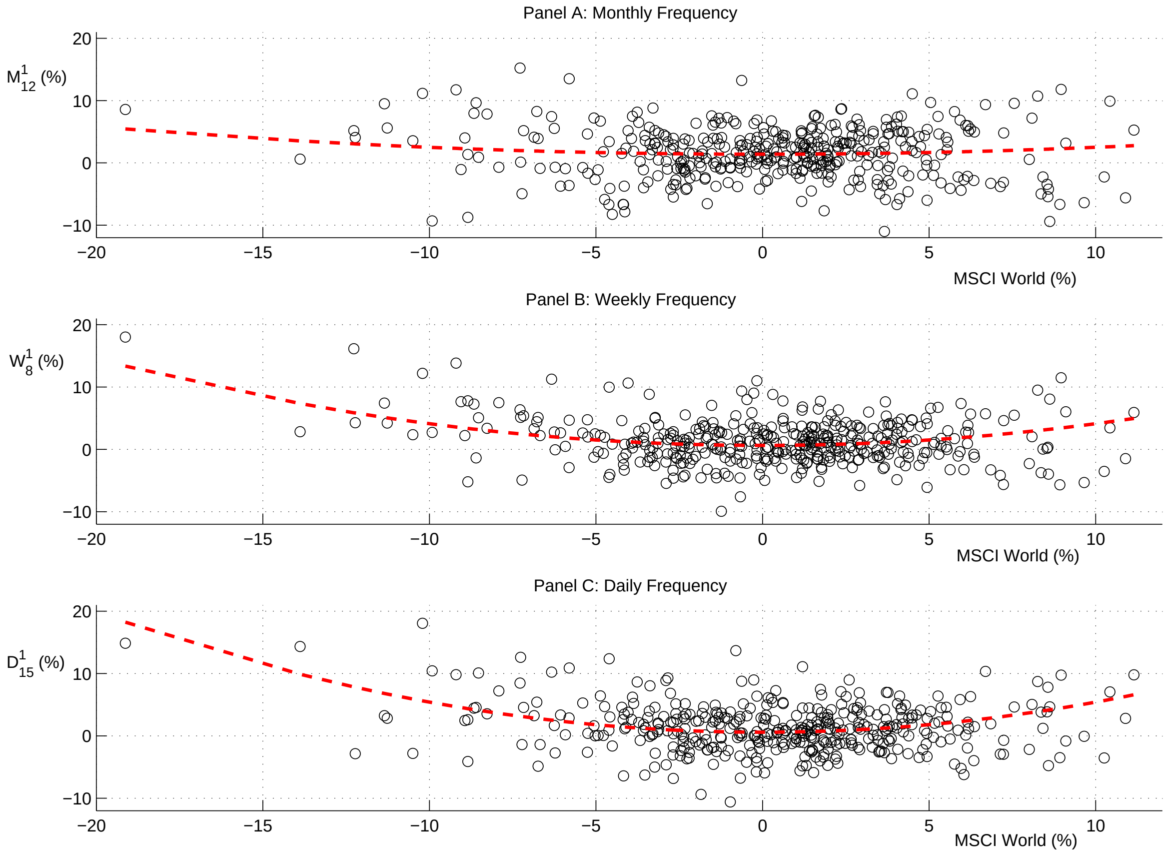

Figure 3: *Time-Series Momentum Smiles*
The figure presents scatterplots of monthly returns of the best monthly (Panel A), weekly (Panel B) and daily (Panel C) time-series momentum strategies (M^1_{12}, W^1_8 and D^1_{15} respectively) against the contemporaneous excess returns of the MSCI World index. The sample period is January 1978 to January 2012.

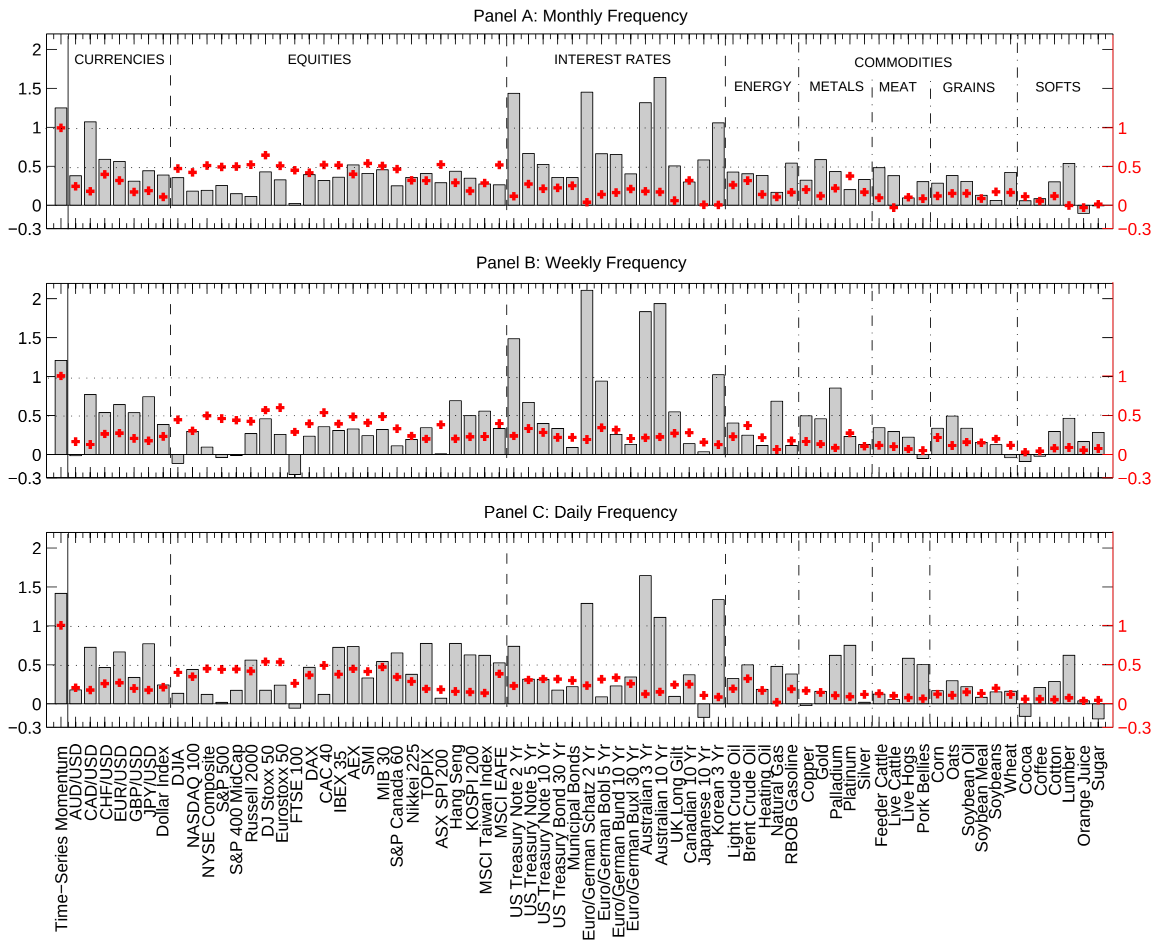

Figure 4: *Sharpe Ratios and Correlations of Univariate Time-Series Momentum Strategies*
The figure presents the Sharpe ratios for the univariate time-series momentum strategies that comprise the best aggregate monthly (Panel A), weekly (Panel B) and daily (Panel C) time-series momentum strategies (M_{12}^1, W_8^1 and D_{15}^1 respectively). For comparison, the first bar of each panel reports the Sharpe ratio of the respective aggregate strategy. Additionally, each panel indicates with a little cross marker ("+") the unconditional correlation that each univariate strategy has with the respective aggregate momentum strategy. The Sharpe ratios and correlations account for the period that each futures contract is traded as reported in Table 1.

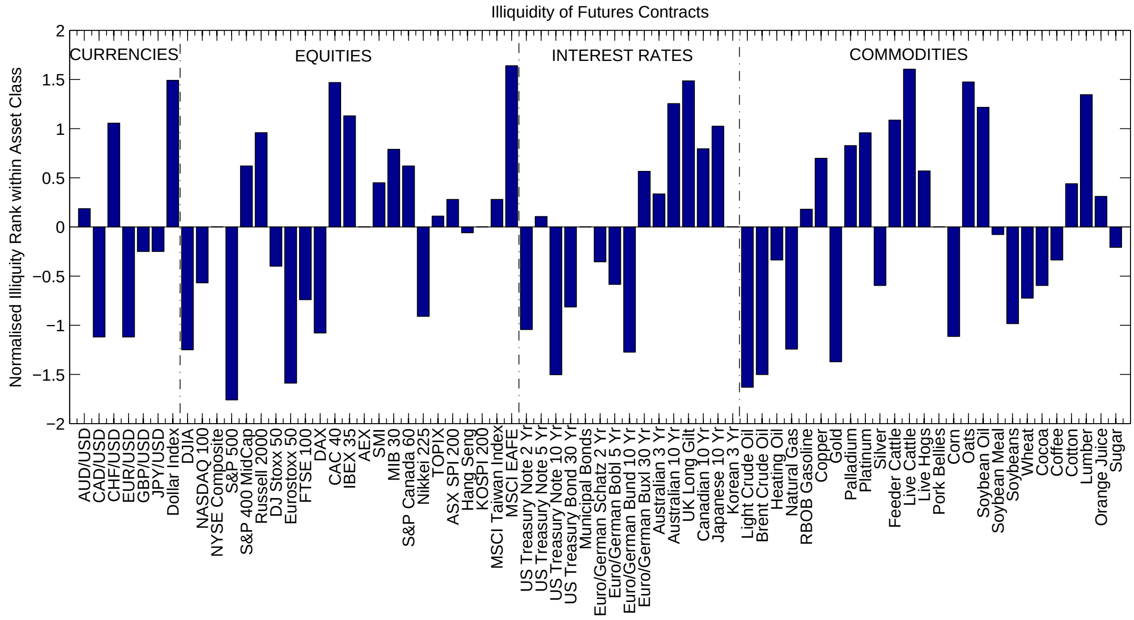

Figure 5: *Illiquidity of Futures Contracts*

The figure presents a measure of illiquidity for the futures contracts of the dataset that is estimated form daily volume data on January 31, 2012. Following Moskowitz, Ooi and Pedersen (2012), the contracts within each asset class are ranked with respect to their daily volume (for N contracts, the contract with the largest volume is given the rank 1 and the contract with the lowest volume is given the rank N) and subsequently the ranks are normalised by subtracting the average rank across the asset class and dividing by the respective standard deviation rank. Positive normalised rank corresponds to larger illiquidity than the average contract within the respective asset class. Respectively, contracts with negative normalised ranks are the most liquid contracts of each asset class.

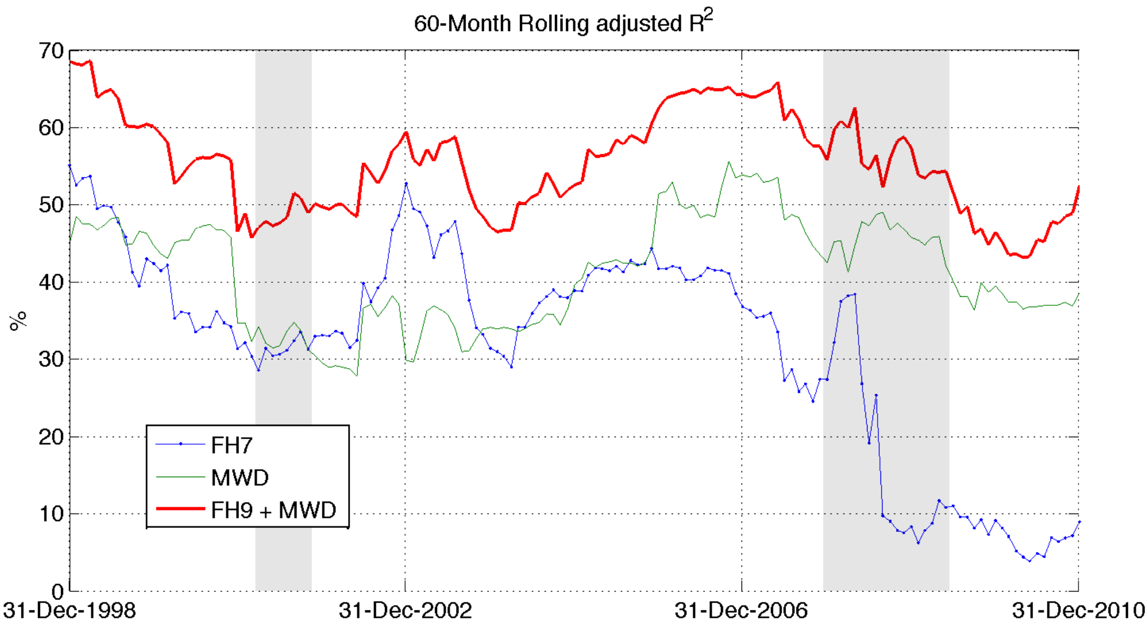

Figure 6: *60-Month Rolling adjusted R^2*

The figure presents the evolution of the rolling adjusted R^2 from regressing the net-of-fee monthly returns of the AUM-Weighted CTA Index (constructed from the BarclayHedge database) on three combinations of factors: (a) the Fung and Hsieh (2004) 7-factor model, denoted by “FH7”, (b) the best monthly, weekly and daily time-series momentum strategies (M^1_{12}, W^1_8 and D^1_{15} respectively), denoted by ‘MWD’ and (c) the extended Fung and Hsieh (2004) 7-factor model that incorporates the remaining two primitive trend-following (PTF) Fung and Hsieh (2001) factors for interest rates and stocks combined with the MWD factors, denoted by “FH9 + MWD”. The regressions are estimated at the end of each month using a window of 60 months. The data period for the regressions is restricted by the availability of the five Fung and Hsieh (2001) PTF factors: January 1994 to December 2010. The grey bands indicate the NBER recessionary periods.

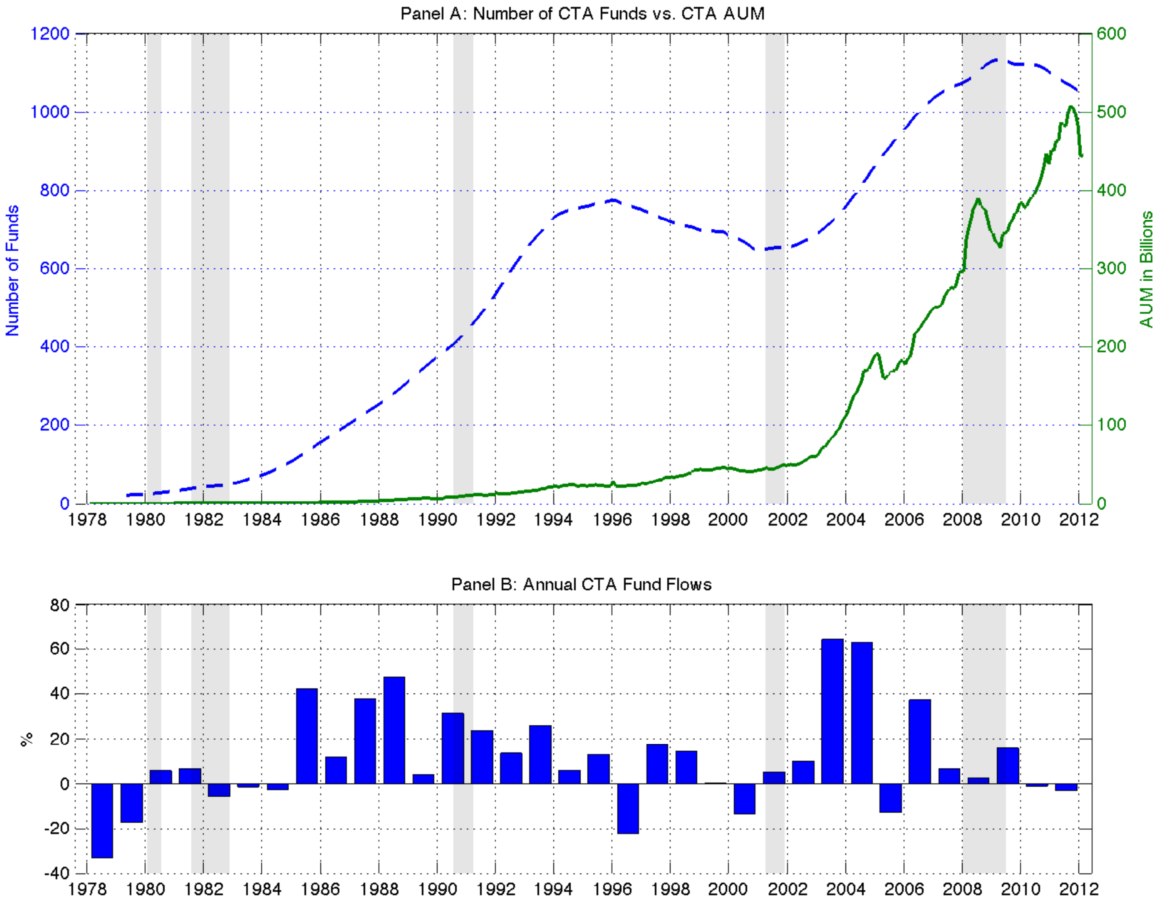

Figure 7: *Number of CTA Funds, Total AUM of CTA Industry and Annual CTA Fund Flows*
The figure presents in Panel A the evolution of the (12-month moving average of the) number of CTA funds (blue dashed line) and the total Assets-under-Management (AUM) is billions (green solid line) of the CTA industry. Panel B presents the annual net flow of funds in the CTA industry. All measures are constructed from the BarclayHedge database. The sample period is January 1978 to January 2012. The grey bands indicate the NBER recessionary periods.

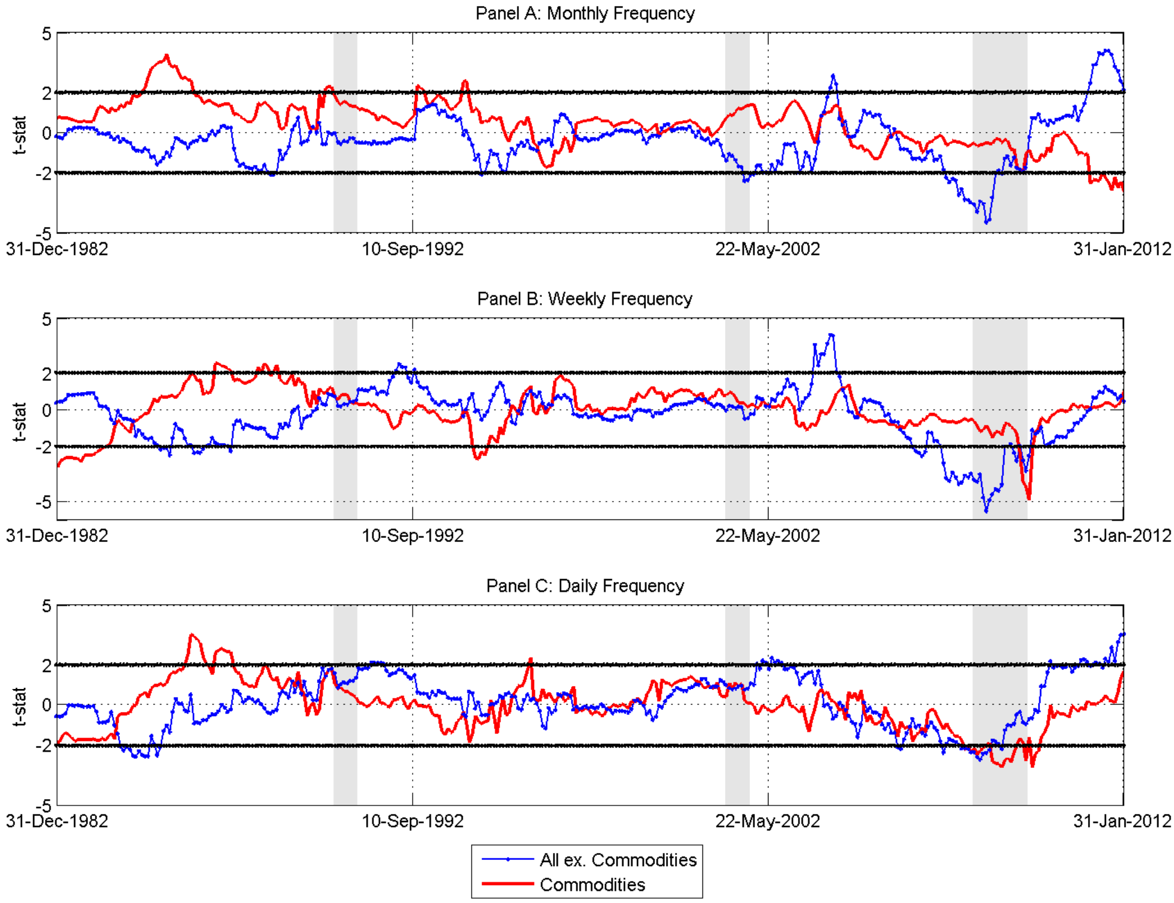

Figure 8: *60-Month Rolling t-statistics of CTA Fund Flows*

The figure presents the evolution of the t-statistics from regressing on a 60-month rolling basis the monthly returns of the monthly (Panel A), weekly (Panel B) and daily (Panel C) time-series momentum strategies (M_{12}^1, W_8^1 and D_{15}^1 respectively) on the sum of past year's fund flows FuF$(t-12 \rightarrow t-1)$. The time-series momentum strategies are constructed (i) using all futures contracts excluding the commodity contracts and (ii) using only commodity contracts. All regressions account additionally for a number of control variables (the MSCI World Index, the Fama and French (1993) size (SMB) and value (HML) risk factors, the S&P GSCI Commodity Index and the Carhart (1997) momentum factor (UMD)). The sample period is December 1982 to January 2012. The grey bands indicate the NBER recessionary periods.

	BarclayHedge CTA Index			Newedge CTA Index			Newedge CTA Trend Sub-I		
	FH9	MWD	Joint	FH9	MWD	Joint	FH9	MWD	Joint
alpha	8.88	-2.38	-1.65	9.03	-3.50	-2.36	14.52	-7.33	-5.18
	(4.61)	(-1.36)	(-0.83)	(3.62)	(-1.49)	(-0.86)	(3.05)	(-1.78)	(-1.07)
S&P500	0.00		0.01	-0.03		0.02	-0.07		0.02
	(0.02)		(0.27)	(-0.59)		(0.42)	(-0.75)		(0.27)
SCMLC	0.02		0.01	0.07		0.03	0.14		0.07
	(0.50)		(0.15)	(1.33)		(0.49)	(1.50)		(0.61)
PTF Bonds	0.03		0.03	0.03		0.03	0.04		0.06
	(2.85)		(3.37)	(1.90)		(2.62)	(1.65)		(2.45)
PTF FX	0.04		0.03	0.03		0.02	0.04		0.02
	(4.40)		(4.19)	(2.77)		(2.19)	(1.79)		(1.10)
PTF Com	0.04		0.00	0.03		0.00	0.06		0.00
	(2.82)		(0.44)	(2.18)		(0.04)	(2.28)		(0.16)
PTF IR	-0.02		-0.01	-0.02		-0.02	-0.03		-0.03
	(-2.63)		(-2.70)	(-3.54)		(-3.73)	(-3.22)		(-3.20)
PTF Stock	0.04		-0.00	0.04		0.00	0.08		0.01
	(3.04)		(-0.01)	(3.49)		(0.32)	(3.27)		(0.66)
TCM 10Y	0.23		0.23	0.10		0.11	0.22		0.22
	(2.80)		(3.20)	(0.99)		(1.19)	(1.25)		(1.40)
BAA Spread	0.05		0.14	0.00		0.10	-0.01		0.17
	(0.70)		(2.20)	(0.00)		(1.61)	(-0.09)		(1.55)
M_{12}^1		0.18	0.19		0.26	0.26		0.49	0.49
		(3.57)	(5.02)		(5.01)	(6.14)		(5.12)	(5.88)
W_8^1		0.28	0.24		0.22	0.23		0.36	0.38
		(4.95)	(4.87)		(3.65)	(3.33)		(3.28)	(2.92)
D_{15}^1		0.13	0.10		0.07	0.07		0.11	0.10
		(3.06)	(2.31)		(1.58)	(1.28)		(1.31)	(1.01)
adj. R^2 (%)	27.24	37.28	50.12	17.67	37.67	45.24	14.95	38.90	44.30
N	204	204	204	132	132	132	132	132	132

Table B.1: *Return Decomposition of CTA Indices*
The table reports the results of regressions (b), (f) and (i) of Table 7 for three CTA indices: the BarclayHedge CTA Index, the Newedge CTA Index and the Newedge CTA Trend Sub-Index. The Newedge CTA Trend Sub-Index is constructed with a subset of CTAs that are originally included in the Newedge CTA Index and are widely recognised in the industry as trend followers. The three regression specifications correspond to the FH9 [extended Fung and Hsieh (2004) model using all primitive trend-following Fung and Hsieh (2001) factors], MWD [best monthly, weekly and daily time-series momentum strategies] and FH9+MWD (denoted as “Joint” in the table) models. The data period for the regressions is restricted by the availability of the five Fung and Hsieh (2001) PTF factors: January 1994 to December 2010 (204 data points). The Newedge indices are available from January 2000.