Momentum Strategies in Futures Markets and Trend-following Funds*

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ABSTRACT

In this paper we rigorously establish a relationship between time-series momentum strategies in futures markets and commodity trading advisors (CTAs), a subgroup of the hedge fund universe that has grown to $300 billion and has attracted a lot of attention during the financial crisis. Building on this relationship, we examine the question of capacity constraints in trend-following investing. Using a cross-section of 71 futures contracts over the period 1974-2012, we first construct one of the most comprehensive sets of time-series momentum portfolios across various trading frequencies. Second, we provide evidence that CTAs follow time-series momentum strategies, by showing that such benchmark 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. Consistent with the view that futures markets are relatively liquid, we do not find evidence of statistically significant capacity constraints when using two different methodologies and several robustness tests. 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 rigorously establish a relationship between time-series momentum strategies in futures markets and commodity trading advisors (CTAs), a subgroup of the hedge fund universe that has grown to USD 300 billion and has attracted a lot of attention due to its positive double-digit performance in 2008. Building on this relationship we examine the question of capacity constraints in trend-following investing; that is, buying assets whose price is rising and selling assets whose price is falling. 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, which are also known as managed futures funds, has not been examined rigorously in the academic literature using replicating portfolios such as the time-series momentum strategies. Moreover, the existing literature has not provided evidence to substantiate the claim that CTAs indeed follow momentum strategies. Covel (2009) and Hurst, Ooi and Pedersen (2010) state that the main driver of many managed futures strategies pursued by CTAs is trend-following or momentum investing but they do not carry out tests to support this statement. Using a comprehensive hedge fund and futures database, 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.

Understanding trend-following strategies and funds is important since the CTA industry is a significant slice of the alternative investment fund universe accounting for $270bn of the $1.8tr assets under management (AUM) in hedge funds and around 10-15 percent of the number of hedge funds (Joenväärä, Kosowski and Tolonen 2012). The term "*Commodity Trading Advisor*" is a bit of a misnomer, since CTAs are not constrained to trade commodities only and in fact they typically trade liquid futures, forwards and other derivatives on financials (equity indices, interest rates and currencies) as well as commodities. Although it is not our focus, our results are, nevertheless, also relevant to the broader discussion about the financialisation of commodities, which refers to both passive products such as ETFs and Commodity-Linked Notes[2] as well as active funds such as CTAs. We focus on active investors such as CTAs and use the term trend-following fund and systematic CTA interchangeably in what follows. Trend-following funds describe themselves as long-term, medium and short-term trend-following funds (Arnold 2012). To approximate CTA strategies as well as we can, as a preliminary step, we first extend existing studies of futures time-series momentum strategies to higher frequencies. We document strong return continuation patterns not only at monthly frequency (as in Moskowitz, Ooi and Pedersen 2012), but also across weekly and daily frequencies.

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

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

[2]See, for example, Büyükşahin and Robe (2012) and Henderson, Pearson and Wang (2012).

attention and inflows in its aftermath[3]. However, in 2009 and 2011, CTA performance was disappointing. Could this be due to the presence of capacity constraints despite the fact that futures markets are typically considered to be relatively liquid? Consistent with the view that futures markets are relatively liquid, we do not find evidence of statistically significant capacity constraints when using two different methodologies and several robustness tests.

Next we present our paper's three main contributions in detail. Our first contribution is 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). Therefore, we extend the work of Moskowitz et al. (2012) and evaluate time-series momentum strategies in futures markets over a broader 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 to December 2009), we not only document the existence of strong time-series momentum effects across monthly, weekly and daily frequencies, 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 perform well in up and down markets, therefore providing important diversification benefits in line with Schneeweis and Gupta (2006). We find that time-series momentum profitability is not concentrated in illiquid contracts and that commodity futures strategies, in particular, 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). Trend-following strategies are typically implemented by means of exchange traded futures and forward contracts which are considered to be relatively liquid and to have relatively low transaction costs compared to cash equity or bond markets. For this reason and for simplicity we do not incorporate transaction costs into the momentum strategies that we study.

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 (such as the 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.

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

[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.

One explanation for this result may be related to 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 on benchmarking 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.

Our third and final contribution is in the form of tests for the presence of capacity constraints in trend-following strategies. The size of the CTA industry has dramatically increased in the recent years. In principle, there are many different ways of defining capacity constraints and testing for them. We choose two different methodologies to make sure that our results do not depend on one methodology only.

The first methodology is based on predictive regressions and we find that lagged fund flows into the CTA industry are not statistically significantly related to the future performance of time-series momentum strategies. In fact, the relationship exhibits time-variation and switches in the sign of the predictive relationship over time. In contrast to the quote from the Financial Times that we used as in the above motivating example, we do not find economically or statistically significant 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). Overall, our findings do not support the hypothesis of capacity constraints and the statistically insignificant impact of lagged CTA flows on the performance of time-series momentum strategies holds for all asset classes.

The second methodology that we employ is based on a thought experiment in which we simulate what would happen if one assumed that the entire AUM of the systematic CTA industry were invested in our monthly momentum strategy. In particular, we focus on the relationship between the number of contracts per asset that are necessary for the construction of the time-series momentum strategy and the open interest of each asset as reported in the CFTC database. Again we do not find evidence of economically significant capacity constraints.

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 there are several theoretical explanations of price trends in the literature based on rational[6] (e.g. Berk et al. 1999, Johnson 2002, Ahn, Conrad and Dittmar 2003, Sagi and Seasholes 2007, Liu and Zhang 2008) and behavioural[7] approaches (e.g. Barberis et al. 1998, Daniel et al. 1998, Hong and Stein 1999, Frazzini 2006) to serial correlation in asset return series. Price trends may, for example, be due to behavioural biases exhibited by investors such as herding or anchoring as well as trading activity by non-profit seeking market participants such as corporate hedging programs and central banks. Finally, adopting a different perspective, Christoffersen and Diebold (2006) and Christoffersen, Diebold, Mariano, 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)

[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 lead to return predictability. 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) show how the return autocorrelation can depend on 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.

show that speculative activity is not destabilising 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. Section 6 presents results from two different methodologies used to test for capacity constraints. Finally, section 7 concludes.

2. Data Description

In this section we briefly describe the various data sets that we use in this paper, namely, futures prices, futures open interest data and the hedge fund data.

2.1. Futures Contracts

The futures dataset that we use consists of daily opening, high, low and closing futures prices for 71 assets: 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 contracts- being December 1974. The sample extends 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].

First, we construct a continuous series of futures prices for each asset by appropriately splicing together different contracts (for further details refer to Baltas and Kosowski 2012). 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 the most liquid contract (based on daily tick volume).

Since the contracts of different assets are traded in various exchanges each with different trading hours and holidays, the data series are appropriately aligned by filling forward any missing asset prices (as for example in Pesaran, Schleicher and Zaffaroni 2009).

Having obtained single price data series for each of the assets, we construct daily *excess* close-to-close returns, which are then compounded to generate weekly (Wednesday-to-Wednesday) and monthly returns for the purposes of our empirical results[9]. Table I presents summary univariate statistics for all

[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 confirm that this is the case and that our results remain qualitatively unchanged without the equity spot price backfill.

[9]We choose this approach for simplicity and since it is unlikely to qualitatively affect our results. We note that this approach abstracts from practical features of futures trading such as the treatment of initial margins, potential margin calls, interest accrued on the margin account and the fact that positions do not have to be fully collateralized positions. Among others, Bessembinder (1992), Bessembinder (1993), Gorton, Hayashi and Rouwenhorst (2007), Miffre and Rallis (2007), Pesaran et al. (2009), Fuertes, Miffre and Rallis (2010) and Moskowitz et al. (2012) compute returns as the percentage change in the

assets in our dataset.

[Table I about here]

In line with the futures literature (e.g. see de Roon et al. 2000, Pesaran et al. 2009, Moskowitz et al. 2012), we find that there is 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, almost all equity contracts have negative skewness. The cross-sectional variation in the volatility of the available contracts is substantial. 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 variation in the volatility profiles is crucial for the construction 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. Finally, regarding the performance of univariate long-only strategies, almost half of the Sharpe ratios are negative (34 out of 71); RBOB Gasoline contract achieves the largest Sharpe ratio of 0.51, while the S&P500 contract exhibits a mere Sharpe ratio of 0.13.

2.2. Positions of Traders

Along with transaction prices, we collect open interest data for the US-traded futures contracts in our dataset from the Commodity Futures Trading Commission (CFTC). In particular, the CFTC dataset covers 43 out of the 71 contracts in our dataset: 25 out of the 26 commodity contracts, all 7 currency contracts, 6 out of the 23 equity contracts and 5 out of the 15 interest rate contracts. When "mini" contracts exist, we add the open interest of the mini contract to the open interest of the respective "full" contract using appropriate scaling[10]. The sample period of the dataset is January 1986 to December 2011.

2.3. CTA Dataset

Finally, we collect monthly return and assets-under-management (AUM) data series for all the CTA funds reporting in the BarclayHedge database. Joenväärä et al. (2012) offer a comprehensive study of the main hedge fund databases and discuss the advantages of the BarclayHedge database among the rest.

After removing duplicate funds[11], the BarclayHedge CTA universe consists of 2663 unique CTA

price level, whereas Pirrong (2005) and Gorton and Rouwenhorst (2006) also take into account interest rate accruals on a fully-collateralized basis.

[10]For example, the size of the S&P500 futures contracts is the value of the index times $250, whereas the size of the mini S&P500 contract is the value of the index times $50. We therefore augment the open interest of the S&P500 futures contract with the open interest of the mini contract scaled by $1/5$.

[11]We thank Pekka Tolonen for his assistance in preparing the BarclayHedge database for the purposes of this study.

funds trading in US Dollars between February 1975 and January 2012 with total AUM at the end of this period being about \$305 billion. Using BarclayHedge's categorisation scheme, we next keep the 1348 CTA funds that are listed as "systematic" funds, since in contrast to "discretionary" CTAs, these systematic funds can be expected to employ systematic momentum strategies in practice. The systematic subgroup accounts for about 87.5% of the total AUM of the CTA industry at the end of the sample period, or \$267 billion. In order to safeguard against our results being driven by outliers, we restrict the dataset to start in January 1980 in order to have at least 10 funds in our sample.

As a measure of aggregate performance of the systematic CTA subgroup we construct an AUM-weighted index of the systematic CTA universe (AUMW-CTA, henceforth).

We also calculate the aggregate flow of capital in the systematic CTA industry at the end of each month as the AUM-weighted average of individual fund flows:

$$\mathrm{FuF}(t) = \frac{\sum_{j=1}^{M_t} \mathrm{AUM}_j(t)\mathrm{FuF}_j(t)}{\sum_{j=1}^{M_t} \mathrm{AUM}_j(t)}, \tag{1}$$

where $\mathrm{FuF}_j(t)$ denotes the individual fund flows of capital net of fund performance, which is computed using standard methodologies (see for example Naik et al. 2007, Frazzini and Lamont 2008):

$$\mathrm{FuF}_j(t) = \frac{\mathrm{AUM}_j(t) - \mathrm{AUM}_j(t-1)\cdot(1+R_j(t))}{\mathrm{AUM}_j(t-1)}, \quad j = 1,\cdots,M_t, \tag{2}$$

where M_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

Next we discuss how we construct the time-series momentum strategy. A ***univariate time-series momentum*** strategy is defined as the trading strategy that takes a long/short position in 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[12].

Following MOP, we subsequently construct the return series of the (aggregate) ***time-series momen-***

[12]One could potentially investigate the quarterly frequency of portfolio rebalancing, but we note that monthly rebalancing can successfully capture long-term trend-following for the following reason. A quarter is by construction a 3-month period. As a consequence, momentum strategies with lookback and holding horizons measured in quarters are effectively monthly strategies with the lookback and holding horizons measured in months. The two approaches can therefore be expected to exhibit large correlation. Note that 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 later in the paper that strategies at monthly, weekly and daily frequency have low cross-correlations, hence they capture distinct return patterns.

tum strategy as the inverse-volatility weighted average return of all available univariate strategies:

$$R_J^K = \frac{1}{N_t}\sum_{i=1}^{N_t} \mathrm{SIGN}_i(t-J,t) \cdot \frac{40\%}{\sigma_i(t;60)} \cdot R_i(t,t+K), \tag{3}$$

where N_t is the number of available assets at time t, $\sigma_i(t;60)$ denotes an estimate at time t of the realized volatility of the i^{th} asset computed using a window of the past 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, 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 III), 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.

The ex-ante volatility adjustment in equation (3) allows for the combination of contracts with different volatility profiles (see Table I) in a single portfolio. 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. Since our dataset consists of daily closing, opening, high and low prices, we can make use of a more efficient *range* estimator, the Yang and Zhang (2000) volatility estimator, which for convenience is presented in Appendix A. Shu and Zhang (2006), Baltas (2011) and Baltas and Kosowski (2012) show that the Yang and Zhang (2000) estimator is the most efficient volatility estimator within a pool of range estimators. 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[13].

4. Time-Series Momentum Strategies

This section describes the construction and performance evaluation of time-series momentum strategies. First, we examine time-series return predictability by means of a pooled panel regression. Then, we

[13]As an example, on Tuesday, August 9, 2011, most major exchanges had 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...*".

construct a series of momentum strategies for different lookback and holding periods as well as portfolio rebalancing frequencies (monthly, weekly and daily).

4.1. Return Predictability

Before constructing momentum strategies, we follow MOP, and 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:

$$\frac{R(t-1,t)}{\sigma_{\mathrm{YZ}}(t-1;60)} = \alpha + \beta_\lambda \frac{R(t-\lambda-1,t-\lambda)}{\sigma_{\mathrm{YZ}}(t-\lambda-1;60)} + \varepsilon(t), \tag{4}$$

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

Regression (4) is estimated for each lag by pooling all the futures contracts. The quantity of interest 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. The t-statistics $t(\beta_\lambda)$ are computed using standard errors that are clustered by time and asset[14], 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 (4) is given by (see Cameron, Gelbach and Miller 2011, Thompson 2011):

$$V_{\mathrm{TIME\&ASSET}} = V_{\mathrm{TIME}} + V_{\mathrm{ASSET}} - V_{\mathrm{WHITE}}, \tag{5}$$

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.

Panel A, B and C of Figure 1 present 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 of the past year's returns. The results are consistent with the findings reported in MOP's Figure 1, Panel A. After the first year there are relatively weak signs of return reversals and all lags up to 60 months fail to document any other significant effect[15].

[Figure 1 about here]

Moving to the weekly frequency and Panel B, we find that return predictability is clustered around two distinct lags. First, the t-statistics of the most recent 8-week period are all positive (with 6 of them

[14] 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.

[15] One slight difference with the results in MOP is that they document large and significant reversals after the first year of return continuation. The difference is due to our larger sample (both in the time-series and cross-section); in unreported results we find significant reversals, when repeating the analysis for the cross-section and sample period used by MOP.

being statistically significant at the 5% level). Second, there exists relatively strong return predictability potential for the period around weekly lags 36 to 52 (i.e. the past 9 to 12 months approximately), which matches the strong yearly effects captured by the monthly frequency results in Panel A[16].

Finally, Panel C similarly documents two regions of significant past return predictability. The first period extends roughly from the 9$^{\text{th}}$ to the 15$^{\text{th}}$ lagged daily returns -which, loosely speaking, corresponds to weekly returns at lags of 2 and 3 weeks- and the second period is located around the 40$^{\text{th}}$ lagged daily return -which again, loosely speaking, corresponds to weekly return at lag of 8 weeks and to monthly return at lag of 2 months. Panel C reports a relatively large t-statistic for the previous day's return, which, in turn, is directly related to ordinary serial correlation. However, a subsample analysis in Table B.1 of the Appendix shows that this effect is largely due to the early sample behaviour and does not represent a stable-over-time significant momentum effect.

Overall, momentum effects seem to exist across all three frequencies, which exhibit interesting cross-commonalities. Building on this evidence, we next construct and evaluate monthly, weekly and daily time-series momentum strategies for a grid of lookback (J) and investment periods (K).

4.2. Momentum Profitability

The return of the aggregate time-series momentum strategy over the investment horizon is the volatility-weighted average of the individual time-series momentum strategies as in equation (3). 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 constructed as the equally-weighted average across the K active portfolios during the period of interest[17]. In other words, $1/K^{\text{th}}$ of the portfolio is only rebalanced every month/week/day.

Panels A, B and C of Table II present out-of-sample performance statistics for the monthly strategy with $K,J \in \{1,3,6,9,12,24,36\}$ months, the weekly strategy with $K,J \in \{1,2,3,4,6,8,12\}$ weeks and the daily strategy with $K,J \in \{1,3,5,10,15,30,60\}$ days respectively. As the strategies of different frequencies have by construction different frequencies of observation, we first aggregate the daily and weekly returns on a monthly frequency before estimating any statistics[18]. We report the following statistics: annualised mean return, annualised Sharpe ratio, growth of an initial investment of $1 in each

[16] Note 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.

[17] 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.

[18] It is straightforward to compound 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 particular week that belong to each of the two months.

particular strategy and annualised alpha for a Carhart (1997) four factor model[19]:

$$R_J^K(t) = \alpha + \beta\left(MSCI(t) - RF(t)\right) + sSMB(t) + hHML(t) + mUMD(t) + \varepsilon(t) \qquad (6)$$

where $MSCI(t)$ is the total return of the MSCI World 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* World index are retrieved from Datastream, and for the rest of the factors from the website of Kenneth French[20]. Statistical significance for the mean return and alpha is based on Newey and West (1987) adjusted t-statistics. Finally, since the longest lookback period in the table 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 evaluation period extends up to January 2012; a total of 409 months or equivalently around 34 years.

[Table II about here]

The evidence from Table II shows that the time-series momentum strategy generates a statistically and economically significant mean return and alpha for all three rebalancing frequencies. The results are highly significant (at the 1% level) for all weekly and daily strategies and most of the monthly strategies, except for a few strategies with lookback and holding periods exceeding 12 months. The monthly results are consistent with those reported by MOP. It is however worth noting 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 frequencies achieve Sharpe ratios above 1.20. For robustness purposes, we conduct a subsample analysis (reported in Table B.1 of the Appendix) and document that the above patterns are significant in both subsamples.

4.3. Representative Benchmark Strategies

After documenting time-series momentum effects, we next show that momentum patters at different frequencies are distinct effects since their time-series exhibit low cross-correlations. For reasons of space, we draw our attention to three representative strategies per rebalancing frequency based on the evidence in Table II: the $(12,1)$, $(9,3)$ and $(1,12)$ monthly strategies, the $(8,1)$, $(12,2)$ and $(1,8)$ weekly strategies and the $(15,1)$, $(60,1)$ and $(1,15)$ daily strategies[21].

[19] 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.

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

[21] In Panel C of Table II it appears that the $(1,1)$ is by far the best daily strategy. However, what becomes evident from the subsample analysis in Table B.1 of the Appendix is that this is due to the extreme performance of this strategy during the first half of the sample period up until the end of 1994, with the respective Sharpe ratio reaching 2.63. Instead, during the second half of the sample period the alpha of the strategy becomes insignificant and the Sharpe ratio suffers a dramatic decrease to 0.37. What might have caused this significant performance drop? One possibility is that past-1994, financial markets became

We acknowledge that these choices are subjective, since they are based on ex-post performance evaluation statistics. However, these choices are designed to capture the greatest amount of time-series momentum potential across the family of strategies and trading frequencies. In unreported results, available upon request, we show that all the main results in our paper remain qualitatively unchanged for other choices from the broad grid of strategies.

Table III presents in Panel A various statistics for the nine chosen time-series momentum strategies and the MSCI World index. The commonalities among various sets of strategies are evident. All but one of the strategies achieve a Sharpe ratio of around 1.25 compared to a mere 0.21 delivered by the MSCI World index. This Sharpe ratio is the result of a relatively large mean annualised return of about 16-19% and a volatility around 12-15% for the six strategies that have an investment horizon of $J = 1$ period (month/week/day). Independent of the trading frequency, strategies with a lookback horizon of $K = 1$ period achieve a similar 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 economically low market exposure with betas ranging from -0.09 down to -0.26. The maximum drawdown estimates show that combining univariate momentum strategies leads to diversification benefits. The MSCI World index has suffered a 55.37% drawdown (over a 16-month period) during the evaluation period January 1978 to January 2012, which is at least twice as large as the drawdowns experienced by the time-series momentum strategies.

[Table III about here]

It is important to bear in mind that the above historical performance statistics exclude transaction costs or management fees. Since futures markets are more liquid and have lower transaction costs than cash equity or bond markets, it is unlikely that transaction costs are going to significantly impact the performance of our monthly and weekly strategies. Furthermore, transaction costs have decreased over time as aggregate liquidity increased (Jones 2002). However, hedge funds' typical fee structure is more likely to have a significant impact on momentum strategy performance than transaction costs.

In order to gauge the relative effects of transaction costs across rebalancing frequencies we report in Panel A of Table III the portfolio turnover of each strategy. Turnover is calculated as the average annual ratio of the total number of contracts traded (expressed in notional dollar amount) over twice the time-series mean of notional dollar amount of the portfolio. As expected, portfolio turnover and therefore transaction costs increase with the trading frequency. Weekly strategies have about three to five times higher turnover than monthly strategies, whereas the turnover of daily strategies is approximately one order of magnitude larger than that of monthly strategies.

progressively more computerised and therefore to a certain extent more efficient, hence eliminating the trivial serial day-to-day return correlation that is captured by the $(1,1)$ daily strategy. Another possibility is that limits-to-arbitrage arguments (see for example Shleifer and Vishny 1997) would impede capitalising such arbitrage opportunities. Following the above observation, we refrain from picking the $(1,1)$ strategy as one of the representative daily strategies and we focus on choosing carefully such strategies that exhibit relatively stable performance over the entire sample period.

Regarding money management fees, we apply a typical 2/20 fee structure that is charged by CTA managers to the time-series momentum strategies, i.e. a 2% management fee and a 20% performance fee subject to a high-watermark. The last three rows of Panel A of Table III report the after-fees annualised mean, Sharpe ratio and dollar growth of the momentum strategies. The performance of the strategies remains high even after accounting for fees. Strategies with an investment horizon of $J = 1$ period (month/week/day) achieve annual return in the region 11-13% and Sharpe ratio of approximately 0.90.

Panel B of Table III reports the unconditional correlation matrix between the nine chosen strategies. At the intra-frequency level, 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. Importantly, strategies with different rebalancing frequencies are not strongly correlated with each other, which means that they capture different empirical features of the data. For instance, the correlation coefficient between the daily $(15, 1)$ strategy and the monthly $(12, 1)$ strategy is just 22%. This is a relatively small number if we take into account that all strategies constitute risk-adjusted portfolios of the same 71 futures contracts and they differ in terms of lookback/holding periods and rebalancing frequency. 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 the exhibit low cross-correlation.

4.3.1. The "FTB" Strategies

Our analysis above shows that time-series momentum effects exist at different frequencies. In order to establish whether a relationship exists between CTA fund returns and time-series momentum strategies, we, therefore, focus on a single strategy per trading frequency: the monthly[22] M^1_{12}, the weekly W^1_8 and the daily D^1_{15} strategies. We henceforth refer to this triplet as the *Futures-based Trend-following Benchmarks* (or "FTB" strategies in short). The chosen triplet[23] is characterised by some of the lowest unconditional cross-correlations as reported in Panel B of Table III (the respective correlations are shown in bold).

Table IV 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[24], (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[25] and (c) an extended Fung and

[22] Both cross-sectional momentum literature (for example Jegadeesh and Titman 1993, Jegadeesh and Titman 2001) and time-series momentum literature (Moskowitz et al. 2012) that study monthly momentum effects use as the major benchmark strategy the one with a 12-month lookback period and a 1-month holding horizon.

[23] Monthly returns of the FTB strategies are available for download at `http://www3.imperial.ac.uk/riskmanagementlaboratory/risklabsections/centreforhedgefundsresearch/baltas_kosowski_factors`

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

[25] 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

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 2011 (216 data points).

[Table IV about here]

The regression results show that all FTB strategies exhibit very significant and economically important alphas in the region 13% to 20% (annualised), which, in turn, implies that great amount of time-series momentum return variability cannot be explained by traditional asset pricing risk factors, hedge-fund return related factors or even trend-following factors. The only factors that succeed in capturing part of the variability of the return series are momentum-related (cross-sectional momentum factor and trend-following factors).

The cross-sectional momentum factor (UMD) is 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.

Regarding the PTF factors, the results shows that different sets of factors explain the return variation of the various FTB strategies, which corroborates our findings that time-series momentum strategies of different rebalancing frequencies capture distinct empirical patterns. The commodity PTF factor is the only factor to be significantly related with all the PTF strategies with a positive and statistically significant coefficient at the 1% (weekly and daily) and 5% level (monthly). The monthly strategy is also negatively exposed to the bond PTF factor. The weekly strategy is positively exposed to the FX and stock PTF factor. Finally, the daily strategy is positively exposed to the bond and stock PTF factors.

Panel A of Figure 2 presents the growth of a $100 investment in the FTB strategies and in the MSCI World Index for the entire evaluation period. We also present the net-of-fee paths for the FTB strategies (in dashed lines) after applying a 2/20 fee structure with a high-watermark. The historical profits from a momentum strategy strongly exceed those of a long-only strategy in a world equity market proxy. Importantly, during all five NBER recession periods in our evaluation period, when MSCI Index suffers dramatic losses, the time-series momentum strategies enjoy positive returns, mainly due to a large number of short positions. The 36-month running Sharpe ratio of the FTB strategies has historically been positive up until the end of 2011 as shown in Panel B of Figure 2.

These findings are also supported by Figure 3 that depicts return scatterplots of the FTB strategies against the MSCI World index. Clearly, the returns of FTB are larger during extreme market movement of either direction[26]; this is what MOP call the "time-series momentum smile".

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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.

[26]An article in the Financial Times FTfm by Eric Uhlfelder entitled "*Tool toughened in testing times*" on June 11, 2011,

[Figure 2 about here]

[Figure 3 about here]

To shed light on the contribution of each asset to the portfolio performance, Figure 4 demonstrates the annualised Sharpe ratio of the univariate time-series momentum strategies that comprise the FTB strategies. The figure also reports the unconditional correlation between each univariate strategy and the respective aggregate strategy. Most individual strategies exhibit positive ex-post Sharpe ratio across all rebalancing frequencies. Hence, they all contribute to the portfolio's overall performance. Bond strategies exhibit the best cross-sectional performance followed by currency and equity strategies. Commodity strategies exhibit the lowest Sharpe ratios, but appear to act as diversifiers, as they tend to have little correlation with the aggregate strategies.

[Figure 4 about here]

Finally, in order to investigate whether momentum profitability is related to contract liquidity, we present in Figure 5 a measure of illiquidity for all futures contracts in 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 and the ranks are then normalised. Positive/negative normalised rank corresponds to larger illiquidity/liquidity than the average contract within the respective asset class. As expected, 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 negligible[27]: -0.01 for the monthly strategies, -0.04 for the weekly strategies and -0.05 for the daily strategies[28]. Momentum patterns are not related to illiquidity effects. In fact, the negative correlation can be interpreted as a slightly more pronounced time-series momentum effect among most liquid contracts.

[Figure 5 about here]

5. The Relationship Between Time-Series Momentum Strategies and CTAs

Previous studies have stated that CTAs pursue trend-following strategies in futures markets, but without providing empirical evidence to support this claim (Covel 2009, Hurst et al. 2010). This section provides

states that "*The strategy excels when trends are clear - especially during protracted downturns.*".

[27]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.

[28]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)

a formal investigation of the performance of CTAs and, by means of time-series analysis, establishes a relationship between CTA performance and the performance of time-series momentum strategies.

Both up and down trends offer profitable opportunities for time-series momentum strategies, which renders them good diversifiers and hedges in equity bear markets[29] as already shown in Figure 3. Panel A of Table V shows that different CTAs indices similarly performed particularly well in down-markets and recessions[30]. Our results complement the literature on the relationship between hedge fund returns and macroeconomic conditions (Avramov, Kosowski, Naik and Teo 2011).

When comparing the returns of our time-series momentum strategies to CTA index returns, it is important to note that, the former, unlike the latter, exclude transaction costs and management fees. According to Table III, a 2/20 fee structure with a high-watermark provision reduces the performance of the FTB strategies by about 30%. This is a similar order of magnitude as the difference between the FTB strategy returns and the CTA index returns in Table V. Therefore, it is not surprising that, on average, the before-fees momentum strategy returns are higher than the CTA index returns. Consequently, we would also expect an alpha when regressing the time-series momentum strategy returns on CTA index returns.

Panel B of Table V reports the average return, volatility and Sharpe ratio for the FTB strategies and the two CTA indices during the NBER recession and expansion periods. All five indices exhibit positive and statistically significant returns during recessionary periods. Furthermore, four out of five of them clearly generate larger returns during recessionary periods than during expansionary periods. Panel B of Table V 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. The positive correlation of the CTA indices with the FTB strategies suggests that CTAs follow strategies that are similar to the FTB strategies. We test this hypothesis rigorously below by means of a time-series regression analysis that includes several control variables.

[Table V about here]

Table VI reports regression coefficients based on regressing the net-of-fee monthly returns of the AUMW-CTA Index on various benchmark models. Columns (a) and (b) report the results for the FH7 and the extended FH9 models. These models achieve adjusted R^2 of 23.57% and 27.24% respectively, with all PTF factors being largely significant. However, the CTA index still exhibits an economically large alpha which is significant at the 1% level.

The explanatory power of the regressions, the magnitude and the significance of the alpha change dramatically when we examine univariate regression results in columns (c), (d) and (e), where the CTA index returns are regressed separately on the monthly, weekly and daily FTB strategies. The alpha

[29] 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.

[30] We construct the AUM-weighted Systematic CTA Index based on the BarclayHedge database and compare it to the BarclayHedge CTA Index. The BarclayHedge database reports the performance of another index (the Barclay Systematic Traders Index) starting from 1987. The correlation between this index and our AUM-weighted Systematic CTA Index is 93.82% for the period 1987-2011.

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 returns after transaction costs and managements fees, while the independent variables (such as the Fama-French, Fung-Hsieh or our FTB strategies) do not include such costs or fees. This has to be borne in mind when interpreting the sign of the alphas.

When the CTA index is regressed against all three time-series momentum strategies (the FTB model - labeled as specification (f)), then the annualised alpha remains insignificant and even turns negative, with the R^2 exceeding 37%. Importantly, all three FTB strategies remain significant at the 1% level. This supports the argument that CTAs follow momentum strategies at different frequencies and that momentum patterns at different frequencies are distinct from each other in line with the arguments of Hayes (2011). The additional explanatory power of the FTB strategies 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 for trend-following behaviour. It is probable that by directly replicating CTA strategies using futures momentum strategies, the FTB factors closely match the underlying instruments used by CTA funds in practice.

It is important to note that in order 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 FTB strategies to support the use of flows into CTA funds, when examining capacity constrains in momentum strategies.

[Table VI about here]

5.1. Robustness Tests

To test the robustness of our results, the remaining three regressions of Table V report results from combining the FTB factors with subsets of the FH9 factors: regression (g) involves the non-trend-following Fung and Hsieh (2004) factors, regression (h) instead uses only the five PTF Fung and Hsieh (2001) factors and regression (i) combines all factors as part of a 12-factor model that is denoted as FH9+FTB. 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 more than doubles.

Furthermore, all three FTB remain largely significant at the 1% level, except for the daily strategy that is significant at the 5% level for the last two specifications. Contrary to the FH7 and FH9 specifications in regressions (a) and (b), not all PTF factors remain significant after combining them with our time-series momentum strategies. The factors that remain significant are those capturing the trend-following features in bonds, foreign exchange and interest rates. Our results show that when tested side by side, the FTB 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.

Our findings show that FTB strategies play an important role in explaining CTA index returns. These results are robust to the choice of CTA index as dependent variable. Table B.2 in Appendix B presents the FT9, FTB and FT9+FTB decompositions for the return series of another three CTA indices: (1) the BarclayHedge CTA Index, (2) the Newedge CTA Index and (3) the Newedge CTA Trend Sub-Index[31]. The FTB 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 FTB factors are added in.

5.2. Rolling Goodness of Fit

So far, we have examined unconditional regression results based on CTA returns. In order to check the stability of the explanatory power of the FTB strategies for CTA returns over time, we present in Figure 6 the 60-month rolling adjusted R^2 for the FH7 benchmark model, FTB and FH9+FTB specifications (regressions (a), (f) and (i) of Table VI). The results are striking, as the explanatory power of the FH7 is almost always lower than that of the FTB model except during the late 2002 and early 2003 period. It is also interesting to note that the fit of the FH7 model becomes significantly worse after 2007 when the adjusted R^2 drops below 10% , while that of FTB model remains close to 40%. Finally, the figure shows that the 12-factor FH9+FTB model achieves relatively 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 V and VI show that the time-series momentum strategies have highly significant explanatory power for CTA index returns even after accounting for the Fung and Hsieh (2004) factors. Accounting for the FTB strategies leads to statistically insignificant alpha for the CTA index returns. On the one hand, this suggests that CTAs do significantly rely on time-series momentum strategies with different trading frequencies. On the other hand, the results imply that it is important to use the FTB strategies as benchmark returns when evaluating the CTA performance.

6. Capacity Constraints and Trend-following Strategies

The systematic CTA industry has significantly grown during the last decade. Figure 7 demonstrates that the AUM of the systematic CTA industry has substantially increased during the last decade, with close to 400 funds being active at the end of the period and close to \$300 billion invested in these funds. Anecdotal evidence[32] that trend-following funds have recently experienced net inflows is also supported by Panel B of Figure 7 which shows that the CTA industry experienced inflows in the period 2009-2011 of about 5% per year.

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

[32] 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.*"

[Figure 7 about here]

However, this dramatic growth in the size of the CTA industry has been followed by lacklustre performance in the period 2009-2011. Table V shows that the years 2009 and 2011 were bad years for the performance of the momentum strategy and CTA funds. This observation raises the question whether there are capacity constraints in trend-following strategies and whether momentum strategy returns can be expected to be lower in the future, despite that fact that futures markets are viewed as relatively liquid markets compared to other financial markets such as cash equities or bonds.

We employ two different methodologies to analyse capacity constraints. The first methodology is based on performance-flow predictive regressions, where we investigate whether flows into the CTA industry historically had a statistically significant effect on the future performance of momentum strategies. The second methodology is based on a thought experiment in which we simulate what would happen if the entire AUM of the CTA industry were invested in our monthly momentum strategy. Every month we compare the momentum strategy's number of futures contracts to the open interest data for each asset traded. The intuition is that if the demanded number of contracts per asset exceeded the available open interest, then this exceedance could be interpreted as a capacity constraint. In the next section we describe these two methodologies and their results in detail.

6.1. CTA Flows and Trend-Following Strategy Performance

In order to examine whether inflows into CTAs reduce the performance of trend-following strategies, we use performance-flow regressions and more than 30 years of data to test this hypothesis rigorously.

Previous studies of the performance-flow relationship examine capacity constraints for different aggregate hedge fund categories (e.g. Naik et al. 2007) and find that past flows have a negative and significant effect on future performance as measured by general fund style indices. One limitation that applies to these studies of the hedge fund literature is that, due to the self-reported nature of hedge fund investment objectives, it is not possible to know for sure whether certain funds labeled as "directional traders", "managed futures" or "CTAs" indeed follow trend-following strategies.

Examining trend-following strategies that are constructed bottom up from futures data to study capacity constraints is one solution to the above limitation. Similarly, Jylhä and Suominen (2011) examine the relationship between fund flows and AUM into fixed income arbitrage funds and a carry-trade strategy that they construct by forming long and short currency portfolios. They report that increased lagged hedge fund AUM decrease the expected returns from carry-trade strategies.

Would we expect a statistically significant negative performance-flow relationship for trend-following strategies as well? One fundamental difference between trend following strategies and arbitrage strategies such as fixed-income relative value arbitrage or convertible bond arbitrage is that trend-following strategies are more difficult to relate to the notion of equilibrium or a no-arbitrage restriction. Carry-trade strategies, for example, represent violations of covered interest rate parity, but they have been shown to suffer large losses as the expected depreciation of high interest rate currencies eventually occurs (see, for example, Brunnermeier, Nagel and Pedersen 2008). Instead, time-series momentum strategies are conceptually and empirically different from carry strategies in futures markets. For trend-following strategies, it is not clear when theoretically a reversal in a trend should occur. In fact, the performance-flow relationship may even be positive. As news is incorporated into prices gradually, it could be expected that price trends develop and investors that follow trend-following strategies may exacerbate these over time (see Hong and Stein 1999, Hong, Lim and Stein 2000). This may lead to an accentuation of momentum effects as additional capital enters the market, potentially in a spirit similar to the model by Vayanos and Woolley (2012). On the other hand, when trades become eventually crowded, it is possible that trend reversals occur. Based on these theoretical observations the relationship between flows and performance may be positive or negative.

Table VII reports the results from regressing separately the return series of the FTB strategies on lagged CTA fund flows and a set of control variables, in order to decompose the performance-flow relationship at different portfolio rebalancing frequencies:

$$R_J^K(t) = \text{const.} + \phi \sum_{\tau=t-12}^{t-1} \text{FuF}(\tau) + \sum_{i=1}^{5} \beta_i X_i(t) + \varepsilon(t) \tag{7}$$

where $\{X_i\}_{i=1}^5$ is the set of MSCI, SMB, HML, GSCI and UMD factors. The fund flow regressor is standardised and is constructed similarly to Naik et al. (2007) by summing up the fund flows from the $t-12$ month up to the last $t-1$ 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 VII 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[33].

[Table VII about here]

Independent of whether we examine the monthly, weekly or daily frequency, the t-statistics show that lagged fund flows have indeed on average a negative (consistent with Berk and Green 2004, Naik et al. 2007, Aragon 2007, Ding et al. 2009), but, in almost all cases, statistically insignificant impact on future performance of time-series momentum strategies. Importantly, the magnitude of the slope coefficient shows that the relationship is not economically significant. The only coefficient that is statistically significant at 5%, without however being economically significant is the one associated with a weekly momentum strategy in equity futures[34].

In unreported results, available upon request, we also add additional control variables to the regressions, including different lags of fund flows and AUM. For robustness, we additionally include lagged

[33]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 variable and also to adjust for potential heteroscedasticity.

[34]Interestingly, the adjusted R^2 of the regressions is relatively small and at times negative, except for monthly strategies that include equities (groups (i), (ii), (v)), where, as expected, the cross-sectional momentum factor (UMD) captures a substantial portion of the return variability.

momentum strategy returns (despite the fact that our focus is on capacity constraints and not on a smart money effect as documented in the mutual fund literature (see Zheng 2002)). Irrespective of the setup, we find that the results do not qualitatively change. Furthermore, despite the fact that our objective is to test for capacity constraints in trend-following strategies across trading frequencies and asset classes, we also estimate regression 7 using the returns of the AUMW-CTA and BH-CTA indices as independent variables and confirm the absence of a significant performance-flow relationship.

6.1.1. Robustness Tests

Could the performance-flow relationship be statistically insignificant, because it switches sign over time? To answer this, we present conditional results of the regressions of Table VII (for all futures contracts excluding commodities and for commodity contracts only). Using a rolling window of 60 months, Figure 8 presents the evolution of the t-statistic of the lagged CTA fund flow variable. Across all rebalancing frequencies, the relationship exhibits a large degree of time-variation. The unconditionally insignificant and negative relationship between performance and lagged flows is therefore not due to a weak negative relationship *on average*, but rather due to a performance-flow relationship that is at times positive and at times negative. During some periods and 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 does not show any clear link between the sign of the performance-flow relationship and the business cycle. As a sensitivity check, Table B.3 in the appendix replicates regression (7) by splitting the fund flow effects between expansionary and recessionary periods using appropriate dummy variables and confirms the above findings.

[Figure 8 about here]

One potential criticism of the unconditional performance-flow analysis is that inflows into CTAs may not immediately be deployed as margin for future contracts, but instead funds may hold them as cash balances. One way to address this criticism is to examine whether inflows that occur when open interest is increasing (an indication that market participants increase their positions) is negatively related to momentum strategy performance. In order to test the hypothesis of whether the sign of the performance flow relationship is dependent on whether open interest is increasing or decreasing, we include interaction terms (ϕ^+ and ϕ^-) between flows and changes in the open interest regression (7):

$$R_J^K(t) = \text{const.} + \phi^+ \left[\sum_{\tau=t-12}^{t-1} \text{FuF}(\tau)\right] \cdot \mathbb{I}_{\Delta[\text{OI}(t)]>0} + \phi^- \left[\sum_{\tau=t-12}^{t-1} \text{FuF}(\tau)\right] \cdot \mathbb{I}_{\Delta[\text{OI}(t)]<0} + \sum_{i=1}^{5} \beta_i X_i(t) + \varepsilon(t) \quad (8)$$

This analysis requires open interest data. We therefore use the CFTC dataset, which covers 43 assets of our universe, as discussed in section 2.2. For tractability reasons, the independent variables in these regressions are the time-series momentum strategies that are constructed using only these 43 assets.

Table VIII presents the regression results and shows that our conclusions do not change when allowing for open interest interaction terms. Not only do the majority of the coefficients remain insignificant, but there is no apparent relationship between the sign of the performance-flow relationship and change in open interest.

[Table VIII about here]

Overall, we interpret the results of the performance-flow regressions as evidence of a lack of statistically significant capacity constraints in time-series momentum strategies followed by CTAs. Importantly, an examination of commodity futures based momentum strategies in isolation does not uncover evidence of a statistically significant performance-flow relationship or capacity constraints. Evidence of capacity constraints can be formally examined using different methodologies and therefore we next turn to an alternative framework to study the question of capacity constraints in trend-following strategies.

6.2. Open Interest and Hypothetical Implementation of Trend-Following Strategies

The second methodology that we employ is based on a thought experiment, in which we simulate what would happen if the entire AUM of the systematic CTA industry were invested in our monthly momentum strategy. In particular, we focus on the relationship between the number of contracts per asset that would be necessary for the construction of the strategy and the respective open interest as reported by the CFTC.

Following from equation 3, the number of contracts per asset that we need to enter -either long or short- for the construction of a time-series momentum strategy at date t is:

$$n_i(t) = \frac{40\%}{\sigma_i(t;D)} \tag{9}$$

In order to form portfolio weights we essentially need to calculate the percentage of capital that needs to be invested in each and every asset at date t. We proceed as follows. Let $S_i(t)$ denote the price of the futures contract at date t for asset i and s_i denote the respective contract size[35]. The notional dollar amount per futures contract of asset i, denoted by $D_i(t)$, is then given by:

$$D_i(t) = S_i(t)\, s_i \tag{10}$$

Let also m_i denote the *margin-to-notional ratio* for asset i, which is assumed to be constant for the entire sample period. In reality the margin-to-notional ratio fluctuates based on the contemporaneous market conditions. Following discussions with market practitioners we decide to use constant ratios of 4% for currency futures, 10% for equity futures, 3% for bond futures and 10% for commodity futures[36].

[35]Contract size information is collected from the respective exchanges that the futures contracts are traded and is also adjusted by the contract units. For example, the size of the S&P500 futures contract is the value of the index times $250, whereas the value of the size of a corn futures contract is 5000 bushels, with the price of the contract being quoted in dollar cents per bushel. In the latter case an adjustment is necessary so that the price is quoted in dollars.

[36]We collected data on margin requirements from the respective exchanges that the futures contracts are traded at the end of January 2012 and the quoted percentages are in line with our end-of-sample estimates.

Constructing a time-series momentum strategy implies that $n_i(t)$ positions of asset i have to be opened at date t. This implies that the notional amount of the positions is $n_i(t) D_i(t)$, which in turn implies that a dollar amount of $n_i(t) D_i(t) m_i$ has to be placed in a margin account. We therefore define the portfolio weights to be the percentage of capital (in other words, the percentage of total margin) that is necessary in order to open the $n_i(t)$ positions for the asset i at date t:

$$w_i(t) = \frac{n_i(t) D_i(t) m_i}{\sum_{k=1}^{M_t} n_k(t) D_k(t) m_k} \tag{11}$$

Using the portfolio weights, we can calculate the dollar amount of investment in every asset, assuming that the total systematic CTA AUM is invested in the time-series momentum strategy. The time-series AUM of systematic CTAs is shown in Figure 7. Following discussions with market practitioners, a reasonable assumption for the *margin-to-equity ratio* is in the range 8% - 12% depending on market conditions. We therefore choose to use an average margin-to-equity ratio equal to 10% for the entire sample period. As a result, the dollar amount that is placed at date t in the margin account in order to open the appropriate number of positions of asset i is equal to $w_i(t)\,\mathrm{AUM}(t)\,10\%$. Dividing this quantity by the margin dollar amount per contract, $D_i(t) m_i$, we can finally back out the number $n_i^{\mathrm{CTA}}(t)$ of futures positions per asset that the systematic CTA industry would have to open at the end of each month if the total AUM was invested in the time-series momentum strategy:

$$n_i^{\mathrm{CTA}}(t) = \frac{w_i(t)\,\mathrm{AUM}(t)\,10\%}{D_i(t) m_i} = n_i(t) \frac{\mathrm{AUM}(t)\,10\%}{\sum_{k=1}^{M_t} n_k(t) D_k(t) m_k}. \tag{12}$$

Using open interest data for each asset as reported in the CFTC database, we are in a position to calculate the average number of months that the number of contracts n_i^{CTA} per asset exceed the respective contemporaneous open interest. This statistic is presented for each asset in Figure 9 for the period that is covered by the CFTC database (January 1986 - December 2011).

[Figure 9 about here]

For about half of the assets, the number of futures contracts employed by the hypothetical trend-following strategy is below the open interest in all months, as evidenced by the exceedance level of zero. Importantly the hypothesis that there are more exceedances of the open interest for commodities than for financial assets is not supported by the data.

For the assets that appear to have open interest exceedances, we can trace back the reason to either (a) the nature of the assets chosen for the implementation of the strategy or (b) the relatively low liquidity of the contracts and the fact that our momentum strategies are not liquidity-optimised.

Regarding (a) the implementation of the strategy, for convenience, we use only futures contracts across all asset classes, including currencies. In practice, trend-following funds predominantly use forwards to implement FX trades, since the latter are more liquid and have advantageous capital requirements. It is likely that if we added the outstanding OTC forward currency contracts to the currency futures contracts open interest, then the number of exceedances would be significantly lower, as one would expect for the relatively liquid currency markets. For a similar reason, the 60% open interest exceedance ratio for the 2Yr US Treasury Note that might appear surprising at first sight can be explained by the fact that trend-following funds tended to trade the Note itself and not the future contract until recently[37]. Indeed, the exceedance ratio drops to about 20% after 2005.

Regarding (b) the liquidity of different contracts, the results highlight one of the caveats of the time-series momentum strategies that we and MOP implement, namely that these strategies do not take into account the relative liquidity of different assets and contracts and therefore are not liquidity-optimised. If we examine, for example the S&P500, the Gold and the Crude Oil contracts, we find zero exceedances according to Figure 9, which is consistent with the evidence in Figure 5 that these three contracts are among the most liquid[38]. Instead, the 47% exceedance for the S&P400 is mainly due to the fact that it is a relatively illiquid contract as shown in Figure 5. Figure 5 and discussions with market practitioners confirm that both the S&P400 contract and the Dollar Index (a futures contract on the trade-weighted dollar index) are relatively illiquid contracts that would not be traded in practice in an unconstrained manner. Lumber is another contract that according to Figure 5 is relatively illiquid and this is the reason why it shows an open interest exceedance ratio of about 58%.

Adjusting the time-series momentum strategy for liquidity as well as transaction costs would make it resemble more strategies that could be expected to be implemented by practitioners, but this goes beyond the scope of our academic work. Importantly, such liquidity and transaction costs adjustments are unlikely to change the insights that one can draw from Figure 9, which shows that for most liquid contracts the vast majority of months do not show any exceedances of open interest and in other cases the total number of exceedances is usually small. Furthermore, it is unlikely that adjusting the strategy returns for transaction costs is going to significantly change the performance-flow relationship that we documented.

As a test of additional robustness, we estimate the fraction of the global OTC derivative market size that would be held by trend-following strategies if the entire AUM of the systematic CTA industry were invested in such strategies. Using data from the end-December 2011 Bank for International Settlements (BIS) report[39], the total notional amount outstanding in global OTC derivative markets (excluding options and swaps when possible) is \$2.3 trillion for commodity contracts, \$30.5 trillion for currency contracts, \$1.7 trillion for equity contracts and \$50.6 trillion for interest rate contracts. At the end of December 2011, the total AUM of the systematic CTA industry amounts to \$264 billion that if it is assumed to be entirely invested in a monthly time-series momentum strategy, then it would result in notional dollar amount of \$52.5 billion invested in commodity contracts, \$63.2 billion in currency contracts, \$48.7 billion in equity contracts and \$457.4 billion in interest rate contracts. The above estimates show that even if the entire AUM of the systematic CTA industry were invested in a trend-following strategy, then it

[37]We thank an anonymous practitioner for making us aware of this.

[38]Not only are the open interest exceedances zero for these examples, but in fact the number of futures contracts entered by the hypothetical trend-following strategy as a percentage of the open interest is relatively low. The time-series average values are 2.5% for S&P500, 1.1% for Crude Oil and 6.3% for Gold.

[39]The report, published in May 2012, is available at `http://www.bis.org/publ/otc_hy1205.pdf`

would only employ 2.3% of the size of the commodity derivative markets, 0.2% of the currency derivative markets, 2.9% of the equity derivative markets and 0.9% of the currency derivative markets at the end of 2011. This piece of evidence corroborates the results of Figure 9 that were discussed above in that the recent dramatic increase in the size of the CTA industry has not had a significant effect in the prices of the underlying securities that are traded.

Overall, our analysis based on the performance-flow regressions and the hypothetical open interest exceedances does not find statistically or economically significant evidence of capacity constraints in time-series momentum strategies. The performance-flow relationship is time-varying and statistically insignificant on average. The extreme assumption that the entire AUM of the systematic CTA industry was invested in the simple momentum strategy does not lead to a systematic exceedance of the CFTC-reported open interest by asset (where for most commodities and liquid financial assets the exceedance is close to zero) and, in addition, the notional amount invested in futures contracts is a small fraction of the global derivatives markets. These results are consistent with other findings in the literature that futures markets are deep and liquid. Brunetti and Büyükşahin (2009), for example, show that activity by speculators does not forecast price movements and volatility in futures markets and that speculative activity is not destabilising. Büyükşahin and Harris (2011) employ Granger causality tests to analyse 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 speculator position changes Granger-cause crude oil price changes. Instead, they report that their results suggest that price changes precede their position changes.

7. Concluding Remarks

In this paper we examine time-series momentum strategies in futures markets and their relationship with a subgroup of the hedge fund universe, which has attracted much attention during and after the recent financial crisis, CTAs. We provide the first comprehensive piece of empirical evidence that CTAs indeed follow futures-based trend-following strategies and carry out the first rigorous test of the hypothesis that capacity constraints exist in such strategies.

Following Moskowitz et al.'s (2012) evidence on profitability of monthly time-series momentum strategies and motivated by the fact that CTA funds differ in their forecast horizons and trading activity (Hayes 2011), we construct a comprehensive set of momentum portfolios across monthly, weekly and daily frequencies for a 35-year period. The different strategies achieve Sharpe ratios of above 1.20 and take advantage of both up and down markets, which results in important diversification benefits. We confirm that strategies at different frequencies have low cross-correlations and therefore reflect different return continuation phenomena. Our time-series regression analysis is consistent with the interpretation that CTA funds employ time-series momentum strategies using futures contracts over multiple frequencies. In fact, the explanatory power of standard factor models used to benchmark CTA performance can be almost doubled when including time-series momentum factors.

The fact that the performance of CTAs has recently been mediocre and the fact that the size of the industry has dramatically increased during the last 30 years raise concerns about the existence of capacity constraints in the time-series momentum strategies. Using two different methodologies we find that there is no statistically or economically significant evidence of capacity constraints in trend-following strategies. The performance-flow relationship is time-varying and statistically insignificant on average whereas the hypothetical assumption that the entire AUM of the systematic CTA industry was invested in a momentum strategy does not lead to systematic exceedances of the open interest by asset. In fact, the notional amount invested in futures contracts employed by trend-followers is estimated to be a small fraction of the global derivatives markets.

Our methodology could be extended in several ways to account for transaction costs and fees as well as optimising for contract liquidity. This is beyond the scope of this academic study since doing so in a realistic way would require gathering detailed information for each contract and over time. We leave this extension for future work.

Our findings 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.

Our results imply that there are no statistically significant capacity constraints momentum strategies, but this leaves a separate important question unanswered, namely, why CTA performance has been lacklustre during the recent period 2009-2011. In principle, there can be three main reasons for poor performance: (a) capacity constraints (which our results do not support), (b) absence of sufficient price trends for individual securities, (c) increased correlation between futures markets, which reduces diversification benefits. Anecdotal evidence suggests that monetary/fiscal policy uncertainty in the 2009-2011 period has been particularly high, which may have driven market sentiment and could explain why price trends during this period tended to reverse more often than in the past. In unreported results, we found evidence that absolute correlations between markets have substantially increased. A simple principal component analysis on the 71 futures contracts in our dataset applied on a rolling window basis shows that the average explained variance of the first principal component has been around 25% up to the end of 2008, but soon after Lehman Brothers collapse, it increases dramatically and averages close to 40% for the period 2009-2011 peaking at 45% at the end of the sample, in January 2012. This piece of evidence could potentially support the hypothesis that the data generating process has changed after the recent financial crisis and the degree of market co-movement has increased. Along these lines, absence of trends within one asset class has a larger probability to co-exist with absence of trends in other asset classes, hence leading to poor overall performance of time-series momentum strategies. We intend to study this question in future research.

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:

$$\begin{aligned}
\text{Normalised Opening price (“overnight jump”): } o(t) &= O(t) - C(t-1) && (13)\\
\text{Normalised Closing price: } c(t) &= C(t) - O(t) && (14)\\
\text{Normalised High price: } h(t) &= H(t) - O(t) && (15)\\
\text{Normalised Low price: } l(t) &= L(t) - O(t) && (16)\\
\text{Daily Close-to-Close return: } r(t) &= C(t) - C(t-1) && (17)
\end{aligned}$$

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:

$$\sigma^2_{\text{YZ}}(t;D) = \sigma^2_{\text{OPEN}}(t;D) + k\sigma^2_{\text{STDEV}}(t;D) + (1-k)\,\sigma^2_{\text{RS}}(t;D) \tag{18}$$

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

$$\begin{aligned}
\sigma^2_{\text{STDEV}}(t;D) &= \frac{261}{D}\sum_{i=0}^{D-1}\left[r(t-i) - \bar{r}(t)\right]^2 && (19)\\
\sigma^2_{\text{OPEN}}(t;D) &= \frac{261}{D}\sum_{i=0}^{D-1}\left[o(t-i) - \bar{o}(t)\right]^2 && (20)\\
\sigma^2_{\text{RS}}(t;D) &= \frac{261}{D}\sum_{i=0}^{D-1}\left[h(t)\left[h(t) - c(t)\right] + l(t)\left[l(t) - c(t)\right]\right] && (21)
\end{aligned}$$

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. Additional Resutls

[Table B.1 about here]

[Table B.2 about here]

[Table B.3 about here]

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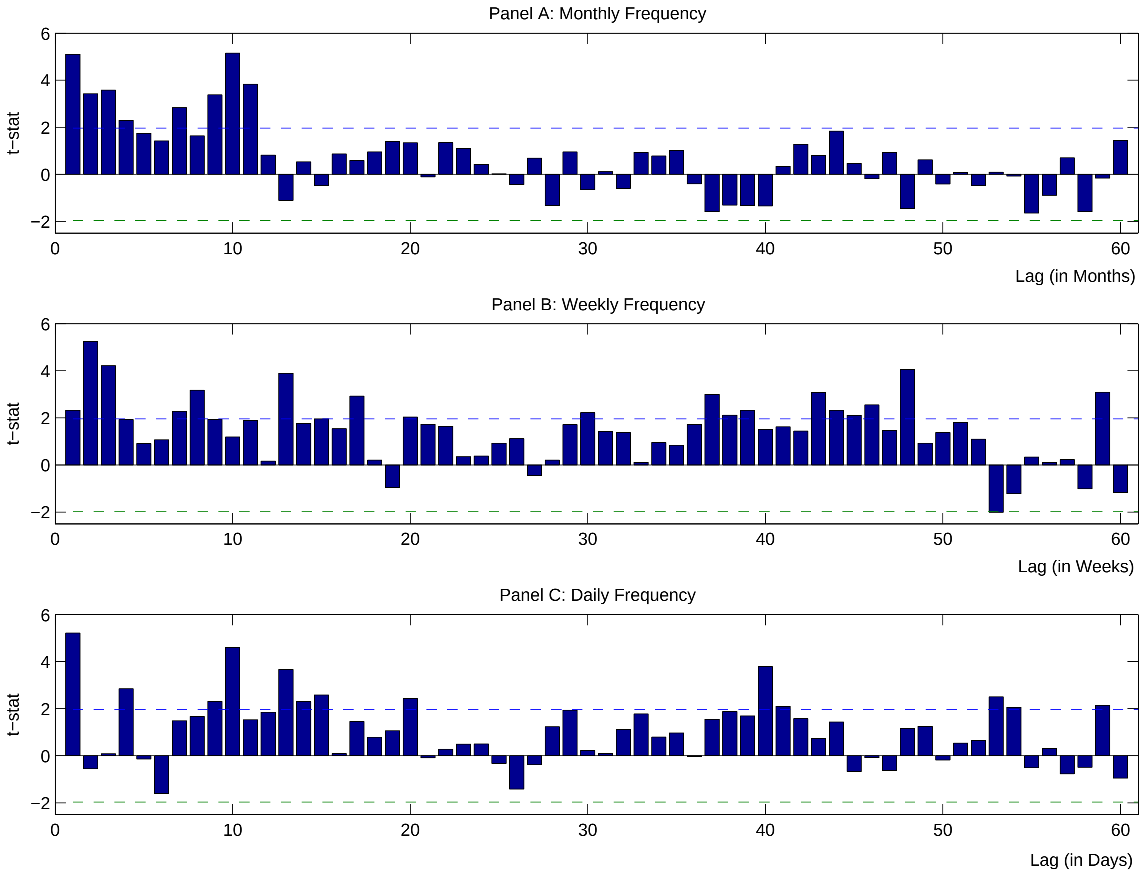

Figure 1: *Return Predictability*

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.

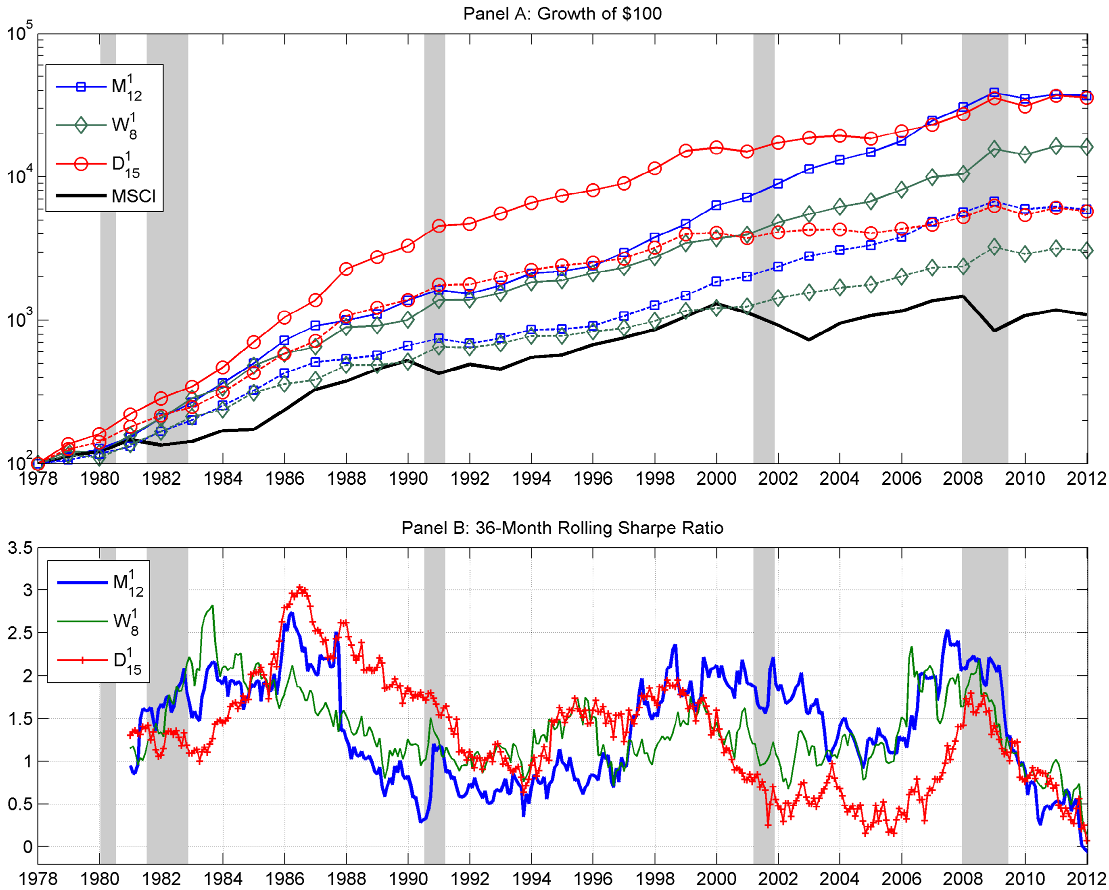

Figure 2: *Historical Performance of Time-Series Momentum Strategies*
The figure presents in Panel A the growth of a \$100 investment in the FTB strategies (M^1_{12}, W^1_8 and D^1_{15}) and in the MSCI World Index for the period January 1978 to January 2012. Additionally the panel presents the net-of-fee (assuming a 2/20 fee structure with a high-watermark) paths for the three time-series momentum strategies in dashed lines. Panel B presents the 36-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.

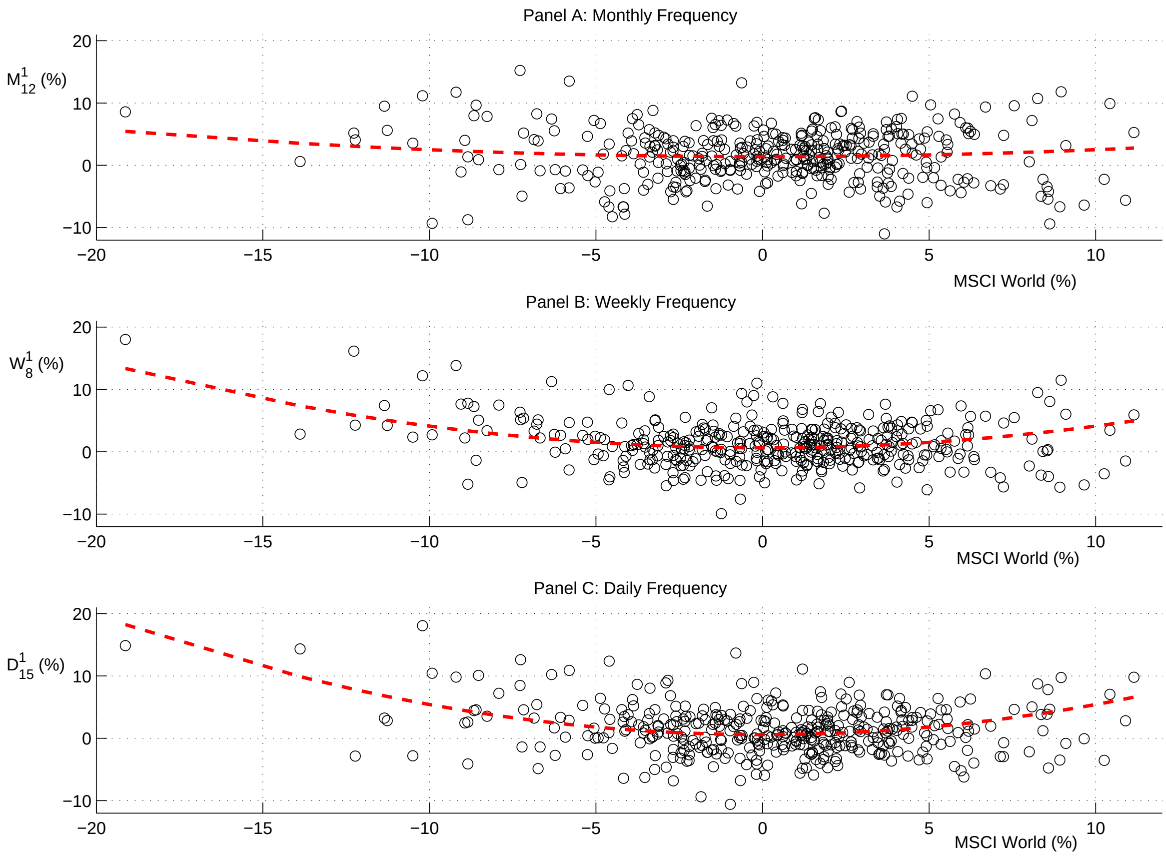

Figure 3: *Time-Series Momentum Smiles*
The figure presents scatterplots of monthly returns of the monthly (Panel A), weekly (Panel B) and daily (Panel C) FTB strategies (M^1_{12}, W^1_8 and D^1_{15} respectively) against the contemporaneous excess returns of the MSCI World index. Additionally, all Panels include a least-squares quadratic fit. The sample period is January 1978 to January 2012.

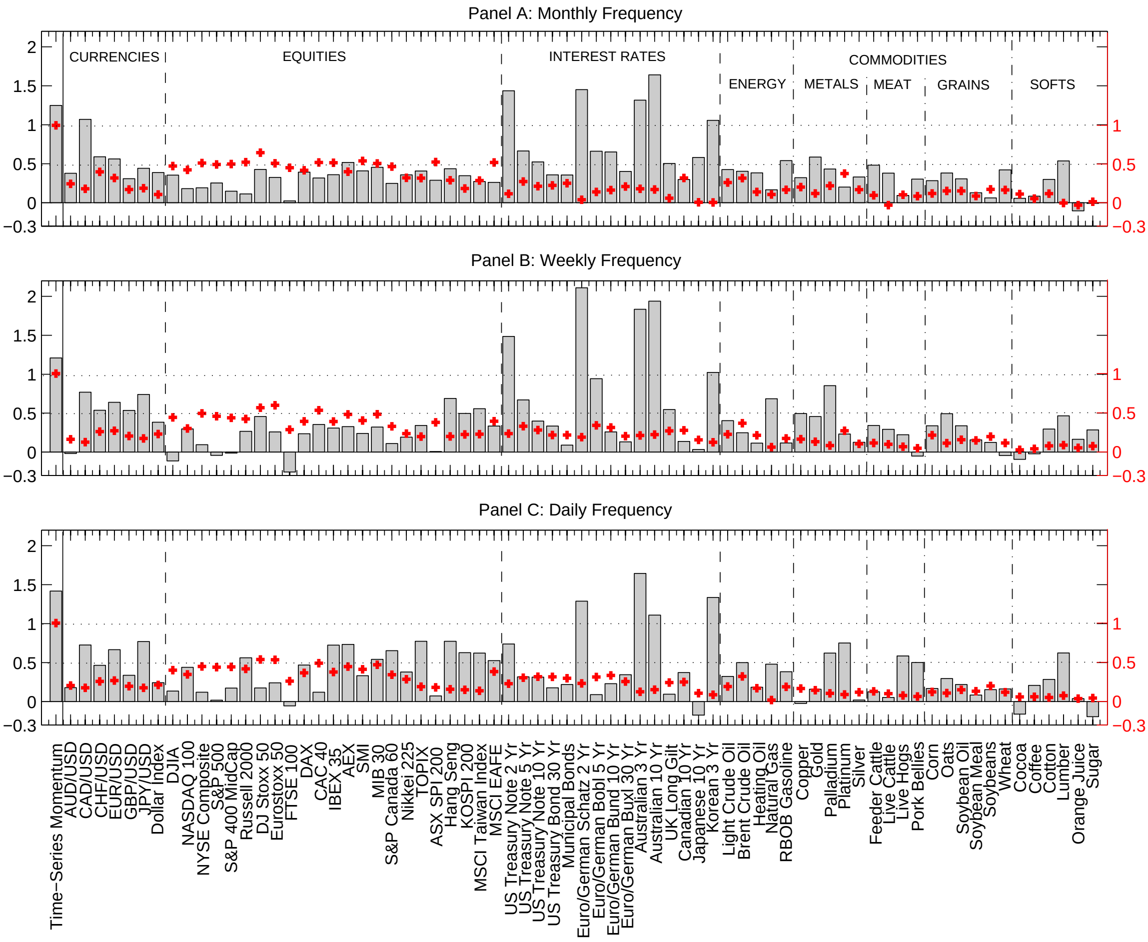

Figure 4: *Sharpe Ratios and Correlations of Univariate Time-Series Momentum Strategies*
The figure presents the Sharpe ratios for the univariate time-series momentum strategies that comprise the aggregate monthly (Panel A), weekly (Panel B) and daily (Panel C) FTB strategies (M^1_{12}, W^1_8 and D^1_{15} 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 I.

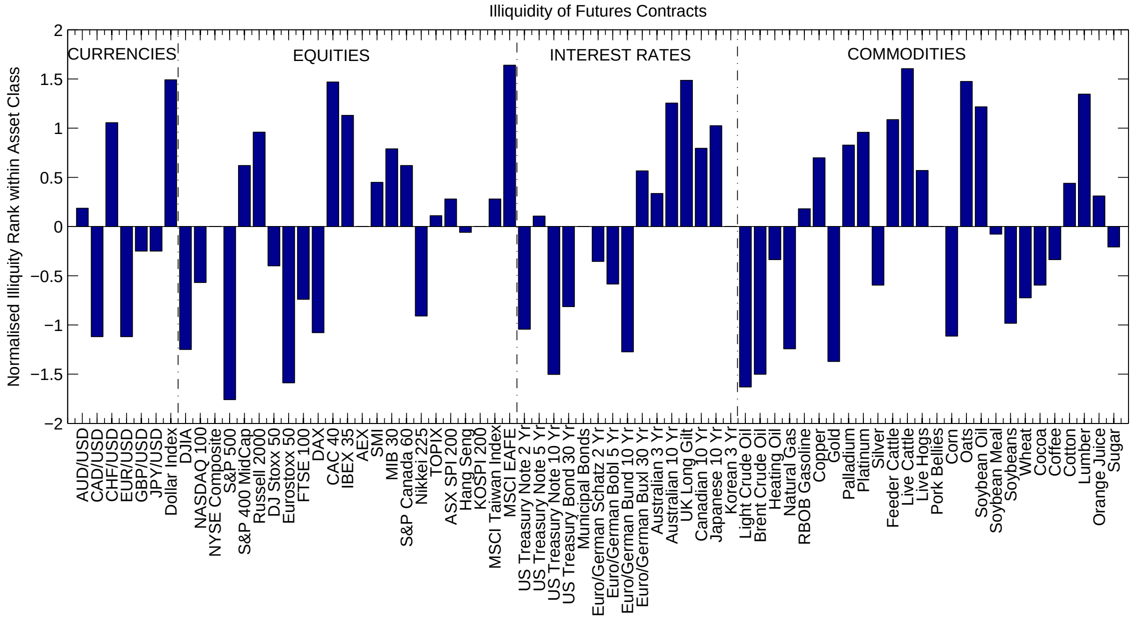

Figure 5: *Illiquidity of Futures Contracts*
The figure presents a measure of illiquidity for the futures contracts of the dataset that is estimated form daily volume data on January 31, 2012. Following Moskowitz, Ooi and Pedersen (2012), the contracts within each asset class are ranked with respect 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.

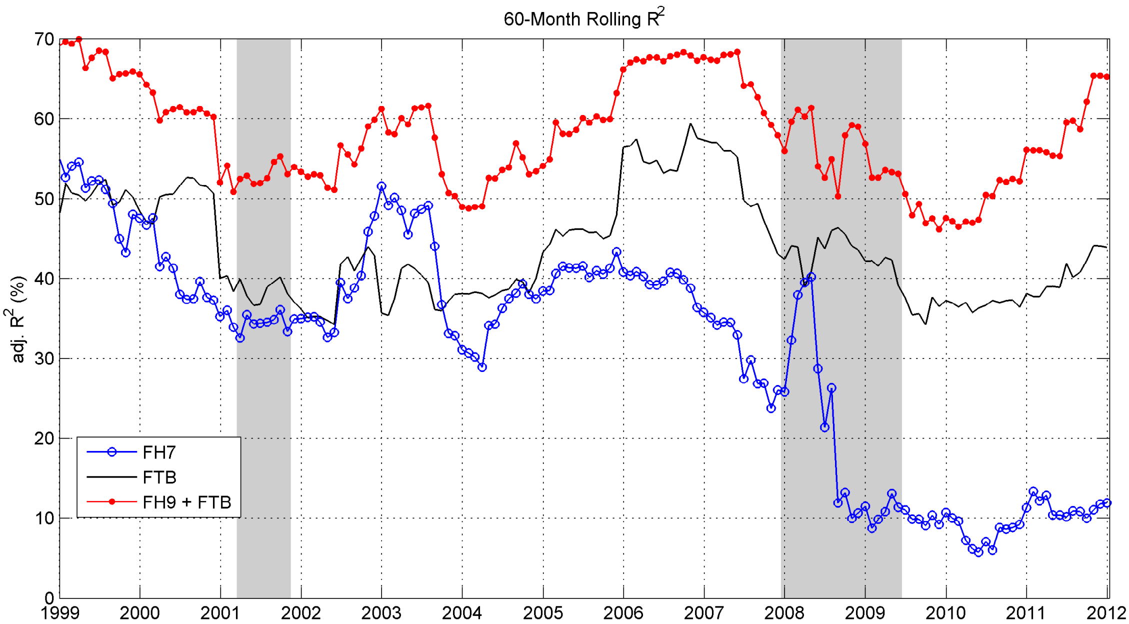

Figure 6: *60-Month Rolling adjusted R^2*
The figure presents the evolution of the rolling adjusted R^2 from regressing the net-of-fee monthly returns of the AUM-Weighted Systematic CTA Index (constructed from the BarclayHedge database) on three combinations of factors: (a) the Fung and Hsieh (2004) 7-factor model, denoted by "FH7", (b) the monthly, weekly and daily FTB strategies (M^1_{12}, W^1_8 and D^1_{15} respectively), denoted by "FTB" 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 FTB factors, denoted by "FH9 + FTB". 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 2011. The grey bands indicate the NBER recessionary periods.

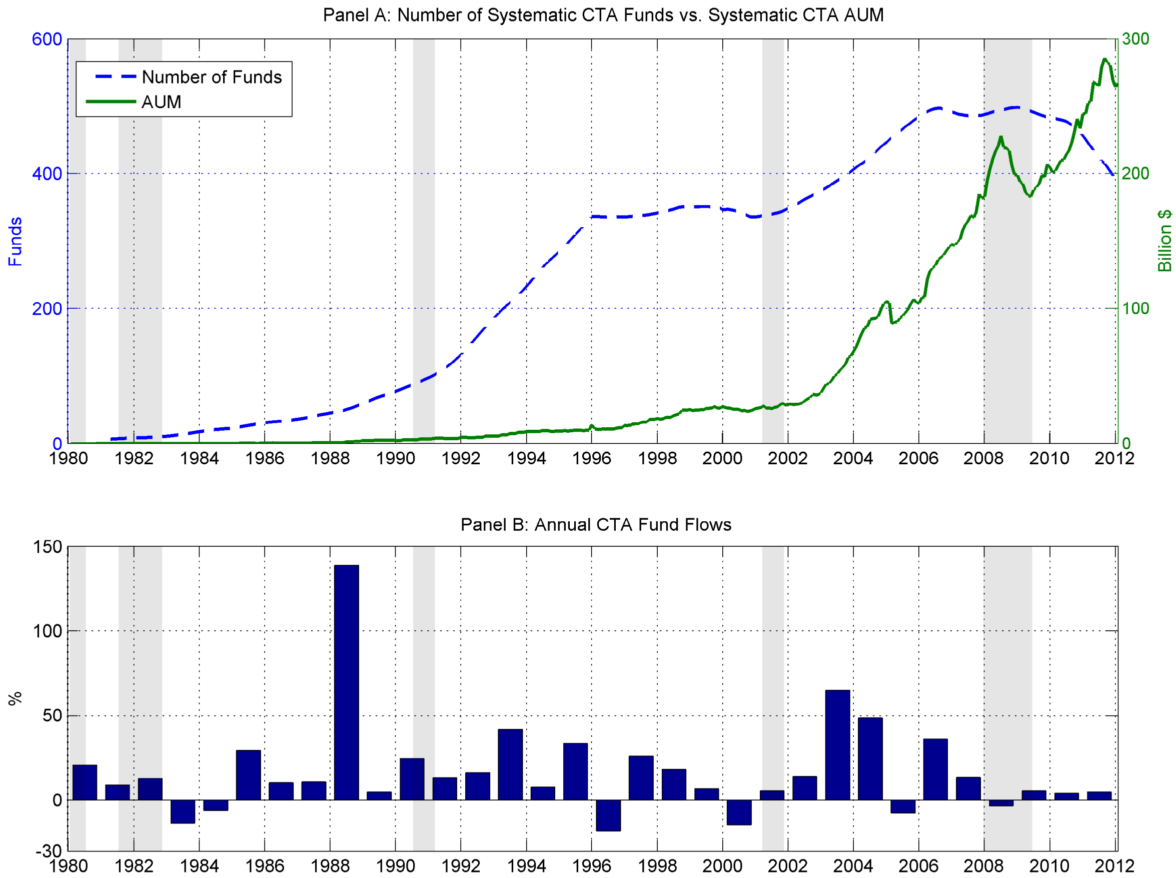

Figure 7: *Number of Systematic CTA Funds, Total AUM of the Industry and Annual Fund Flows*
The figure presents in Panel A the evolution of the (12-month moving average of the) number of systematic CTA funds (blue dashed line) and the total Assets-under-Management (AUM) is billions (green solid line) of the systematic CTA industry. Panel B presents the annual net flow of funds in the systematic CTA industry. All measures are constructed from the BarclayHedge database. The sample period is January 1980 to January 2012. The grey bands indicate the NBER recessionary periods.

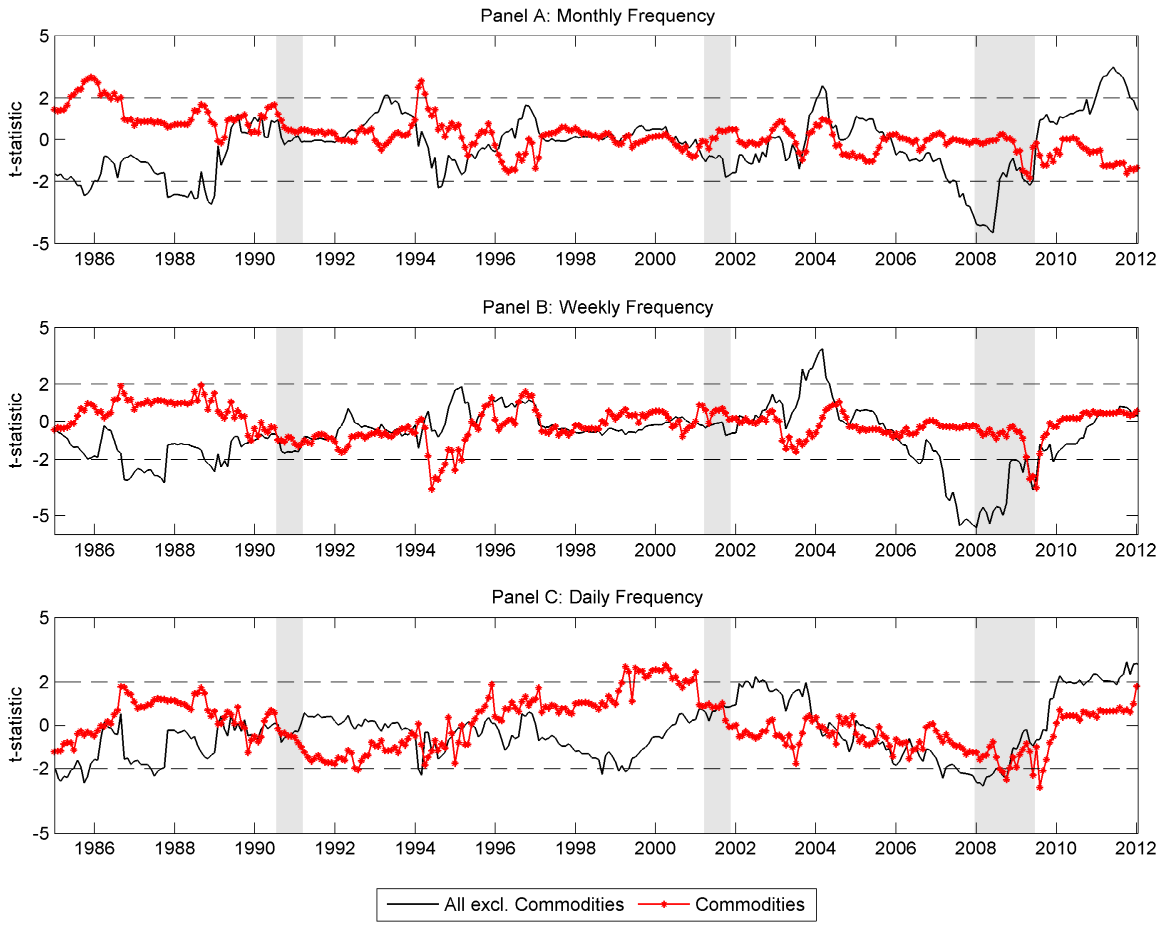

Figure 8: *60-Month Rolling t-statistics of Systematic CTA Fund Flows*
The figure presents the evolution of the t-statistics from regressing on a 60-month rolling basis the monthly returns of the monthly (Panel A), weekly (Panel B) and daily (Panel C) FTB strategies on the sum of past year's fund flows $\sum_{\tau=t-12}^{t-1}$ FuF(τ). 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 1984 to January 2012. The grey bands indicate the NBER recessionary periods.

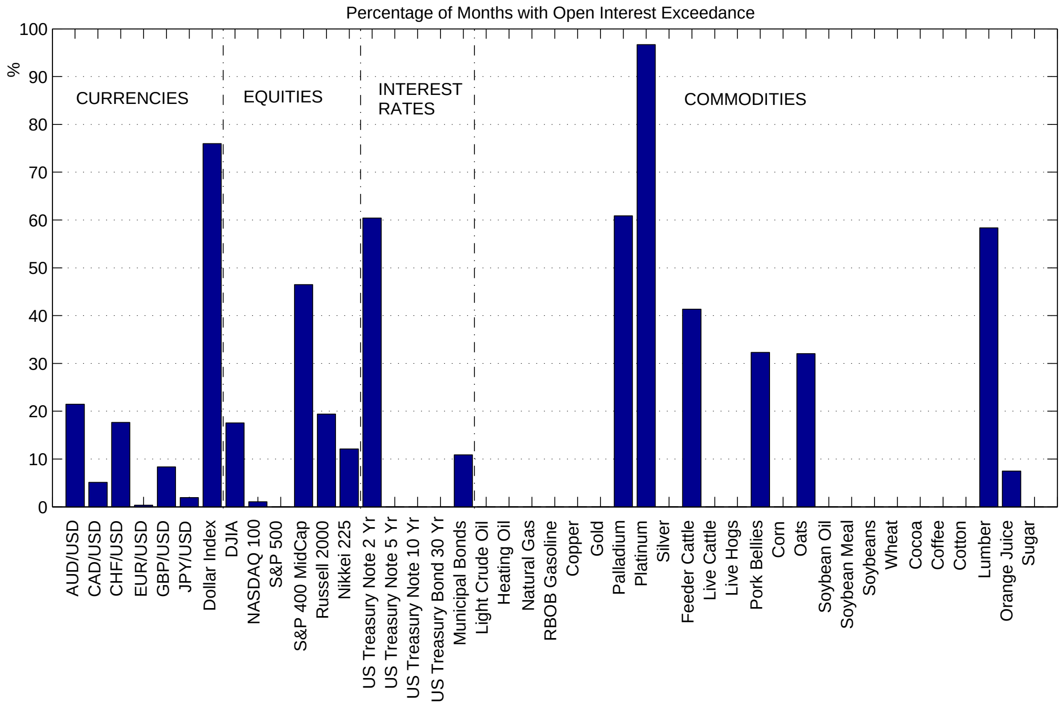

Figure 9: *Percentage of Months with Open Interest Exceedance*
The figure presents the percentage of months that the number of contracts necessary to construct a time-series strategy with the total systematic CTA AUM exceed the CFTC reported open interest. The sample period is January 1986 to December 2011.

	Exchange	From	Mean	t(Mean)	Vol.	Skew	Kurt.	SR
CURRENCIES								
AUD/USD	CME	Feb-1987	5.28	2.11	11.75	-0.41	4.94	0.13
CAD/USD	CME	Feb-1977	0.98	0.84	6.89	-0.30	8.23	-0.62
CHF/USD	CME	Dec-1974	0.84	0.38	12.65	0.06	3.77	-0.35
EUR/USD	CME	Dec-1974	0.60	0.30	11.42	-0.07	3.55	-0.41
GBP/USD	CME	Oct-1977	1.84	0.90	10.77	0.05	4.95	-0.31
JPY/USD	CME	Apr-1977	1.26	0.56	11.99	0.49	4.49	-0.33
Dollar Index	ICE	Aug-1989	-1.77	-0.90	8.82	0.41	3.80	-0.60
EQUITIES								
DJIA	CBOT	Dec-1974	9.01	3.43	15.38	-0.46	5.37	0.25
NASDAQ 100	CME	Feb-1983	12.06	2.39	25.76	-0.33	4.23	0.30
NYSE Composite	ICE	Dec-1974	7.74	2.94	15.30	-0.59	5.32	0.16
S&P 500	CME	Dec-1974	7.16	2.71	15.44	-0.47	4.66	0.13
S&P 400 MidCap	CME	Jul-1991	9.51	2.36	17.44	-0.67	5.06	0.37
Russell 2000	ICE	Feb-1988	7.99	1.91	19.42	-0.48	3.96	0.22
DJ Stoxx 50	EUREX	Jan-1987	6.64	1.70	16.80	-0.82	4.78	0.17
Eurostoxx 50	EUREX	Jan-1987	6.04	1.40	19.19	-0.65	4.30	0.12
FTSE 100	NYSE LIFFE	Feb-1978	8.47	3.19	16.30	-0.71	5.58	0.20
DAX	EUREX	Dec-1974	8.52	2.39	20.29	-0.51	5.00	0.16
CAC 40	NYSE LIFFE	Aug-1987	6.04	1.30	21.06	-0.27	4.02	0.10
IBEX 35	MEFF	Feb-1987	8.08	1.78	22.06	-0.52	4.99	0.20
AEX	NYSE LIFFE	Feb-1983	8.72	2.05	20.69	-0.74	5.31	0.21
SMI	EUREX	Aug-1988	7.64	1.96	16.97	-0.49	4.12	0.23
MIB 30	BI	Jan-1998	0.61	0.09	22.87	0.03	3.99	-0.09
S&P Canada 60	MX	Feb-1982	8.01	2.44	15.98	-0.66	5.80	0.22
Nikkei 225	CME	Dec-1974	3.26	0.97	19.42	-0.29	4.28	-0.10
TOPIX	TSE	Dec-1974	4.51	1.37	17.77	-0.21	4.71	-0.04
ASX SPI 200	ASX	Jun-1992	5.09	1.49	13.59	-0.66	3.75	0.15
Hang Seng	SEHK	Dec-1974	17.79	3.72	29.15	-0.23	5.60	0.43
KOSPI 200	KRX	Feb-1990	9.29	1.34	31.65	0.90	7.03	0.19
MSCI Taiwan Index	SGX	Jan-1988	12.35	1.56	35.52	0.46	4.72	0.24
MSCI EAFE	NYSE LIFFE	Dec-1974	7.79	2.62	15.98	-0.61	5.38	0.16
INTEREST RATES								
US Treasury Note 2 Yr	CBOT	Feb-1991	1.74	3.75	1.79	0.24	3.30	-0.83
US Treasury Note 5 Yr	CBOT	Aug-1988	3.34	3.53	4.31	0.03	3.56	-0.08
US Treasury Note 10 Yr	CBOT	Feb-1983	4.91	3.72	6.99	0.14	3.91	0.08
US Treasury Bond 30 Yr	CBOT	Nov-1982	6.08	3.17	10.62	0.23	4.47	0.16
Municipal Bonds	CBOT	Jul-1985*	5.57	3.30	8.04	-0.58	4.62	0.13
Euro/German Schatz 2 Yr	EUREX	Apr-1997	1.04	2.37	1.42	0.07	3.51	-1.20
Euro/German Bobl 5 Yr	EUREX	Feb-1997	2.69	2.74	3.28	0.01	2.73	-0.02
Euro/German Bund 10 Yr	EUREX	Feb-1997	4.09	2.77	5.28	0.11	2.92	0.25
Euro/German Buxl 30 Yr	EUREX	Oct-2005	5.31	1.09	12.14	1.19	4.86	0.28
Australian 3 Yr	ASX	Aug-2001	0.49	1.24	1.07	0.36	2.73	-1.22
Australian 10 Yr	ASX	Aug-2001	0.34	1.14	0.93	0.12	2.72	-1.58
UK Long Gilt	NYSE LIFFE	Aug-1998	2.90	1.69	5.94	0.19	3.51	0.07
Canadian 10 Yr	MX	May-1990	4.91	3.83	5.95	-0.06	3.18	0.26
Japanese 10 Yr	TSE	Aug-2003	1.67	1.72	3.15	-0.68	4.52	-0.05
Korean 3 Yr	KRX	Sep-2003*	1.69	1.63	3.08	0.88	6.64	-0.09

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	Exchange	From	Mean	t(Mean)	Vol.	Skew	Kurt.	SR
COMMODITIES								
ENERGY								
Light Crude Oil	NYMEX	Feb-1987	14.15	1.76	34.46	0.40	5.42	0.30
Brent Crude Oil	NYMEX	Sep-2003	15.98	1.13	32.25	-0.64	4.78	0.44
Heating Oil	NYMEX	Feb-1984	13.80	2.06	34.18	0.50	4.75	0.28
Natural Gas	NYMEX	Feb-1993	-0.11	-0.01	62.55	1.03	5.65	-0.05
RBOB Gasoline	NYMEX	Oct-1987	22.27	2.89	36.71	0.37	5.39	0.51
METALS								
Copper	COMEX	Jan-1990	10.22	1.53	26.79	-0.06	5.41	0.25
Gold	COMEX	Feb-1984	2.31	0.86	15.55	0.30	4.10	-0.12
Palladium	NYMEX	Feb-1994	14.83	1.57	35.95	0.33	5.57	0.33
Platinum	NYMEX	Aug-2003	11.04	1.03	26.90	-0.98	8.10	0.34
Silver	COMEX	Jan-1984	3.27	0.66	27.87	0.26	4.23	-0.03
MEAT								
Feeder Cattle	CME	Feb-1978	3.07	1.25	14.53	-0.39	5.30	-0.15
Live Cattle	CME	Dec-1974	5.06	1.80	16.65	-0.14	4.34	-0.01
Live Hogs	CME	Dec-1974	3.67	0.89	25.77	-0.05	3.30	-0.06
Pork Bellies	CME	Dec-1974*	0.80	0.15	36.87	0.44	4.23	-0.12
GRAINS								
Corn	CBOT	Aug-1982	-1.98	-0.41	25.24	0.48	5.83	-0.25
Oats	CBOT	Aug-1982	-2.50	-0.39	34.33	2.88	27.32	-0.20
Soybean Oil	CBOT	Aug-1982	2.55	0.52	26.49	0.58	6.14	-0.07
Soybean Meal	CBOT	Aug-1982	7.63	1.67	24.94	0.24	3.99	0.13
Soybeans	CBOT	Aug-1982	3.64	0.88	23.36	0.14	4.28	-0.03
Wheat	CBOT	Aug-1982	-3.17	-0.72	25.44	0.33	4.97	-0.30
SOFTS								
Cocoa	ICE	Aug-1986	-3.75	-0.72	29.46	0.57	4.12	-0.26
Coffee	ICE	Feb-1987	-0.25	-0.03	38.38	0.97	5.56	-0.11
Cotton	ICE	Feb-1987	1.33	0.22	25.98	0.35	3.76	-0.10
Lumber	CME	Dec-1974	-4.59	-0.89	29.34	0.31	3.68	-0.34
Orange Juice	ICE	Aug-1987	3.73	0.60	31.58	0.70	4.77	-0.00
Sugar	ICE	Aug-1986	9.73	1.43	33.38	0.32	3.81	0.18

Table I: *Summary Statistics for Futures Contracts*
The table presents summary statistics for the 71 futures contracts of the dataset, which are estimated using monthly return series. The statistics are: annualised mean return in %, Newey-West t-statistic, annualised volatility in %, skewness, kurtosis and annualised Sharpe ratio (SR). The table also indicates the exchange that each contract is traded at the end of the sample period as well as the starting month and year for each contract. All but 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). The exchanges that appear in the table are listed next: CME: Chicago Mercantile Exchange, CBOT: Chicago Board of Trade, ICE: IntercontinentalExchange, EUREX: European Exchange, NYSE LIFFE: New York Stock Exchange / Euronext - London International Financial Futures and Options Exchange, MEFF: Mercado Español de Futuros Financieros, BI: Borsa Italiana, MX: Montreal Exchange, TSE: Tokyo Stock Exchange, ASX: Australian Securities Exchange, SEHK: Hong Kong Stock Exchange, KRX: Korea Exchange, SGX: Signapore Exchange, NYMEX: New York Mercantile Exchange, COMEX: Commodity Exchange, Inc.

Panel A: Monthly Frequency

K	1	3	6	9	12	24	36	1	3	6	9	12	24	36
J	Annualised Mean (%)							Sharpe ratio						
1	11.9***	9.4***	7.1***	7.1***	7.4***	4.6***	3.2***	0.92	1.04	1.04	1.11	**1.27**	0.94	0.75
3	14.0***	10.6***	8.7***	10.3***	9.4***	6.2***	4.5***	0.97	0.83	0.83	1.05	1.05	0.84	0.66
6	13.3***	11.1***	12.1***	11.6***	9.9***	6.5***	4.2***	0.89	0.82	0.99	1.00	0.92	0.74	0.51
9	**16.6*****	**16.8*****	15.2***	13.3***	11.5***	7.3***	5.0***	1.13	**1.23**	1.16	1.07	0.98	0.74	0.57
12	**18.5*****	16.3***	13.6***	12.1***	10.5***	6.8***	4.6**	**1.25**	1.15	1.01	0.95	0.87	0.65	0.51
24	11.5***	10.6***	9.4***	8.1***	7.0***	4.4*	3.2	0.78	0.73	0.66	0.61	0.55	0.38	0.30
36	8.4***	7.5***	6.6**	5.5**	4.4*	2.9	2.6	0.60	0.55	0.50	0.42	0.35	0.24	0.22
J	Annualised Alpha (%)							Dollar Growth						
1	13.2***	8.9***	6.2***	5.9***	6.4***	3.7***	2.6***	42.2	21.0	10.4	10.3	11.8	4.5	2.9
3	11.8***	8.4***	6.3***	8.0***	7.3***	4.7***	3.2**	80.3	27.5	16.0	27.7	21.0	7.5	4.2
6	11.2***	8.0***	9.3***	9.1***	7.6***	4.7***	2.7	62.2	31.5	47.3	40.9	23.5	7.9	3.8
9	13.2***	**13.6*****	12.5***	10.8***	9.3***	5.6***	3.6**	**189.3**	**213.2**	126.9	70.5	38.9	10.1	4.8
12	**15.7*****	**13.6*****	11.4***	10.2***	8.8***	5.3***	3.5*	**365.0**	176.7	73.6	46.4	27.6	8.3	4.2
24	9.6***	8.9***	8.0***	7.1***	6.2**	3.7	2.7	33.8	25.5	16.1	11.5	8.2	3.5	2.4
36	7.7***	6.8**	6.0**	4.9*	4.0	2.7	2.2	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	8.6***	10.8***	10.4***	9.0***	6.9***	7.0***	6.0***	0.65	0.99	1.15	1.13	1.07	1.24	1.20
2	13.1***	12.4***	11.4***	9.5***	7.5***	8.1***	7.1***	0.95	1.02	1.08	1.01	0.98	1.15	1.15
3	15.7***	13.7***	11.9***	10.0***	8.8***	9.1***	8.4***	1.20	1.14	1.09	0.99	1.02	1.12	1.18
4	15.7***	13.7***	11.8***	10.6***	9.8***	9.7***	89.0***	1.20	1.13	1.04	0.99	1.00	1.07	1.12
6	14.9***	13.1***	12.2***	11.3***	11.0***	10.7***	9.7***	1.14	1.06	1.03	0.98	1.02	1.05	1.05
8	**15.7*****	15.1***	13.9***	12.8***	11.8***	11.6***	10.5***	**1.25**	1.22	1.14	1.08	1.04	1.05	1.04
12	**16.6*****	**16.6*****	15.4***	14.3***	13.2***	12.5***	11.2***	**1.25**	**1.28**	1.21	1.13	1.06	1.03	0.98
J	Annualised Alpha (%)							Dollar Growth						
1	10.1***	12.0***	11.5***	9.6***	7.3***	7.1***	6.0***	13.9	31.8	30.1	19.2	9.7	10.0	7.3
2	14.5***	13.4***	12.0***	9.9***	7.7***	8.0***	6.9***	62.0	52.2	39.7	21.4	11.6	14.2	10.5
3	**17.1*****	14.5***	12.4***	10.3***	9.0***	9.0***	8.0***	151.0	81.0	45.5	24.6	17.6	19.8	15.6
4	**16.6*****	14.4***	12.3***	11.0***	9.8***	9.4***	8.4***	151.7	81.5	44.2	30.0	23.3	23.5	18.8
6	15.5***	13.4***	12.2***	11.1***	10.6***	10.0***	8.8***	116.9	66.1	49.4	36.2	34.0	31.1	22.9
8	**16.1*****	15.2***	13.6***	12.2***	11.1***	10.7***	9.4***	**156.2**	127.5	85.1	59.7	44.4	42.0	29.7
12	15.9***	15.7***	14.4***	13.0***	11.8***	11.0***	9.5***	**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	**18.6*****	5.7***	5.1***	4.4***	4.8***	3.0***	2.6***	**1.51**	0.69	0.81	0.80	0.99	0.86	0.89
3	15.9***	6.1***	4.1***	5.4***	6.2***	4.3***	3.7***	1.22	0.61	0.49	0.74	0.97	0.93	1.01
5	17.6***	8.0***	5.2***	7.5***	8.1***	5.7***	5.2***	1.24	0.65	0.46	0.78	0.98	0.98	1.11
10	15.6***	10.1***	9.3***	10.4***	9.6***	6.7***	6.5***	1.06	0.73	0.71	0.89	0.95	0.91	1.07
15	**18.4*****	14.5***	12.9***	12.4***	10.4***	8.0***	7.9***	1.21	1.02	0.96	1.02	0.96	0.92	1.08
30	17.0***	14.3***	13.2***	12.2***	11.3***	10.2***	9.5***	**1.24**	1.07	1.02	0.98	0.95	0.93	1.00
60	**18.1*****	17.1***	16.4***	16.0***	15.0***	13.1***	11.2***	**1.26**	1.23	1.20	1.19	1.13	1.02	0.96
J	Annualised Alpha (%)							Dollar Growth						
1	**19.8*****	6.8***	6.1***	5.3***	5.5***	3.5***	2.7***	**412.0**	6.1	5.3	4.2	4.8	2.7	2.4
3	17.6***	7.5***	5.3***	6.4***	7.1***	4.8***	3.8***	164.7	6.6	3.6	5.7	7.6	4.1	3.4
5	**19.7*****	10.1***	7.1***	8.9***	9.2***	6.2***	5.2***	271.9	11.7	4.7	10.8	13.7	6.5	5.6
10	17.7***	11.8***	11.0***	11.5***	10.1***	6.9***	6.2***	135.4	22.1	17.7	27.1	21.9	9.0	8.5
15	**20.6*****	16.5***	14.6***	13.3***	10.9***	8.1***	7.3***	**348.6**	97.4	58.5	51.6	28.2	13.3	13.1
30	18.1***	15.1***	13.8***	12.2***	11.1***	9.6***	8.4***	227.2	93.5	65.9	47.4	36.7	25.9	21.4
60	17.7***	16.5***	15.7***	15.1***	13.7***	11.5***	9.4***	**319.8**	231.4	185.7	166.7	118.7	64.0	35.7

Table II: *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 three largest values per statistic are shown in bold. The dataset covers the period January 1978 to January 2012.

Panel A: Performance Statistics

	MSCI	M_{12}^{1}	M_{9}^{3}	M_{1}^{12}	W_{8}^{1}	W_{12}^{2}	W_{1}^{8}	D_{15}^{1}	D_{60}^{1}	D_{1}^{15}
Mean (%)	8.34	18.54	16.77	7.44	15.72	16.61	6.95	18.44	18.08	4.75
Volatility (%)	15.19	14.88	13.66	5.88	12.57	13.00	5.61	15.25	14.34	4.79
Skewness	-0.65	-0.34	-0.46	-0.30	0.73	0.54	0.97	1.61	0.47	2.54
Kurtosis	4.57	4.75	5.35	5.40	4.93	4.51	5.76	10.75	3.60	18.15
CAPM β	1	-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	0.21	1.25	1.23	1.27	1.26	1.29	1.23	1.21	1.27	0.99
MDD (%)	55.37	22.12	25.10	9.18	12.03	15.63	6.86	15.65	17.68	7.18
MDD Period	16	2	6	2	16	8	7	16	10	25
Dollar Growth	11.4	365.0	213.2	11.8	156.2	207.3	10.0	348.6	319.8	4.8
Turnover (%)	-	23.5	22.2	26.6	77.1	64.1	100.2	238.1	146.9	326.7
After 2/20 Fees										
Mean (%)		13.22	11.98	4.01	11.12	11.96	3.53	13.46	13.44	1.73
Sharpe ratio		0.89	0.88	0.68	0.88	0.92	0.63	0.88	0.94	0.36
Dollar Growth		59.4	37.4	3.6	30.9	40.3	3.2	57.7	57.2	1.8

Panel B: Correlation Matrix

	M_{12}^{1}	M_{9}^{3}	M_{1}^{12}	W_{8}^{1}	W_{12}^{2}	W_{1}^{8}	D_{15}^{1}	D_{60}^{1}	D_{1}^{15}
M_{12}^{1}	1.00								
M_{9}^{3}	0.89	1.00							
M_{1}^{12}	0.84	0.88	1.00						
W_{8}^{1}	**0.41**	0.38	0.38	1.00					
W_{12}^{2}	0.52	0.50	0.50	0.80	1.00				
W_{1}^{8}	0.43	0.41	0.44	0.84	0.74	1.00			
D_{15}^{1}	**0.22**	0.20	0.20	**0.52**	0.43	0.55	1.00		
D_{60}^{1}	0.51	0.47	0.48	0.78	0.89	0.72	0.52	1.00	
D_{1}^{15}	0.33	0.30	0.31	0.52	0.46	0.57	0.84	0.56	1.00

Table III: *Time-Series Momentum Best Strategies*

The table presents in Panel A various performance statistics for MSCI World Index and 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, annualised Sharpe 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. Additionally, Panel A presents the annualised mean return in %, the annualised Sharpe ratio and the dollar growth for the time-series strategies after incorporating a conventional hedge fund 2/20 fee structure. Panel B reports the unconditional correlation matrix of the above nine strategies. Correlations of the three chosen FTB 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)
ann. alpha (%)	13.81	16.15	18.44	13.69	14.56	19.22	13.12	12.23	18.42
	(4.77)	(5.11)	(5.00)	(5.36)	(6.06)	(6.57)	(5.21)	(5.22)	(7.53)
MSCI	0.05			-0.14			-0.15		
	(0.49)			(-1.90)			(-1.93)		
S&P500		0.03	0.03		-0.04	-0.02		-0.07	-0.05
		(0.31)	(0.32)		(-0.62)	(-0.45)		(-1.18)	(-0.98)
SMB	-0.01			-0.11			-0.06		
	(-0.22)			(-1.62)			(-0.71)		
SCMLC		0.08	0.08		-0.03	-0.03		0.01	0.02
		(1.02)	(1.00)		(-0.49)	(-0.36)		(0.18)	(0.37)
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	0.01		0.04	0.03
		(-2.58)	(-2.53)		(0.86)	(0.40)		(2.49)	(2.36)
PTF FX		0.01	0.01		0.03	0.02		0.02	0.00
		(0.44)	(0.44)		(2.33)	(2.02)		(1.17)	(0.39)
PTF Cmdty		0.05	0.06		0.07	0.07		0.07	0.07
		(2.35)	(2.41)		(4.20)	(4.58)		(3.08)	(3.29)
PTF IR			-0.01			-0.00			0.01
			(-1.40)			(-0.18)			(0.91)
PTF Stock			0.03			0.08			0.11
			(1.41)			(4.11)			(6.72)
TCM 10Y		0.15	0.12		-0.01	-0.06		-0.05	-0.11
		(1.05)	(0.88)		(-0.13)	(-0.69)		(-0.50)	(-1.35)
BAA Spread		-0.24	-0.25		-0.25	-0.16		-0.10	0.06
		(-1.47)	(-1.38)		(-1.29)	(-0.96)		(-0.66)	(0.54)
adj. R^2 (%)	14.89	6.32	6.62	5.88	19.63	26.43	1.95	17.89	32.96
N	264	216	216	264	216	216	264	216	216

Table IV: *Return Decomposition of the Monthly, Weekly, Daily FTB 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 FTB strategies (M^1_{12}, W^1_8 and D^1_{15}) 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 (a) is December 1989 to November 2011 (264 data points) and for models (b) and (c) January 1994 to December 2011 (216 data points).

Panel A: Yearly Performance												
	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
M_{12}^1	10.3	15.3	19.4	37.2	28.2	36.7	37.3	44.3	27.1	8.8	10.4	24.2
W_8^1	21.8	-2.5	32.7	31.7	37.5	17.7	43.2	21.6	11.5	37.3	2.4	9.8
D_{15}^1	36.9	17.2	38.0	29.0	20.6	36.4	50.4	48.1	32.0	65.3	21.3	19.5
AUMW-CTA	-	-	78.1	33.6	34.0	1.0	34.5	24.4	-8.1	49.2	11.24	0.0
BH-CTA	-	-	63.7	23.9	16.7	23.8	8.7	25.5	3.8	57.3	21.8	1.8
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
M_{12}^1	18.5	-5.7	14.0	21.2	3.5	9.1	24.2	27.5	24.0	34.9	13.2	24.7
W_8^1	37.5	0.4	11.5	19.0	3.0	11.8	9.8	17.7	25.7	7.7	6.3	21.8
D_{15}^1	37.7	3.5	18.1	18.9	11.8	9.1	11.3	27.2	32.8	5.6	-6.3	15.1
AUMW-CTA	22.4	13.6	3.7	13.9	-4.5	17.4	14.1	13.5	16.7	1.7	9.6	7.0
BH-CTA	21.0	3.7	-0.9	10.4	-0.7	13.6	9.1	10.9	7.0	-1.2	7.9	0.8
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011		
M_{12}^1	26.4	15.9	13.2	19.8	38.6	24.1	26.4	-9.4	7.3	-2.3		
W_8^1	14.1	12.9	9.2	20.3	21.9	5.3	49.8	-8.8	14.5	-1.1		
D_{15}^1	8.2	3.2	-4.3	12.4	10.8	19.6	28.8	-12.3	18.5	-3.7		
AUMW-CTA	15.2	16.0	5.0	6.4	5.5	10.3	12.0	-3.1	15.4	3.1		
BH-CTA	12.4	8.7	3.3	1.7	3.5	7.6	14.1	-0.1	7.1	-3.1		

Panel B: Correlation Matrix & Recession/Expansion Performance											
				AUMW	BH	Return		Volatility		Sharpe ratio	
	M_{12}^1	W_8^1	D_{15}^1	CTA	CTA	REC	EXP	REC	EXP	REC	EXP
M_{12}^1	1.00					18.1**	18.6***	17.8	14.3	1.03	1.30
W_8^1	0.43	1.00				28.1***	13.6***	17.5	11.4	1.62	1.19
D_{15}^1	0.22	0.55	1.00			25.1***	17.3***	23.6	13.3	1.08	1.30
AUMW-CTA	0.39	0.54	0.43	1.00		19.5**	13.1***	17.7	15.4	0.76	0.55
BH-CTA	0.31	0.46	0.37	0.89	1.00	18.9***	10.3***	17.8	14.5	0.72	0.38

Table V: *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 monthly, weekly and daily FTB strategies (M_{12}^1, W_8^1 and D_{15}^1 respectively), the AUM-weighted Systematic 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 have data for 348 expansionary months, whereas the AUM-weighted Systematic CTA Index 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 Systematic CTA Index									
	(a) FH7	(b) FH9	(c)	(d)	(e)	(f) FTB	(g)	(h)	(i) FH9+ FTB
ann. alpha (%)	5.48	8.55	0.25	-0.00	2.53	-2.77	-4.45	0.32	-1.82
	(2.92)	(4.09)	(0.12)	(-0.00)	(1.24)	(-1.55)	(-2.55)	(0.14)	(-0.83)
S&P500	0.01	0.01					-0.00		0.01
	(0.22)	(0.23)					(-0.08)		(0.46)
SCMLC	0.03	0.03					0.03		0.02
	(0.76)	(0.75)					(0.53)		(0.48)
PTF Bonds	0.03	0.03						0.04	0.04
	(2.85)	(3.07)						(4.43)	(3.83)
PTF FX	0.04	0.04						0.03	0.03
	(3.43)	(3.79)						(3.36)	(3.35)
PTF Cmdty	0.04	0.05						0.02	0.01
	(2.85)	(3.17)						(1.58)	(1.27)
PTF IR		-0.01						-0.02	-0.01
		(-2.23)						(-2.50)	(-2.44)
PTF Stock		0.04						0.01	0.01
		(3.27)						(0.86)	(0.46)
TCM 10Y	0.31	0.27					0.35		0.27
	(3.48)	(3.08)					(4.61)		(3.40)
BAA Spread	0.11	0.10					0.20		0.18
	(1.49)	(1.33)					(2.21)		(2.86)
M_{12}^1			0.33			0.20	0.19	0.23	0.22
			(6.47)			(4.12)	(4.05)	(5.75)	(5.59)
W_8^1				0.45		0.28	0.29	0.21	0.22
				(7.60)		(4.79)	(6.06)	(3.89)	(4.29)
D_{15}^1					0.32	0.16	0.16	0.10	0.10
					(6.02)	(3.33)	(3.56)	(2.13)	(2.31)
adj. R^2 (%)	26.54	29.83	19.40	29.98	15.44	37.70	44.13	48.10	51.65

Table VI: *Return Decomposition of the AUM-Weighted Systematic 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 Systematic 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 monthly, weekly and daily FTB 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 2011 (216 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	0.01	0.02	0.02	0.01	0.01	0.01
	(6.87)	(9.32)	(6.84)	(4.89)	(8.03)	(5.87)	(4.36)	(5.41)	(5.08)
ϕ	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00
	(-0.72)	(-1.52)	(-0.01)	(-0.95)	(-2.09)	(0.04)	(1.04)	(0.56)	(-0.22)
β_{MSCI}	0.11	-0.14	-0.19	0.20	-0.15	-0.25	-0.01	-0.10	-0.08
	(0.92)	(-1.82)	(-2.19)	(1.11)	(-1.36)	(-1.93)	(-0.10)	(-1.81)	(-1.50)
β_{SMB}	0.05	-0.13	-0.08	0.01	-0.17	-0.15	0.11	-0.07	-0.00
	(0.74)	(-1.85)	(-0.92)	(0.11)	(-1.82)	(-1.16)	(1.59)	(-1.06)	(-0.05)
β_{HML}	0.08	-0.02	0.02	0.12	-0.01	-0.01	0.02	-0.05	0.04
	(0.99)	(-0.31)	(0.21)	(1.06)	(-0.17)	(-0.11)	(0.30)	(-0.83)	(0.57)
β_{GSCI}	-0.04	-0.01	-0.02	-0.04	0.02	0.02	-0.04	-0.06	-0.05
	(-0.58)	(-0.20)	(-0.41)	(-0.45)	(0.29)	(0.23)	(-0.51)	(-1.24)	(-1.18)
β_{UMD}	0.36	0.09	-0.04	0.51	0.09	-0.10	0.12	0.09	0.04
	(5.82)	(2.22)	(-0.99)	(5.75)	(1.52)	(-1.56)	(2.52)	(2.28)	(1.07)
adj. R^2 (%)	12.84	5.43	3.54	13.18	3.19	2.96	0.93	2.23	0.43

	(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.	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02
	(3.70)	(4.04)	(3.45)	(1.54)	(2.86)	(4.32)	(4.85)	(4.68)	(3.94)
ϕ	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00
	(-0.69)	(-0.68)	(-0.37)	(-0.30)	(-2.02)	(0.76)	(-0.77)	(-0.98)	(-0.65)
β_{MSCI}	-0.10	-0.15	-0.07	0.36	-0.17	-0.31	0.10	-0.04	-0.20
	(-0.86)	(-1.52)	(-0.79)	(1.33)	(-0.98)	(-1.58)	(0.53)	(-0.28)	(-1.36)
β_{SMB}	0.02	-0.08	0.06	0.08	-0.12	-0.20	-0.19	-0.42	-0.14
	(0.14)	(-0.63)	(0.57)	(0.51)	(-0.92)	(-0.91)	(-1.18)	(-3.38)	(-1.10)
β_{HML}	0.21	0.13	0.20	0.12	0.01	-0.02	-0.01	-0.20	-0.10
	(1.53)	(1.10)	(2.00)	(0.72)	(0.05)	(-0.10)	(-0.08)	(-1.41)	(-0.66)
β_{GSCI}	-0.06	-0.08	-0.09	-0.07	0.03	0.02	0.10	0.07	0.07
	(-0.98)	(-0.98)	(-1.34)	(-0.54)	(0.27)	(0.23)	(1.00)	(0.82)	(0.83)
β_{UMD}	0.17	0.06	0.04	0.78	0.12	-0.12	0.19	0.08	-0.15
	(1.60)	(0.65)	(0.48)	(6.47)	(1.16)	(-1.04)	(1.85)	(1.13)	(-1.51)
adj. R^2 (%)	0.95	0.66	-0.30	17.59	1.44	2.06	0.35	0.77	-0.27

Table VII: *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 FTB 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 standardised sum of past year's Systematic CTA fund flows, $\sum_{\tau=t-12}^{t-1}$ FuF(τ), 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 1981 to January 2012 (373 data points).

	(i) All Contracts ($N=43$)			(ii) All ex-Commodities			(iii) Commodities ($N=25$)		
	M^1_{12}	W^1_8	D^1_{15}	M^1_{12}	W^1_8	D^1_{15}	M^1_{12}	W^1_8	D^1_{15}
const.	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00
	(5.80)	(5.16)	(6.36)	(4.57)	(3.55)	(4.85)	(4.44)	(4.12)	(3.85)
ϕ^+	0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.35)	(-1.10)	(-0.34)	(0.28)	(-1.40)	(-2.01)	(-0.17)	(-1.49)	(-0.07)
ϕ^-	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.00
	(-0.47)	(-1.81)	(-1.03)	(0.23)	(-0.09)	(-0.40)	(0.15)	(-0.59)	(-0.01)
β_{MSCI}	0.01	-0.02	0.01	0.02	-0.00	0.01	0.00	-0.03	0.00
	(0.15)	(-0.73)	(0.58)	(0.16)	(-0.11)	(0.53)	(0.03)	(-1.21)	(0.35)
β_{SMB}	0.03	-0.01	-0.01	-0.04	-0.02	-0.00	0.08	-0.00	-0.01
	(0.55)	(-0.36)	(-0.49)	(-0.43)	(-0.43)	(-0.20)	(1.16)	(-0.01)	(-0.59)
β_{HML}	0.02	0.02	-0.02	0.07	0.07	-0.01	-0.01	-0.00	-0.02
	(0.36)	(0.73)	(-0.71)	(0.74)	(1.18)	(-0.48)	(-0.11)	(-0.10)	(-0.84)
β_{GSCI}	-0.00	-0.01	-0.01	-0.03	-0.02	-0.02	0.01	-0.00	-0.00
	(-0.08)	(-0.39)	(-0.95)	(-0.35)	(-0.69)	(-1.52)	(0.21)	(-0.09)	(-0.14)
β_{UMD}	0.23	-0.00	-0.02	0.35	0.01	-0.03	0.15	-0.00	-0.01
	(4.65)	(-0.08)	(-1.74)	(4.93)	(0.36)	(-1.74)	(2.92)	(-0.21)	(-1.19)
adj. R^2 (%)	7.77	-0.33	0.60	7.46	-0.49	1.19	1.72	-0.98	-1.55

	(iv) Currencies ($N=7$)			(v) Equities ($N=6$)			(vi) Interest Rates ($N=5$)		
	M^1_{12}	W^1_8	D^1_{15}	M^1_{12}	W^1_8	D^1_{15}	M^1_{12}	W^1_8	D^1_{15}
const.	0.01	0.00	0.00	0.00	-0.00	0.00	0.02	0.01	0.00
	(2.68)	(2.12)	(2.82)	(0.62)	(-0.03)	(1.66)	(4.38)	(3.38)	(2.26)
ϕ^+	0.01	-0.00	-0.00	0.01	-0.00	-0.00	-0.01	-0.00	-0.00
	(1.24)	(-0.98)	(-0.07)	(0.69)	(-1.30)	(-2.42)	(-1.08)	(-0.73)	(-1.45)
ϕ^-	0.00	-0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.00
	(0.22)	(-0.52)	(0.17)	(-1.58)	(0.44)	(0.90)	(0.36)	(0.27)	(-0.74)
β_{MSCI}	-0.01	-0.01	0.03	0.24	0.01	-0.05	-0.01	0.02	0.02
	(-0.08)	(-0.33)	(1.69)	(0.71)	(0.26)	(-1.58)	(-0.07)	(0.31)	(0.62)
β_{SMB}	-0.04	-0.02	0.03	0.02	0.05	0.00	-0.20	-0.05	-0.06
	(-0.33)	(-0.37)	(1.31)	(0.12)	(0.72)	(0.15)	(-1.01)	(-0.85)	(-1.70)
β_{HML}	0.09	0.14	-0.02	0.02	0.08	0.02	-0.01	0.01	-0.05
	(0.68)	(1.88)	(-0.66)	(0.12)	(0.80)	(0.53)	(-0.06)	(0.11)	(-0.78)
β_{GSCI}	-0.02	-0.06	-0.03	-0.00	-0.01	-0.02	0.00	0.03	0.00
	(-0.34)	(-1.77)	(-2.20)	(-0.02)	(-0.34)	(-0.59)	(0.04)	(0.73)	(0.17)
β_{UMD}	0.17	0.01	-0.01	0.74	-0.01	-0.06	0.22	0.03	-0.04
	(1.80)	(0.25)	(-1.01)	(4.97)	(-0.22)	(-2.50)	(2.00)	(0.68)	(-0.94)
adj. R^2 (%)	-0.35	1.39	0.59	12.88	-1.35	3.38	-0.44	-1.58	-0.12

Table VIII: *Time-Series Momentum Profitability, CTA Fund Flows and Open Interest Changes*
The table replicates the results of table VII after splitting the CTA fund flows variable based on the sign of the change in the open interest of the 43 futures contracts that are covered in the CFTC database. The independent variables in the regressions are the monthly returns of the best monthly, weekly and daily time-series momentum strategies formed using only these 43 futures contracts. The number of contracts per group is denoted by N in the table. The sample period is January 1986 to December 2011 (312 data points). The reported t-statistics are estimated using Newey and West (1987) standard errors with 11 lags.

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 B.1: *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.

	BarclayHedge CTA Index			Newedge CTA Index			Newedge CTA Trend Sub-I		
	FH9	FTB	Joint	FH9	FTB	Joint	FH9	FTB	Joint
ann. alpha (%)	4.44	-3.56	-2.68	6.78	-3.50	-3.01	10.59	-7.24	-6.66
	(2.63)	(-2.81)	(-1.56)	(2.40)	(-1.64)	(-1.16)	(2.06)	(-1.95)	(-1.50)
S&P500	0.02		0.03	-0.04		0.01	-0.06		0.01
	(0.66)		(1.15)	(-0.67)		(0.18)	(-0.67)		(0.21)
SCMLC	0.02		0.01	0.07		0.03	0.14		0.07
	(0.55)		(0.34)	(1.32)		(0.48)	(1.51)		(0.62)
PTF Bonds	0.02		0.02	0.02		0.03	0.03		0.05
	(2.48)		(2.98)	(1.38)		(2.37)	(1.27)		(2.38)
PTF FX	0.04		0.04	0.04		0.03	0.05		0.02
	(6.31)		(6.12)	(3.21)		(2.60)	(2.17)		(1.38)
PTF Cmdty	0.04		0.02	0.03		0.00	0.05		0.00
	(3.27)		(1.93)	(1.93)		(0.31)	(1.76)		(0.11)
PTF IR	-0.01		-0.01	-0.02		-0.02	-0.03		-0.02
	(-3.06)		(-3.26)	(-3.08)		(-3.72)	(-2.54)		(-2.99)
PTF Stock	0.02		-0.00	0.03		-0.00	0.06		0.00
	(2.35)		(-0.16)	(1.97)		(-0.04)	(2.10)		(0.19)
TCM 10Y	0.14		0.14	0.09		0.09	0.19		0.19
	(2.14)		(2.33)	(0.86)		(1.02)	(1.16)		(1.30)
BAA Spread	0.06		0.12	0.01		0.11	-0.01		0.18
	(1.11)		(3.13)	(0.14)		(1.84)	(-0.04)		(1.72)
M^1_{12}		0.12	0.14		0.26	0.27		0.49	0.51
		(3.03)	(4.42)		(5.59)	(7.15)		(5.96)	(6.97)
W^1_8		0.24	0.19		0.22	0.22		0.37	0.37
		(5.80)	(5.01)		(3.99)	(3.51)		(4.07)	(3.49)
D^1_{15}		0.09	0.05		0.05	0.05		0.08	0.07
		(2.43)	(1.47)		(1.14)	(0.96)		(0.98)	(0.78)
adj. R^2 (%)	33.98	35.41	52.18	17.08	37.60	45.16	13.37	39.98	45.35
N	216	216	216	144	144	144	144	144	144

Table B.2: *Return Decomposition of CTA Indices*
The table reports the results of regressions (b), (f) and (i) of Table VI 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], FTB [best monthly, weekly and daily time-series momentum strategies] and FH9+FTB (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 2011 (216 data points). The Newedge indices are available from January 2000.

	(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	0.01	0.02	0.02	0.01	0.01	0.01
	(6.26)	(8.76)	(6.93)	(4.31)	(7.78)	(6.05)	(4.41)	(5.01)	(4.58)
ϕ^{REC}	-0.01	-0.00	0.01	-0.02	-0.00	0.01	0.01	-0.00	-0.00
	(-1.22)	(-0.96)	(1.28)	(-1.58)	(-0.70)	(1.71)	(1.36)	(-1.42)	(-0.74)
ϕ^{EXP}	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(-0.20)	(-1.28)	(-0.25)	(-0.32)	(-1.97)	(-0.30)	(0.64)	(0.88)	(0.07)
β_{MSCI}	0.11	-0.14	-0.19	0.20	-0.15	-0.25	-0.01	-0.10	-0.08
	(0.96)	(-1.81)	(-2.22)	(1.16)	(-1.36)	(-1.97)	(-0.15)	(-1.77)	(-1.45)
β_{SMB}	0.05	-0.13	-0.08	0.01	-0.17	-0.15	0.11	-0.07	-0.00
	(0.76)	(-1.85)	(-0.92)	(0.12)	(-1.82)	(-1.16)	(1.57)	(-1.06)	(-0.04)
β_{HML}	0.09	-0.02	0.02	0.13	-0.01	-0.02	0.02	-0.05	0.05
	(1.03)	(-0.29)	(0.19)	(1.13)	(-0.17)	(-0.16)	(0.25)	(-0.79)	(0.59)
β_{GSCI}	-0.04	-0.01	-0.02	-0.04	0.02	0.02	-0.04	-0.06	-0.06
	(-0.62)	(-0.21)	(-0.37)	(-0.51)	(0.29)	(0.26)	(-0.49)	(-1.27)	(-1.21)
β_{UMD}	0.36	0.09	-0.04	0.52	0.09	-0.11	0.11	0.09	0.05
	(5.68)	(2.27)	(-1.05)	(5.69)	(1.50)	(-1.59)	(2.52)	(2.41)	(1.12)
adj. R^2 (%)	12.97	5.20	3.47	13.75	2.93	3.15	0.95	2.16	0.25

	(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.	0.02	0.02	0.02	0.00	0.01	0.02	0.03	0.02	0.02
	(3.45)	(3.95)	(3.68)	(1.14)	(2.72)	(4.22)	(4.96)	(4.45)	(4.40)
ϕ^{REC}	-0.01	-0.00	0.02	-0.03	-0.01	0.01	0.01	-0.00	0.02
	(-0.41)	(-0.31)	(1.33)	(-2.52)	(-0.65)	(0.56)	(1.90)	(-0.01)	(2.60)
ϕ^{EXP}	-0.00	-0.00	-0.00	0.00	-0.00	0.00	-0.01	-0.00	-0.01
	(-0.60)	(-0.62)	(-0.65)	(0.81)	(-1.84)	(0.54)	(-1.07)	(-1.02)	(-1.14)
β_{MSCI}	-0.10	-0.15	-0.08	0.37	-0.17	-0.31	0.09	-0.04	-0.22
	(-0.83)	(-1.52)	(-0.89)	(1.40)	(-0.97)	(-1.58)	(0.48)	(-0.29)	(-1.45)
β_{SMB}	0.02	-0.08	0.06	0.08	-0.12	-0.20	-0.20	-0.42	-0.14
	(0.14)	(-0.63)	(0.55)	(0.53)	(-0.91)	(-0.91)	(-1.20)	(-3.40)	(-1.15)
β_{HML}	0.21	0.13	0.19	0.14	0.01	-0.02	-0.02	-0.20	-0.11
	(1.52)	(1.09)	(1.87)	(0.85)	(0.06)	(-0.12)	(-0.14)	(-1.44)	(-0.80)
β_{GSCI}	-0.06	-0.08	-0.09	-0.08	0.03	0.02	0.10	0.07	0.08
	(-1.00)	(-0.99)	(-1.27)	(-0.61)	(0.27)	(0.23)	(1.02)	(0.83)	(0.91)
β_{UMD}	0.17	0.06	0.03	0.80	0.12	-0.13	0.18	0.08	-0.17
	(1.58)	(0.64)	(0.30)	(6.64)	(1.15)	(-1.01)	(1.73)	(1.04)	(-1.91)
adj. R^2 (%)	0.71	0.39	0.02	18.68	1.18	1.83	0.39	0.50	0.08

Table B.3: *Time-Series Momentum Profitability, Systematic CTA Fund Flows and Recession Dummy*
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 cross-terms of the standardised sum of past year's Systematic CTA fund flows with the NBER recession and expansion dummies (regression coefficients are denoted by ϕ^{REC} and ϕ^{EXP} respectively) 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 1981 to January 2012 (373 data points).