Time Series Momentum: Benchmarking the Managed Futures Industry and the Potential Benefit from Mixing Trend-Following with Contrarian Position Taking[1,2]

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Abstract : We examine 'time series momentum' and its relationship to the Managed Futures Industry. We observe that time series momentum profitability is time-varying, sensitive to the particular lookback- and holding period, and tends to break down in particular asset markets for considerable periods of time. These findings motivate us to explore more dynamic- as well contrarian approaches to exploiting time series momentum. We find that, whereas simple dynamic approaches based on past performance are unsuccessful, contrarian risk-taking tends to provide considerable diversification benefits and seems to dampen the recent breakdown in time series momentum profitability. Finally, we examine the relationship between our proposed diversified- and asset-specific time series momentum benchmarks and Managed Futures' trading behavior.

JEL classification: G11; G23
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1. Introduction

Time series momentum differs from momentum in the cross-section of asset returns. Whereas cross-sectional momentum relies on past winners outperforming past losers, time series momentum depends on a continuation of the price direction of a particular asset. The presence of such a "trend" effect was first documented in a systematic manner by Moskowitz, Ooi, and Pedersen (2012) for a broad range of futures and forward contracts. The authors show how a diversified portfolio relying on time series momentum strategies across different asset classes consistently delivers large and significant abnormal returns.

Yet, return predictability based on past prices is not new. The concept of time series momentum is closely related to earlier academic literature on return autocorrelation. For example, Fama and French (1988) and Lo and Mackinlay (1988) observe a deviation from the random walk hypothesis in that they find positive (negative) return autocorrelation in equities at short (longer) horizons. Moskowitz et al. (2012) also find a similar pattern in the case of time series momentum, which also tends to partially reverse over the long-term. Such a pattern, the authors argue, is consistent with initial under-reaction and delayed over-reaction put forth by several theoretical models (for a discussion, see Moskowitz et al. (2012) and references therein).

Regardless of the potential drivers, research that examines quantitative approaches to potentially exploit predictability has also emerged in recent years. For example, Szakmary, Shen, and Sharma (2010) investigate whether commonly cited trend-following strategies in commodity futures markets yield positive excess returns and find this to be the case for the vast majority of the contracts considered. Similarly, Hurst, Johnson, and Ooi (2010) and Hurst, Ooi, and Pedersen (2010) also discuss the likely gains of trend-following approaches in futures markets.

Even though time series momentum remains a relatively new phenomenon in academia, the Managed Futures industry has been attempting to exploit predictability in futures markets since the early 1970s. As of June 2014, Managed Futures are the second largest hedge fund category after Fixed-Income Arbitrage with assets-under-management (AUM) of approximately $320 billion, according to BarclayHedge. However, despite the size of the Managed Futures industry, no objective benchmarks are available to represent the industry. Most often, practitioners tend to benchmark CTAs against a basket of peers. The broadest of these fund-based benchmarks is the Barclay CTA Index which, as of July 2014, includes 551 programs out of 1073 operating managers.

Baltas and Kosowski (2012) are the first who attempt to establish market-based objective benchmarks for Managed Futures, extending the work of Moskowitz et al. (2012). Baltas and Kosowski evaluate the phenomenon of time series momentum over a broader grid of lookback periods and investment horizons. The authors find evidence of time-series momentum at different lookback and holding periods and low correlations among the selected momentum strategies. They coin the selected strategies Futures-based Trend-following Benchmarks (TFBS) and suggest that time series momentum at different frequencies captures distinctly different variations of time series momentum. The authors also conclude that time series momentum factors do a good job explaining Managed Futures' returns.

We make several contributions to the currently expanding literature on time series momentum and its relationship with Managed Futures. First, we document substantial time-variation in the profitability of time series momentum strategies. This implies that the optimal specification for applying time series momentum strategies varies considerably over time and asset class. Applying time series momentum strategies therefore seems to be less self-evident than might be expected. Second, we extend the existing work on time series momentum along the asset class dimension. An extension along this line has the benefit that we can employ the resulting asset class benchmarks in the context of a standard style analysis. In the seminal work on trend-following funds, Fung and Hsieh (2001) construct Primitive Trend-following Strategy (PTFS) Factors for bonds, currencies, commodities, short-term interest rates and equities using lookback straddles, arguing they capture trend-following funds' profit opportunities[1]. Our asset-class specific time series momentum factors allow for a similar decomposition of funds' performance along the different asset classes. In particular, the benchmarks allow allocators to analyze both the time dimension as well as the asset class dimension of the trend-following funds under consideration. As the vast majority of Managed Futures are diversified across different asset classes, a breakup of the exact exposures might be a relevant consideration in the industry.

[1] Baltas and Kosowski (2012) report that time series momentum factors come to replace the PTFS-factors in terms of explaining Managed Futures' returns.

Third, the observed time-varying nature of time series momentum profitability and considerable differences across asset classes motivate us to construct *dynamic* time series momentum strategies that take positions based on strategies' past performance. At the same time, we also analyze the potential value of allowing for contrarian position-taking. While taking the opposite side to the time series momentum trade is straightforward given the particular nature of futures markets, its benefits have not yet been investigated. Interestingly, we find that contrarian position-taking can significantly improve the overall performance of strategies that attempt to exploit time series momentum. Especially in recent years, blending a standard time series momentum approach with contrarian position-taking would have yielded considerable benefits.

Finally, we find that the estimated alphas in the context of performance evaluation using our benchmarks do not differ statistically from the level of trading costs typically incurred by Managed Futures programs. This confirms an earlier argument voiced by Kazemi and Li (2009). The authors suggest that negative alphas in Managed Futures might be explained by the fact that, while Managed Futures returns are net-of-fees, the futures-based benchmarks do not consider transaction costs. As such, an important factor in explaining industry-wide underperformance of CTAs *vis-à-vis* the time series momentum based benchmarks might be fees and transaction costs, which as discussed by Kazemi and Li (2009) have very little impact on the estimated factor exposures, but on the estimated alphas.

2. Data Description

We briefly describe the data sources we use in our subsequent analysis.

2.1. Futures Data

The dataset that we use consists of daily Opening, Low, High, and Close Price as well as Open Interest and Volume for 92 futures contracts across four asset classes. Individual futures contract data are obtained from CSI Data and covers the period from January 1990 to July 2014. In Table 1 we report the list of futures contracts covered: 13 currencies, 27 equity indices, 19 government bond contracts, and 33 commodity contracts. Since some contracts only started trading or were discontinued during the sample period, we also report in the period over which each contract is actually included in the analysis.

[Table 1 about here]

Since futures contracts are short-lived contracts that expire at a predetermined delivery month, we first need to construct a continuous times series of futures prices for each contract. To this end, we follow the standard approach in the literature by ensuring that we are always using the price on the most liquid contract at each point in time (see Miffre and Rallis 2007, Moskowitz et al. 2012, Baltas and Kosowski 2012). In practice, the nearest-to-delivery contract is often the most liquid. However, as market participants start to roll over their contracts a couple of days/weeks before delivery of the nearest-to-deliver contract, the second-to-delivery contract becomes the dominant, more commonly traded contract. Using the Open Interest for every contract we determine the most liquid contract at every point in time and roll over when the Open Interest of a more distant contract exceeds the Open Interest of the contract currently held.

In addition to the roll over date, we also need to adjust the price of the contract on the roll date. This is because futures contracts on the same underlying asset that have different expiry dates typically trade at different prices. These differences are driven by contango- and backwardation factors which materialize in the so-called roll yield. Consequently, selling the current contract and buying the second-to-delivery contract at a higher (lower) price will cause an artificial return if we do not take into consideration that this price difference is due to the fact that these are two distinct and different contracts. In order to avoid this feature of futures contracts to distort the observed returns, we proportionally back-adjust the entire futures series at each roll date. This means that the continuous price series up to the roll date is multiplied by the ratio of the futures prices of the new and the old contract. While other methods for joining the futures contracts into a continuous series exist[2], proportional back-adjustment ensures a constant relationship between prices across the newly constructed time series and is thus strictly necessary for a percentage-based analysis method such as the one conducted here.

The daily returns we calculate from the above constructed continuous futures price series are equivalent to fully collateralized (unleveraged) returns in excess of the risk-free rate (for a thorough discussion, see Baltas and Kosowski (2014) and references therein). As such, the returns constructed as

[2] For an overview, see Masteika, Rutkauskas, and Alexander (2012).

$$r_t = \frac{F_t - F_{t-1}}{F_t}$$

where F_t and F_{t+1} correspond to the futures prices from the continuous futures price series at time t and time $t + 1$ are daily *excess* returns.

2.2. Managed Futures Data

For the analysis of the relationship between time series momentum and Managed Futures' performance we collect monthly net-of-fee returns of live and dead funds labeled CTA in the BarclayHedge Database[3]. We employ data on Managed Futures funds which covers the period January 1994 to July 2014. We employ data from January 1994 to mitigate a potential survivorship bias, since most databases only started collecting information on defunct programs from 1994 onwards. We then filter the sample of funds by looking at their self-declared strategy description and remove funds whose description is not consistent with the definition of CTAs. In the process, we also determine whether the program under consideration is the fund's flagship program and discard duplicates. Finally, we focus on funds that report their returns either in USD or EUR and engage in systematic trading. The EUR-denominated returns and assets-under-management (AUM) are converted to USD using the end-of-month EUR/USD spot rate.

Determining which Managed Futures are *systematic* is based on the self-declared strategy description as well as an analysis of the fund's return characteristics. From this classification, we choose the set of funds that we label as systematic trend-followers, systematic short-term traders, systematic commodity, and FX specialists [4].

[3] Although reporting to hedge fund databases is voluntary, Joenväärä et al. (2012) – in a thorough analysis of the different available hedge fund databases – conclude that BarclayHedge is the most comprehensive hedge fund database, especially for Managed Futures.

[4] This classification corresponds to the in-house classification employed by RPM, the Swedish Managed Futures specialist. Managed Futures programs that are engaged in trend-following strategies, apply relatively long holding periods (i.e., more than one month), and which show a fairly higher correlation with the Newedge trend Index are assigned to the systematic trend-followers group. These programs are usually diversified and invest across many liquid futures markets. In contrast, the short-term trading programs generally trade more frequently and use holding periods that are usually less than one month. In this group, managers frequently employ non-trend-following strategies, such as short-term mean reversion strategies. As for the systematic commodity and the FX specialists, the focus of these groups is rather on the asset class. FX and commodity specialists are typically less diversified and concentrate on a few futures markets within the respective asset class.

After applying the above adjustments, we obtain a sample of 1550 systematic CTA funds. From this set of systematic funds, we construct a value-weighted index of systematic CTA funds. The funds are weighted using the reported assets under management. We rebalance the portfolio once a year, with rebalancing occurring at the end of June. When funds become defunct during the holding period, the remainder of the allocation to the fund is held in cash, earning the risk-free rate until the next rebalancing date.

Figure 1 shows the weighted average AUM of the funds included in the index and the AUM of the largest CTA in the index. The AUM of the largest fund included is more than three times larger than the industry average[5]. Figure 2 depicts the composition of the index in terms of number of CTAs and AUM. The latter suggests that the average program employs longer term trend-following approach in the industry.

[Figure 1 about here]

[Figure 2 about here]

In addition to an AUM-weighted Systematic Managed Futures index, we also construct an AUM-weighted Managed Futures index of CTAs that employ systematic strategies with *contrarian* components. To determine whether Managed Futures also engage in contrarian position-taking, we search for keywords in managers' trading program description that suggest that they are at least partly engaged in contrarian trading[6]. This does not imply that these funds are predominantly contrarian, but in principle the funds have a mandate to behave contrarian whenever the environment favors such an approach.

Figure 3 suggests that the AUM-weighted contrarian index suffers from *one-manager-risk*, meaning that the largest manager is assigned an unjustifiably large weight in the index. Therefore, and in addition to the AUM-weighted indices, we also construct equal-risk-weighted indices. The

[5] We note that the Managed Futures industry is higly concentrated. The average Gini coefficient in the sample period was 0.87 and has been increasing further recently, reaching 90% in July 2014. The AUM-weighted index can thus be considered as a *large capitalization* Managed Futures index.

[6] We have looked for the following characters in the funds' description provided to BarclaHedge: „conver", „rever", „contra", „counter" taking into account negation and false results like „contract", „converting", „convertible". Out of 1.550 managers in our dataset, 228 claim that they take contrarian positions at least time-to-time.

descriptive statistics for all indices are presented in Table 2. The contrarian indices tend to perform better benefiting from substantially lower volatility that is thanks to much lower tail-risk.

[Figure 3 about here]

[Table 2 about here]

3. Methodology

For the construction of the time series momentum strategies, we apply a similar methodology as Moskowitz et al. (2012) and Baltas and Kosowski (2012) (hereinafter MOP and BK, respectively). We consider time-series momentum strategies with different lookback- and holding periods. In particular, the future *k*-period return of a futures contract is predicted based on the sign of past *j*-period return, that is, *j* is the lookback and *k* is the holding period. In this study we consider daily, weekly, and monthly lookback and rebalancing frequencies. The reported returns, however, are always monthly. Hereinafter, we will refer to these strategies as *M/W/D(j,k)*, where *M*, *W*, and *D* stands for monthly, weekly, and daily strategies, respectively. That is,

$$r_{T+1,T+k,i} = \frac{1}{L}\sum_{l=1}^{L} sgn(r_{T-j,T,l,i})\frac{0.4}{\sigma_{T-59,T,l,i}} r_{T+1,T+k,l,i}, \tag{1}$$

where sgn is the signum function, L is the number of assets in the strategy, $i = [M, W, D]$ depending on the frequency, and $\sigma_{T-59,T,l,i}$ is based on RiskMetrics' standard exponentially weighted moving average (EWMA) estimator of volatility with a 60-day rolling window. Algebraically, the EWMA estimator is calculated as follows

$$\sigma_T^2 = (1-\lambda)\cdot\sum_{t=0}^{T}\lambda^{t-1}\cdot(r_t-\bar{r})^2 \tag{2}$$

where λ is the decay factor, which we set equal to the conventional 0.94. We follow Moskowitz et al. (2012) in using this simple model for estimating volatility because of its ease of implementation. To avoid look-ahead bias we lag the obtained volatility estimate one period.

The correction factor of 0.4 to the estimated volatility in Equation 1 is suggested by MOP as to achieve an ex ante volatility of 40%. The reasoning behind the scaling factor is to get risk factors with ex post volatility of around 12% per annum, which matches roughly the volatility of the factors in Fama and French (1993) (see Asness, Moskowitz, and Pedersen, 2010).

Similarly to MOP and BK we first form diversified strategy portfolios that invest in all four asset classes (equities, fixed income, FX, and commodities). In a second stage, and contrary to previous studies, we also analyze single asset class time series momentum strategies.

4. Results

In this section we first construct standard time series momentum benchmarks along the lines of the work of MOP and BK. We analyze the stability of time series momentum profitability and extend the analysis to consider single asset class-based portfolios as well. We find that time series momentum is quite sensitive to the particular specification and that there is considerable time-variation in the profitability of time series momentum strategies. Given these two findings, we consider possible extensions to improve the time series momentum benchmarks. We consider strategies that select the optimal parameter specification depending on strategies' past (risk-adjusted) performance. In addition, we explore the likely gains of contrarian position-taking. Finally, we look at the relationship between the different sets of benchmarks obtained and Managed Futures' performance, with particular focus on Managed Futures' dismal performance since 2012.

4.1. Baseline Time Series Momentum Benchmarks

To avoid confusion later on, we refer to the portfolios constructed using the standard time series momentum approach of MOP as 'baseline' time series momentum portfolios or benchmarks. BK in their work propose to use diversified *M(12,1)*, *W(8,1)*, and *D(15,1)* strategies as benchmarks, as they show low correlations with each other and do a good job explaining Managed Futures' returns. We repeat BK's analysis for the three different frequencies and consider lookback and holding periods of up to 60 days, 60 weeks, and 60 months for the daily, weekly, and monthly strategies, respectively.

We start off by reporting the results for the strategies proposed by BK for our particular sample of futures contracts over the period 1995-2014[7]. Applying the same approach to a somewhat different

[7] While the futures data covers the period 1990-2014, we consider lookback periods of up to 60 months back. As such, data on the benchmarks is only available from 1995 onwards.

sample period allows us to gauge the impact of the sample period on time series momentum profitability. In the process, we construct both diversified portfolios as well as portfolios consisting of a single asset class. The results, which we report in Panel A of Table 3, suggest that the particular specifications of the time series momentum strategies suggested by BK seem to have lost their luster recently. The underperformance is evident when we analyze the performance of the different asset classes separately. For example, both the monthly and daily FX and the daily equity strategies have posted negative Sharpe ratios in the second half of the sample period. In addition, the weekly FX strategy posted a timid Sharpe ratio of 0.07, which is only a fraction of the Sharpe ratio of the MSCI World (Total Return) Index over the same period (0.33). The weekly equity and fixed-income strategies also underperformed a simple buy-and-hold equity strategy in the second half.

These results suggest that the profitability of time series momentum strategies is time-varying and/or quite sensitive to the particular lookback- and holding period employed. In addition, negative performance for periods of approximately 10 years using a particular specification could be undesirable for at least one reason. If we wish to employ time series momentum strategies as benchmarks for the Managed Futures industry, it might be inappropriate to benchmark an industry against trend-following strategies that break down for extended periods of time. The benchmarks are unlikely candidates when the median fund age is only 3.8 years. Managers relying on unprofitable strategies for too long will quickly experience investor outflows or will be shut down. Instead, Managed Futures should be expected to adjust to changing market environments within months and adopt more profitable specifications and strategies. Otherwise, they risk termination and new managers with improved strategies should be expected to take their place.

For our particular data set, we review different lookback and holding period combinations for the time series momentum strategies and we propose an alternative set of parameters for the daily, weekly, and monthly strategies (Table 3, Panel B). In particular, we apply *M(11,1)*, *W(14,1)*, and *D(21,1)* for the monthly, weekly, and daily strategies, respectively. The strategies' performance is more robust over both halves of our sample period for all asset classes (with the notable exception of the daily commodity strategy) and shows a similar correlation structure as the strategies suggested by BK.

We note that we do not suggest that the above combinations of lookback windows and holding periods should be preferred to BK for *exploiting* time series momentum. Our aim is not to backtest the optimal parameter combination, with the intention of applying time series momentum strategies out-of-sample. Rather, we construct benchmarks that should proxy for profitable time series momentum opportunities that *existed* in the futures markets considered during the relevant sample period. Such benchmarks are then suitable for testing Managed Futures' ability to successfully capture time series momentum and can thus serve in the context of manager selection. The high degree of time-variation (infra) as well as the divergence between our results and those of BK actually caution against a static application of time series momentum strategies. In addition, our proposed baseline (static) benchmarks are not a one-size-fits-all for all asset classes. For example, the monthly FX strategies generate a negative Sharpe ratio in the second part of the sample period and the daily FX and equity strategies underperform the MSCI World (Total Return) Index. This suggests that a separate analysis along the asset class dimension could potentially yield additional insights.

Table 3 reports the (Pearson) correlation coefficients between the diversified benchmarks and the single asset class benchmarks. Clearly, the diversified benchmarks exhibit a relatively high average correlation with the single asset class portfolios, ranging from 0.56 to 0.61. Nevertheless, the single asset class benchmarks are only lowly correlated with each other. This indicates that there are considerable diversification benefits from capturing time series momentum in different asset markets. This finding also fits the industry practice of Managed Futures, where the vast majority of the programs are diversified across asset classes. The finding of time series momentum across different asset classes also corroborates the finding of MOP that time series momentum is remarkably consistent across very distinct asset classes. At the same time, the low correlations suggest that diversified momentum benchmarks alone are not to be the full story.

The results in Table 3 also suggest that *single asset* benchmarks can potentially add value over diversified benchmarks in decomposing Managed Futures' exposures when analyzing Managed Futures' performance. Low correlations between the different single asset class benchmarks do not distort statistical inference, however, multicollinearity issues can still arise when including single asset benchmarks with different evaluation periods. This might be the case particularly for weekly strategies, which exhibit high correlations of up to 0.6, both with monthly and daily strategies.

We now further analyze the stability of time series momentum's profitability. To do so, we report in Figure 4 the lookback period that corresponds to the best performing monthly, weekly, and daily diversified momentum strategies using one-year rolling data. We vary the lookback period from 2 to 12 months, 2 to 24 weeks, and 1 to 25 days. At the same time, we hold the holding period fixed at 1 month, 1 week, and 1 day for monthly, weekly, and daily strategies, respectively. In gray, we also highlight periods in which any of the best-performing monthly, weekly or daily strategies produces an annualized Sharpe ratio of less than 0.3[8]. We find that, independently from the particular frequency, the lookback period that corresponds to the best performing strategy is highly time-varying.

Despite this time-varying nature of the optimal time series momentum specification, we can still draw several conclusions from the results. First, in periods of financial stress, shorter lookback periods seem to be preferable, whereas in calm periods longer lookback periods typically perform better. Second, before 2012, there were only a few months when at least one of the three strategies exhibited a Sharpe ratio below 0.3. However, as of 2012 onwards, time series momentum strategies have experienced difficulties in generating performance. This reflects the unusual environment in which the Managed Futures were forced to operate and matches Managed Futures underperformance in recent years.

Overall, the results in Figure 4 indicate that our baseline 'static' Managed Futures benchmarks might be inappropriate to serve as benchmarks for Managed Futures. We find that there are extended periods of time during which none of the strategies, regardless of the frequency, succeed in generating desirable performance. This raises the question whether these benchmarks suffice to proxy for the performance of the Managed Futures industry.

[Table 3 about here]

[Figure 4 about here]

4.2. Dynamic Time Series Momentum Benchmarks

We find that there is considerable time-variation in the profitability of the time series momentum strategies. If this performance is secular, it is hard to expect managers not adapting to survive in the long run. Therefore, it is unlikely for the Managed Futures industry as a whole to following

[8] The (annual) Sharpe ratio threshold of 0.3 corresponds roughly to the Sharpe ratio of the MSCI World (Total Return) Index over the sample period.

specifications which turn out to be unprofitable for considerable periods of time when at the same time there other specifications provide better opportunities for profit. Therefore, in this subsection we propose a more 'dynamic' approach to applying time series momentum and investigate whether such an approach could add value with respect to the baseline 'static' benchmarks considered so far.

We do this by constructing two types of dynamic benchmark portfolios. The first set of dynamic portfolios evaluates the past performance of a wide range of potential time series momentum strategies and takes positions based on the strategies' past risk-adjusted performance. In particular, while we keep the holding period fixed at 1 day/week/month, the lookback period depends on the frequency and ranges from 1 to 25 days, 2 to 24 weeks, and 2 to 12 months for daily, weekly, and monthly strategies, respectively. At month-end we evaluate this spectrum of potential time series momentum strategies. If – for the preceding one year evaluation period – the best performing strategy for a particular frequency has produced an annual Sharpe ratio in excess of 0.3, then we allocate to that particular strategy[9]. The allocation is proportional to the squared Sharpe ratio of each strategy in the previous year. Hence, the stronger the signal, the more we allocate to the strategy. However, if none of the specifications reaches the minimum required Sharpe ratio at month-end, we invest in the baseline static strategies reported in Section 4.1.. We note that our approach only employs *past* information in deciding on whether or not we should allocate to a particular strategy and thus does not suffer from a look-ahead bias.

In addition to the above basic dynamic benchmark portfolios, we also consider a second, slightly more involved approach where we allow our strategy to take contrarian positions. With contrarian we refer to a position where we take the opposite side to the time series momentum trade (i.e. short the corresponding time series momentum portfolio). As such, when the one-year past performance of the *contrarian* strategy yields a higher risk-adjusted return than being trend-following, we take a contrarian position. Here too, we consider the annual Sharpe ratios of the set of potential contrarian strategies and allocate if the Sharpe ratio from executing the contrarian strategy exceeds 0.3 over the past year. The weighting scheme remains the same. If none of the strategies produce the desired minimum Sharpe ratio, then the portfolio again allocates to the baseline static (i.e. trend-

[9] The MSCI World (Total Return) Index has produced a Sharpe ratio of approximately 0.37 over the sample period which is comparable to our choice of minimum performance needed to initiate a position.

following) strategies. Thus, the portfolio formation rules for the dynamic and (enhanced dynamic) portfolios are as follows:

1, Determine at month-end (*T*) whether the momentum (momentum/contrarian) strategy *l* has produced a $SR_{T-11,T,l,i} \geq 0.3$ in the preceding year, where

$$if\ i = \begin{cases} M, & j = [2,12] \\ W, & j = [2,24]. \\ D, & j = [1,25] \end{cases}$$

2, If $SR_{T-11,T,l,i} \geq 0.3$, then assign $w_{T+1,T+1,l,i} = SR^2_{T-11,T,l,i} / \sum_{l=1}^{L} SR^2_{T-11,T,l,i}$ weight to strategy *l*, where *L* is the number of strategies which have produced a Sharpe ratio of at least 0.3 over a period of *[T-11,T]*.

3, If *L=0*, then use the corresponding static benchmark with a weight $w_{T+1,T+1,1,i} = 1$, where

$$j = \begin{cases} 11\ if & i = M \\ 14\ if & i = W. \\ 21\ if & i = D \end{cases}$$

In Table 4 we report the performance and correlation structure of both types of dynamic benchmarks. Similarly to the results on the static benchmarks in Section 4.1. we find that the diversified benchmarks remain highly correlated with single asset class benchmarks, single asset class benchmarks with the same frequency exhibit low correlations with each other, and weekly strategies remain highly correlated with the respective monthly and daily strategies.

[Table 4 about here]

Performance-wise however, the results for the dynamic and the enhanced dynamic strategies diverge. While the dynamic portfolios continue to suffer in the second half of our sample – with daily FX and equity benchmarks exhibiting negative performance – the enhanced dynamic benchmarks strategy exhibit performance that is much more even. Interestingly, while the overall profitability for the enhanced dynamic strategies has also dropped recently, the decline is not as large as in the cases of other benchmarks. In some cases, profitability has even *in*creased; the monthly and daily fixed-income, monthly and daily equity, and weekly fixed-income and weekly

FX strategies perform better. Clearly, not imposing the strategies to consider only trend-following strategies when no clear trends emerge and allowing room for successful contrarian position-taking seems to add value.

To put the advantage of the enhanced portfolios in perspective, we plot in Figure 5 one-year rolling Sharpe ratios for the monthly, weekly, and daily enhanced dynamic strategies as well as a proxy for performance of the Managed Futures industry. The latter equals an AUM-weighted index of *systematic* Managed Futures reporting to BarclayHedge. Figure 5 illustrates that, until 2010, the performance of the enhanced portfolios strongly follows the performance of the BarclayHedge index. However, more often than not our enhanced indices outperform on a risk-adjusted basis. The pattern becomes especially pronounced in the final period of our sample, which coincides with the worst performance Managed Futures since the industry's inception[10]. While Managed Futures' (risk-adjusted) performance was unprecedentedly weak in the past few years, our enhanced dynamic strategies seem to have successfully combined trend-following with contrarian strategies. Especially the daily and weekly strategies have managed to generate similar performance recently as in the past thanks to contrarian position-taking.

These results illustrate the potential value added from incorporating contrarian strategies. The improved performance of the enhanced portfolios sheds some light on the importance of portfolio construction and blending different strategy approaches. It also suggests that the Managed Futures industry as a whole does not rely on contrarian strategies. Consequently, this raises the question whether the enhanced dynamic benchmarks are representative of the industry. We will turn back to this question in later sections.

[Figure 5 about here]

4.3. Performance of Time Series Momentum Benchmarks

We further analyze the characteristics of the dynamic strategies. To this end, we provide further descriptive statistics in Table 5. For comparison, we also report our baseline static benchmarks as well as the benchmarks proposed by BK.

[10] In the Appendix Figure A1 shows the one-year rolling Sharpe ratio for the dynamic strategies and the systematic BarclayHedge index. Unlike enhanced dynamic strategies, dynamic strategies have not performed any better than the industry in recent years.

[Table 5 about here]

The dynamic benchmarks generally post lower Sharpe- and Sortino ratios than the static benchmarks except for the monthly FX and equity benchmarks. However, the difference in maximum drawdown is inconclusive, with almost as many benchmarks exhibiting higher drawdowns as lower drawdowns. This suggests that performance-wise, the dynamic benchmarks do not seem to be far better than the baseline benchmarks.

The results for the *’enhanced’* dynamic benchmarks paint a different picture. First, we observe a large drop in the magnitude of drawdowns, lying within reasonable levels for trend-following strategies. This in contrast to the drawdowns of the standard benchmarks, which are at times considerably higher than those typically experienced by Managed Futures programs. Second, the reduction in downside risk has contributed to remarkably higher performance statistics. In particular, in a number of instances Sortino ratios are twice as high as for the baseline benchmarks. The risk reduction also causes Sharpe ratios to be substantially higher for the enhanced dynamic benchmarks compared to the baseline or simple dynamic benchmarks. Clearly, the benefits from applying more dynamic approaches seems to be driven by the ability of these approaches to take contrarian positions in addition to trend-following positions. In such circumstances, the benchmarks experience much lower levels of tail risk and thus seem to offer a better risk-return tradeoff.

5. Managed Futures’ Returns and Time Series Momentum Benchmarks

We now turn to employing the above benchmarks as risk factors in a performance evaluation model to see how they relate to Managed Futures’ returns. To be more precise, we regress the *excess* returns[11] of the systematic AUM-weighted BarclayHedge CTA index against our baseline benchmarks, the baseline benchmarks suggested by BK, and the dynamic and enhanced dynamic strategies introduced above. The results for the different set of factors are reported in Panel A, B, C, and D of Table 6 and Table 7, respectively.

[Table 6 about here]

[11] While the benchmarks are based on individual futures' excess returns, Managed Futures typically report returns including the risk-free rate earned on the cash held as margin as investors are entitled to these returns as well. Since this return is risk-free, it should be excluded in performance evaluation as it is not a compensation for bearing risk.

[Table 7 about here]

In terms of adjusted-R^2s, our baseline benchmarks and the dynamic benchmarks outperform the benchmarks suggested by BK. This is the case both for the asset class specific factors (see Panel A, B, and C of Table 6) as well as the diversified benchmarks (see Panel A, B, and C of Table 7). This indicates that the standard asset allocation of the industry over our sample period was closer to *M(11,1)*, *W(14,1)*, and *D(21,1)* strategies and that there is some evidence for dynamic asset allocation decisions. The weekly and monthly dynamic benchmarks produce higher R^2s than our baseline benchmarks. This result suggests that medium- to longer term trend-followers adjust strategies following a breakdown in performance. However, we do not find evidence for this for the managers with relatively shorter investment horizons[12].

When we employ diversified benchmarks (Table 7) instead of single asset class benchmarks (Table 6), the adjusted-R^2s drop. However, the performance of weekly (diversified) dynamic benchmark is impressive. This factor alone explains over 50% of the variation in Managed Futures' returns, which is high considering the earlier results in BK. In their work, using a similar dataset, applying their proposed (static) benchmarks resulted in an adjusted-R^2 of 37.7%, whereas, the Fung and Hsieh (2004) 7 and the extended Fung and Hsieh (2001) 9 factors produced adjusted-R^2s of 26.54% and 29.83%, respectively.

The multivariate regressions suggest the weekly benchmarks to dominate, as these explain most of the variation in Managed Futures' returns. On the other hand, the estimated coefficients for the benchmarks at different frequencies are quite close to each other, suggesting that the benchmarks are to some extent interchangeable. This seems to be especially the case for the weekly benchmarks vis-à-vis the daily or monthly benchmarks. We conclude from this that, when the aim is to employ a parsimonious model, weekly factors should be preferred as they perform best and are able to capture most of the variation in short and long-term strategies as well. Consequently, it is not advisable to combine all three frequencies in the same model, given the possibility of multicollinearity issues.

[12] The one-year evaluation period for the daily strategies is perhaps too long to capture Managed Futures' strategy adjustment process. Calibrating the optimal length of the evaluation period of the dynamic benchmarks is beyond the scope of the current paper and we leave this for future research.

The results in Panel B of Table 7 match the specification suggested in BK and the results do not differ qualitatively. Adjusted-R^2s are somewhat higher than in their original work, which would be explained primarily by the fact that BK's dataset spans January 1994 to December 2011 and the authors use 71 futures contracts whereas we include a somewhat wider set of contracts. In particular, our sample is more comprehensive in that we also include a number of commonly traded metal-related futures from LME as well a wider set of currency pairs[13].

The regressions that exhibit higher R^2s and the models that apply enhanced dynamic strategies (Panel D in Table 6 and 7) generally produce significantly *negative* alphas. However, we would refrain from interpreting these results as evidence for CTA underperformance at this stage. Our models still exclude a number of potential risk factors have been found to explain Managed Futures' returns. In the next section, we address this particular question by extending the models using Fung and Hsieh's proposed factors (2001, 2004) and a number of buy-and-hold portfolios on various asset classes.

5.1. Style Analysis of Managed Futures' Returns

The strategies identified above can serve in the context of style analysis of CTA returns. It is a common practice in mutual fund- and hedge fund literature to decompose fund's returns into two distinct components. The exposure to different style benchmarks is termed the style of the manager, whereas the unexplained residual part reflects the manager asset picking ability, at least when the style benchmarks are appropriately specified (Sharpe, 1992).

For the sake of correct inference, we follow the approach of Dor and Jagannathan (2002) and use forward stepwise least-squares regressions to determine the most important factors that explain Managed Futures' returns. In doing so, we hold a 'horse race' among competing factors. Altogether 64 possible factors take part in the race including the 48 single asset class time series momentum benchmarks, the 5 lookback straddle options-based primitive trend-following factors (PTFS) of Fung and Hsieh (2001, 2004) for bonds, commodities, FX, interest rates and stocks, the remaining Fung-Hsieh factors; the S&P 500 and MSCI Emerging Market index returns, the monthly change in the 10-year T-note yield, the monthly change in the credit spread (the BAA bond yield over the 10-year T-note yield) and the small firm factor that is defined as the difference between Russell

[13] Our volatility measure is also slightly differ which could cause the factors to deviate slightly.

2000 and S&P 500 returns. Furthermore, we add total return indices such as the MSCI All Country World Index, MSCI All Country World Index excluding the US, MSCI Europe, Australasia and Far East (EAFE), MSCI World Index, Goldman Sachs Commodity Index (GSCI) and Citigroup World Government Bond Index (WGBI) as potential candidates to capture Managed Futures' performance.

To avoid multicollinearity and improper inference, a list of restrictions are put in place when running the stepwise regressions[14]. The restrictions have been calibrated in such a way that, if a factor comes in in an earlier step, the factor with which it highly correlates (in absolute value) cannot come in in a later step. The iteration stops if no factor can be added that produces a significant t-statistic at 10% level; the results are reported in Table 8. The risk factors have been adjusted to have the same volatility of 10% per annum, applying one-year moving standard deviation. To avoid a potential look-ahead bias the rolling data used to calculate volatility is lagged one month[15].

For our baseline portfolio, the asset-weighted systematic CTA index (Table 8, Eq. (1)), the most important asset class is clearly fixed income, with long-term bond market momentum allocations being the largest exposure in the industry. Risk-wise, the industry's second-largest exposure is commodities. Interestingly, exposure to commodity momentum strategies and simple buy-and-hold investments in commodities seem to be equally important. Finally, CTAs allocate a non-negligible amount to FX momentum strategies. The set of selected risk factors is able to explain 64% of the variation in Managed Futures returns, which is quite high.

Among the competing momentum benchmarks, dynamic strategies appear to be most important explaining the major part of the variation in Managed Futures returns. Dynamic benchmarks are successful in describing equity and fixed-income momentum strategies. The baseline benchmarks

[14] For example, the correlations between different types of single asset class momentum benchmarks referring to the same asset class are generally high. Moreover, PTF factors exhibit high correlation with daily and weekly momentum benchmarks and weekly momentum strategies with daily and monthly momentum benchmarks. The buy-and-hold equity benchmarks are also highly correlated. The change in the 10-year yield exhibits high negative correlations with weekly and monthly fixed income momentum benchmarks, the Citigroup WGBI index and the credit spread. The credit spread is negatively correlated with equity benchmarks.

[15] This way the estimates can be directly compared. Volatility adjustment is a common practice in the Managed Futures industry as portfolio volatility can easily be adjusted to a desired target volatility raising or reducing the leverage of the portfolio. It is similar to standardization in the sense it does not change the significance of independent variables, but here the intercept is of utmost interest, thus we do not demean the variables.

however, especially the ones proposed in this paper, are useful in explaining commodity and FX momentum exposures in the CTA industry. Nevertheless, the role of buy-and-hold asset benchmarks is also significant given the inclusion the GSCI index. Interestingly, *none* of the enhanced dynamic indices have entered in the regression. This confirms that, generally, the Managed Futures industry does not engage in contrarian position-taking.

Compared to the above proposed time series momentum strategies, Managed Futures seem to underperform by approximately 5% per annum, which is significant at any usual significance level. We should note, however, that all the above benchmark strategies do not take into consideration trading costs, which can be substantial. Indeed, in one of RPM's flagship large capitalization funds, trading costs incurred amounted to 1.58% of AUM between August 2013 and July 2014[16]. Furthermore, according to Elaut et al. (2013) the typical fee structure of hedge funds and CTAs consists of a management fee of usually 2% of AUM and an incentive fee of usually 20% of profit. The average return of the single asset class naïve momentum strategies is 12% per annum, which would result in an incentive fee of approximately 2.4% of AUM per annum depending on the crystallization frequency. Altogether, costs would be close to 6% per annum which would exceed the observed 'underperformance'. This suggests that CTAs can recuperate only a fraction of the costs associated with investing with them and the performance of Managed Futures strategies is not worse than the performance of naïve momentum strategies. As such, the measured underperformance would be entirely due to trading and fund costs.

5.2. A Closer Look at Managed Futures and Contrarian Position-taking

The above analysis points to a potentially important factor from which Managed Futures programs could benefit. As we have shown, time series momentum profitability seems to be highly time-varying and there are periods in which standard time series momentum strategies are not profitable at all. During such spells, mechanically taking into account the time-varying nature of momentum profitability does not seem to work. At least, our dynamic benchmarks that take into account past performance are unable to improve performance. An interesting hypothesis worth testing is

[16] The trading costs include all the trading related costs such as gross commission, clearing fee, exchange fee, NFA charge, brokerage fee, and execution fee.

therefore whether managers that also take contrarian positions tend to outperform classic trend-followers.

[Table 8 about here]

To this end, we first rerun the stepwise regression on the AUM-weighted index of *contrarian* managers; Table 8, Eq. (2) shows the estimates. The magnitude of the coefficients and the R^2 have dropped. Although the results seem to support the hypothesis that Managed Futures with both pro- and contra-trend allocations tend to outperform simple trend-following strategies, we have to note that the drop in explanatory power is likely due to under-diversification of the index. Figure 3 shows that the average AUM of the contrarian index is quite close to the AUM of the largest manager included in the index. That is, the contrarian AUM-weighted index is not representative for contrarian managers but for the specific manager having the highest AUM. Thus, we abjure from interpreting the results in details, and instead rerun the regression on an equal-risk-weighted contrarian index[17].

For comparison, we first run the stepwise regression on the equal-risk-weighted index that includes *all systematic* managers and Eq. (3) in Table 8 shows the results. The equal-risk-weighted index of systematic managers can be considered as a small capitalization index as it assigns larger weights to smaller managers and thus lower weights to larger managers. The allocations of small capitalization managers are substantially different from those of their larger peers. First of all, asset class-wise, the portfolio is more diversified; almost an equal amount of risk seems to be allocated to each asset class with fixed-income remaining the most important and stock exposure being the least important. Moreover, position-taking is skewed to shorter-term strategies which also contrasts to the results for the AUM-weighted index, which exhibits more or less equal exposures to shorter- and longer term strategies. One other notable difference is that smaller managers follow more dynamic approaches than their larger peers loading more on static factors. Finally, on a risk-adjusted basis, smaller managers perform better than their larger counterparts as the annualized alpha has increased to -3.06% (see column (3), Table 8).

[17] We have excluded all CTAs managing less than 10 million at the time of portfolio formation (at the end of each June) to avoid allocating unjustifiably large amounts to too small managers.

It is important to emphasize that we find better performance for a regression specification that explains more variation in CTAs' returns (i.e. an adjusted-R^2 of 70%). This better performance of smaller managers is unlikely to be related to a more favorable cost structure. An in-house analysis by RPM suggests that AUM-weighted management- and incentive fees do not differ across small and large managers[18]. However, we have to note that the better performance of the equal-risk-weighted index is not necessarily related to superior managerial skills of small managers, but might be related to better diversification of the index[19].

Next, we turn our attention to the equal-risk-weighted index of *contrarian* managers in column (4) of Table 8. We observe a further drift to shorter-term strategies at the expense of longer-term strategies and a more balanced portfolio from a diversification perspective. Dynamic strategies prevail in explaining portfolio returns. However, Fung and Hsieh's FX PTFS factor best captures returns generated from FX momentum. The explanatory power of the model is lower than for the large capitalization index, but remains high compared to previous models reported in related literature. Interestingly, there is some minor evidence for significant short-term systematic contrarian position-taking in equity markets. While we have refrained from interpreting the results for the AUM-weighted contrarian index, the negative coefficient for the MSCI World Index suggests some contra-trend positioning in the stock markets[20]. Contrarian managers, in contrast to trend-followers, do not underperform naïve momentum strategies and seem to fully cover their costs.

The fact that the enhanced dynamic indices do not enter any of the regressions of the contrarian index suggests that the managers included in the contrarian index initiate contra-trend bets less frequently than would be signaled by our proposed enhanced dynamic strategies. Therefore, an interesting question is the potential benefits for managers from more frequent contrarian position-taking.

[18] In the report small (large) managers are defined as below (above) the industry's median AUM at the time of portfolio formation (at each June).

[19] Disentangling the puzzle of the better performance of the equal-risk-weighted index is beyond the scope of the current paper and it is left for future research.

[20] Positive trends are more frequent in equity markets than negative trends, thus the combination of a short buy-and-hold portfolio and a trend-following portfolio suggests overall a contrarian setup, but in practice means a less bullish attitude in uptrends and a more bearish attitude in downtrends.

To tackle this final question, we can quantify the potential benefits our proposed trading approach by applying the stepwise regression methodology to explain the enhanced dynamic factors' performance. At the same time, we constrain the set of potential factors to the baseline and dynamic strategies. In other words, we employ the performance evaluation approach with the enhanced dynamic factors' proxying for the performance of a diversified Managed Futures program that engages in contrarian risk-taking as described Section 4.2.

The results are in reported Table 9. As expected, we find that the enhanced dynamic strategies produce significant positive alphas (gross of fees) when benchmarked against dynamic and static momentum strategies. The abnormal return is declining in the frequency of the portfolio rebalancing. For example, the daily enhanced dynamic strategy posts a spectacular alpha of 11.04%, which is significant at any conventional level. Considering trading costs of approximately 6% per annum, a 5% annualized alpha is still remarkable. The weekly and monthly strategies generate less attractive alphas when taking into consideration the impact of trading costs; -1.71% and -3.45%, respectively. Nevertheless, the level of performance of the weekly strategy would still exceed the performance of the AUM-weighted and equal-risk-weighted systematic BarclayHedge index. The monthly strategy however, would only exceed the performance of the AUM-weighted CTA index.

[Table 9 about here]

Interestingly, the contrarian index suggests a preference for shorter term strategies (Table 8, Eq. 4) and we find that shorter-term enhanced dynamic strategies are superior. Moreover, both the daily and weekly enhanced dynamic strategy load negatively on buy-and-hold equity portfolio, the former on the S&P 500, the latter on the MSCI All Country World Index. This indicates that the contrarian profitability comes from shorter-term contrarian equity positions as we suspected when analyzing the BarclayHedge contrarian index. This is not striking in virtue of the fact the Sharpe ratio of the enhanced dynamic equity strategy exhibits the best improvement with respect to other daily equity momentum strategies.

5.3. Robustness Checks

In light of the above results we analyze the stability of our results along two dimensions that might have a material impact on the above findings.

To analyze whether our results are representative for popular manager-based CTA indices, we repeat the style analysis using the Barclay CTA Index, Barclay Systematic Traders Index, BTOP50 index, Newedge CTA Index and Newedge Trend Index[21]. The results, reported in Table A1, suggest that the results are robust to this consideration.

Second, the dynamic portfolio approach proposed in Section 4.2 relies on a minimum required Sharpe ratio – which corresponds roughly to the Sharpe ratio from a buy-and-hold strategy in MSCI World (Total Return) Index – for the strategies to initiate a position. A natural question is to analyze the sensitivity of our results with regard to the minimum required Sharpe ratio. To this end, we report the performance of the various strategies using both a minimum required Sharpe ratio of 0.2 as well as 0.4. Table A2 reports the performance of specifications that employ a Sharpe ratio of 0.2 and 0.4. Clearly, the properties of the benchmarks don't change. Actually, the table indicates that a 0.4 cutoff value leads to performance that slightly exceeds the performance of the baseline model. In Table A3 we repeat the regressions and find that our results do not change materially.

6. Conclusion

We analyze the phenomenon of time series momentum for a broad set of futures contracts and across 4 distinct asset classes and find that time series momentum profitability is time-varying and sensitive to the particular specification of the lookback period. In addition, while time series momentum across different asset classes is positively related, single asset class portfolios capture sufficiently different time series momentum patterns to warrant a separate treatment.

Despite the time-varying nature of time series momentum profitability, improving time series momentum strategies by incorporating past performance of the strategy does not seem to be an obvious way of improving the performance of time series momentum strategies. More interestingly, there seems to be considerable gains from contrarian position-taking, i.e. taking the opposite trade of the time series momentum portfolios, when past risk-adjusted performance suggests this to be a profitable trade.

[21] The Barclay CTA index and BTOP50 are considered as the industry's benchmarks among practitioners. While the former is a broad index, the latter is a large cap index that represents, in aggregate, no less than 50% of the investable assets of the Barclay CTA Universe as of 2014 with 551 and 20 constituents, respectively.

We then continue to explore the relationship between time series momentum and Managed Futures' returns. We conclude, based on a performance evaluation that the measured underperformance in Managed Futures returns seems to stem from two sources. First, systematic strategies underperform in periods when momentum strategies are not profitable due to the fact that combining trend-following strategies with contrarian strategies is not widespread in the industry. Furthermore, trading costs are non-negligible in Managed Futures' returns, thus benchmarks disregarding transaction costs overestimate the underperformance. Moreover, the performance of enhanced dynamic benchmarks that combine trend following strategies with contrarian strategies sheds some light on the importance of portfolio construction and thus on the potential diversifying role of Funds of Hedge Funds.

Exchange	Contract	Inception Date	End Date	Mean Return	Standard Deviation	Skewness	Kurtosis	MDD	Sharpe	CAGR
CME	Mexican Peso	25/04/1995	31/07/2014	0.51%	3.06%	-1.065	7.013	31.2%	0.168	5.72%
CME	Swiss Franc	02/01/1990	31/07/2014	0.15%	3.25%	0.022	3.901	49.4%	0.046	1.16%
CME	British Pound	02/01/1990	31/07/2014	0.19%	2.68%	-0.640	5.482	29.4%	0.070	1.81%
CME	Canadian Dollar	02/01/1990	31/07/2014	0.10%	2.22%	-0.274	6.407	28.2%	0.045	0.89%
CME	Japanese Yen	02/01/1990	31/07/2014	-0.03%	3.17%	0.593	6.028	58.4%	-0.008	-0.91%
CME	Australian Dollar	02/01/1990	31/07/2014	0.31%	3.32%	-0.373	4.934	41.3%	0.092	3.04%
FINEX	USD Index	02/01/1990	31/07/2014	-0.13%	2.45%	0.421	3.935	44.3%	-0.055	-1.94%
CME	Euro Fx Day-Only	04/01/1999	31/07/2014	0.10%	3.02%	-0.067	3.877	31.9%	0.034	0.67%
CME	South-African Rand Day Only	07/05/1997	31/07/2014	0.25%	4.85%	-0.220	3.669	46.9%	0.052	1.63%
CME	Brazilian Real	10/11/1995	31/07/2014	0.60%	5.27%	-1.639	14.786	42.6%	0.113	5.46%
FINEX	USD/Swedish Krona	12/05/2000	06/08/2014	-0.11%	3.43%	0.220	3.547	45.5%	-0.033	-2.04%
FINEX	USD/Norway Krone	12/05/2000	06/08/2014	-0.26%	3.34%	0.636	4.808	50.8%	-0.077	-3.66%
CME	New-Zealand Dollar Day Only	07/05/1997	31/07/2014	0.40%	3.85%	-0.197	4.479	41.3%	0.105	4.01%
MATIF	CAC-40 Inx (10 Euro)	02/01/1990	31/07/2014	0.36%	5.61%	-0.343	3.199	62.9%	0.064	2.42%
CME	Nikkei 225 Index	25/09/1990	31/07/2014	-0.05%	6.34%	-0.078	3.305	77.5%	-0.008	-3.01%
CME	Russell 2000 Index	04/02/1993	11/06/2008	0.53%	5.13%	-0.443	4.245	42.7%	0.104	4.86%
CME	S&P Midcap 400 Index	13/02/1992	31/07/2014	0.79%	4.85%	-0.677	5.300	52.7%	0.163	8.34%
HKFE	Hang Seng Index	02/01/1990	31/07/2014	1.01%	7.60%	0.246	5.351	58.9%	0.133	9.01%
EUREX	Dax Index	23/11/1990	31/07/2014	0.59%	6.02%	-0.533	4.951	71.7%	0.099	4.99%
CME	S&P 500 Stock Ix Day	02/01/1990	31/07/2014	0.54%	4.28%	-0.636	4.205	58.6%	0.126	5.44%
TSE	Topix Index Combine	03/04/1990	31/07/2014	-0.02%	5.81%	-0.151	4.042	73.1%	-0.004	-2.28%
LIFFE	FTSE 100 Index	02/01/1990	31/07/2014	0.30%	4.24%	-0.401	3.435	52.8%	0.071	2.56%
EUREX	Swiss Market Index	09/11/1990	23/07/2014	0.75%	4.56%	-0.612	4.562	52.7%	0.165	8.03%
MEFF	Ibex 35 Index	20/04/1992	31/07/2014	0.69%	6.36%	-0.249	3.544	59.2%	0.108	5.91%
MIF	MIB 30 Stock Index	28/11/1994	10/06/2004	0.62%	7.04%	0.363	3.335	57.0%	0.088	4.58%
CME	Nasdaq 100 Index	10/04/1996	31/07/2014	0.96%	7.92%	-0.284	3.921	83.0%	0.121	7.94%
SGX	MSCI Taiwan Index	09/01/1997	31/07/2014	0.52%	7.87%	0.106	3.691	64.7%	0.066	2.53%
CBT	DJ Industrial Avg	06/10/1997	31/07/2014	0.41%	4.44%	-0.607	4.172	49.8%	0.093	3.80%
KSE	Kospi 200 Index	20/01/1998	31/07/2014	0.97%	8.70%	0.316	3.914	58.6%	0.112	7.40%
EUREX	Dow Jones Stoxx 50	22/06/1998	31/07/2014	0.14%	4.85%	-0.532	3.841	66.7%	0.028	0.22%
EUREX	Dow Jones Euro Stoxx	22/06/1998	31/07/2014	0.24%	5.75%	-0.455	3.828	64.0%	0.042	0.85%
ME	S&P Canada 60 Index	07/09/1999	31/07/2014	0.49%	4.41%	-0.747	4.595	51.8%	0.112	4.81%
CFE	CBOE Volatility Inde	29/03/2004	31/07/2014	-3.58%	16.79%	1.718	8.395	99.8%	-0.214	-44.71%
SOM	OMX Index Futures	12/10/1992	31/07/2014	0.99%	6.37%	0.027	4.641	72.4%	0.156	9.90%
LIFFE	US Mini Msci Eafe	27/09/2010	31/07/2014	0.82%	4.71%	-0.554	3.365	24.5%	0.176	8.66%
EOE	Amsterdam EOE Index	12/10/1992	31/07/2014	0.62%	5.72%	-0.746	4.818	68.9%	0.109	5.54%
NYFE	NYSE Composite Index	02/01/1990	11/06/2003	0.45%	4.00%	-0.568	4.007	38.3%	0.114	4.53%
NYFE	NYSE Comp Index Revi	01/10/2003	09/09/2011	0.19%	4.79%	-0.961	5.346	57.4%	0.039	0.84%
SFE	All Ordinary Spi Rth	02/01/1990	20/09/2001	0.29%	4.07%	-0.318	2.900	28.7%	0.071	2.47%
SFE	SPI 200 Rth	03/05/2000	31/07/2014	0.34%	3.77%	-0.801	3.901	51.9%	0.091	3.29%
CBT	Treasury Bonds	02/01/1990	31/07/2014	0.42%	2.70%	0.109	5.235	15.8%	0.157	4.73%
ME	Canada 10yr Gov Bond	02/01/1990	31/07/2014	0.33%	1.74%	-0.091	3.234	14.8%	0.192	3.87%
CME	Eurodollar (3 Month)	02/01/1990	31/07/2014	0.06%	0.26%	0.683	5.567	2.8%	0.246	0.76%
CBT	10-Yr Treasury Note	02/01/1990	31/07/2014	0.36%	1.74%	0.127	4.695	11.7%	0.205	4.15%
TSE	Japan Govt Bond, 10y	04/04/1990	31/07/2014	0.31%	1.24%	-0.571	6.655	9.6%	0.252	3.70%
LIFFE	Long Gilt	02/01/1990	31/07/2014	0.26%	1.98%	0.006	3.518	17.2%	0.129	2.86%
CBT	2-Y Treasury Note	22/06/1990	31/07/2014	0.14%	0.48%	0.226	3.492	3.8%	0.280	1.61%
SFE	10 Yr Bonds Rth	02/01/1990	23/07/2014	0.05%	0.34%	-0.099	3.602	4.1%	0.154	0.62%
SFE	90-Day Bank Bill Rth	02/01/1990	31/07/2014	0.05%	0.32%	0.487	6.380	2.7%	0.152	0.57%
SFE	3 Year Bonds Rth	02/01/1990	23/07/2014	0.07%	0.40%	-0.058	5.132	3.6%	0.180	0.86%
CBT	5-Yr Treasury Note	02/01/1990	31/07/2014	0.26%	1.18%	0.096	3.867	8.5%	0.220	3.06%
CBT	Muni Note Index	02/01/1990	12/12/2005	0.40%	2.00%	-0.486	3.712	18.0%	0.202	4.66%
EUREX	Euro Buxl	02/10/1998	31/07/2014	0.39%	2.96%	0.884	5.672	16.0%	0.134	2.99%
EUREX	Euro German Bund	05/10/1998	31/07/2014	0.30%	1.55%	0.140	2.890	9.9%	0.193	3.46%
EUREX	Euro German Bobl	05/10/1998	31/07/2014	0.21%	0.95%	0.066	2.708	7.4%	0.222	2.50%
EUREX	Euro German Schatz	05/10/1998	31/07/2014	0.08%	0.39%	0.181	3.816	4.0%	0.197	0.92%
KOFEX	Korean Bond, 3 Year	29/09/1999	10/12/2007	0.23%	1.02%	-0.127	3.773	5.4%	0.231	2.76%
MATIF	Pibor	02/01/1990	16/06/1999	0.00%	0.44%	-1.546	11.470	6.6%	-0.003	-0.03%
EUREX	Euribor (3 Month)	21/09/1998	31/07/2014	0.03%	0.18%	2.349	20.832	2.1%	0.156	0.33%
IPE	Gas Oil	03/01/1990	31/07/2014	1.06%	9.14%	0.417	5.305	71.2%	0.116	8.10%
NYMEX	Natural Gas	03/04/1990	31/07/2014	-0.85%	14.05%	0.567	4.532	99.7%	-0.061	-19.80%
IPE	Brent Crude Oil	03/01/1990	14/08/2014	1.26%	9.46%	0.668	7.250	73.2%	0.134	10.41%
NYMEX	Heating Oil Fin Penu	12/06/2006	31/07/2014	0.13%	7.64%	-0.501	4.675	69.1%	0.017	-2.02%
NYMEX	Light Crude Combined	02/01/1990	31/07/2014	0.81%	9.57%	0.459	5.497	77.2%	0.085	4.41%
NYMEX	Unleaded Gas	02/01/1990	20/11/2006	1.34%	10.59%	0.848	6.042	63.2%	0.127	10.06%
GLBX	Rbob Electronic	03/10/2005	31/07/2014	0.88%	9.42%	-0.748	6.409	70.4%	0.094	4.99%
COMEX	Copper, High Grade	03/01/1990	31/07/2014	0.76%	7.51%	-0.052	5.676	63.9%	0.101	5.79%
NYMEX	Platinum	03/01/1990	31/07/2014	0.56%	5.88%	-0.608	6.671	62.3%	0.096	4.71%
COMEX	Silver	03/01/1990	31/07/2014	0.50%	8.31%	0.079	3.836	62.7%	0.060	1.81%
COMEX	Gold	03/01/1990	31/07/2014	0.25%	4.58%	0.149	4.253	61.5%	0.054	1.72%
NYMEX	Palladium	09/01/1990	31/07/2014	0.99%	9.51%	0.481	6.704	86.2%	0.104	6.68%
CME	Live Cattle	02/01/1990	31/07/2014	0.08%	3.76%	-0.725	6.104	45.1%	0.022	0.12%
CME	Live Hogs	02/01/1990	31/07/2014	-0.31%	7.06%	-0.087	3.744	92.3%	-0.045	-6.57%
CME	Pork Bellies	02/01/1990	15/07/2011	0.53%	10.93%	0.843	4.673	80.0%	0.049	-0.45%
CME	Feeder Cattle	03/01/1990	31/07/2014	0.30%	3.82%	-0.515	5.550	38.6%	0.080	2.78%
CBT	Corn	02/01/1990	31/07/2014	-0.13%	7.46%	0.287	4.052	84.5%	-0.018	-4.77%
CBT	Oats	02/01/1990	31/07/2014	0.08%	8.59%	0.619	4.624	88.8%	0.009	-3.30%
CBT	Soybeans	03/01/1990	31/07/2014	0.54%	6.72%	-0.065	3.807	50.5%	0.081	3.84%
CBT	Soybean Meal	03/01/1990	31/07/2014	0.99%	7.24%	0.274	3.824	43.7%	0.137	9.08%
CBT	Soybean Oil	03/01/1990	31/07/2014	0.08%	7.02%	0.117	4.785	68.9%	0.012	-1.97%
CBT	Wheat	02/01/1990	31/07/2014	-0.44%	7.78%	0.451	4.842	93.1%	-0.056	-8.46%
KCBT	Wheat	02/01/1990	31/07/2014	0.10%	7.72%	0.565	4.802	76.3%	0.013	-2.29%
CSCE	Cocoa	02/01/1990	31/07/2014	0.04%	8.52%	0.592	4.675	90.2%	0.005	-3.70%
NYCE	Cotton No. 2	02/01/1990	31/07/2014	-0.12%	7.64%	0.278	3.876	93.1%	-0.015	-4.76%
CSCE	Coffee	02/01/1990	31/07/2014	0.04%	11.09%	1.183	6.050	93.8%	0.004	-6.19%
NYCE	Frozen Orange Juice	03/01/1990	31/07/2014	-0.20%	8.76%	0.488	4.281	92.0%	-0.023	-6.67%
CSCE	Sugar No. 11	02/01/1990	31/07/2014	0.45%	8.94%	0.230	3.610	65.2%	0.051	0.67%
CME	Lumber	03/01/1990	31/07/2014	-0.43%	9.09%	0.409	4.046	97.2%	-0.048	-9.62%
LME	Nickel	02/01/1990	31/07/2014	0.70%	8.60%	0.073	3.388	75.4%	0.082	4.09%
LME	Aluminum Alloy	06/10/1992	31/07/2014	0.34%	5.13%	-0.337	8.344	59.8%	0.065	2.44%
LME	Lead	02/01/1990	31/07/2014	0.64%	7.05%	-0.016	5.272	71.6%	0.091	4.77%
LME	Zinc	30/03/1990	31/07/2014	0.39%	6.32%	-0.095	5.560	69.6%	0.062	2.27%

Table 1 Summary statistics

This table reports summary statistics for the set of futures contracts employed in this paper. The columns report a shorthand notation of the Exchange on which the futures contract trades, the contract name, the monthly (excess) return, monthly standard deviation of (excess) returns as well as the corresponding skewness and kurtosis, maximum drawdown (MDD), the annual Sharpe, and the Compound Annual Growth Rate (CAGR).

	AUM-weighted		Equal-Risk-Weighted	
	Market	Contrarian	Market	Contrarian
Mean (%)	0.62	0.26	0.38	0.41
Median (%)	0.54	0.16	0.28	0.16
Maximum (%)	10.23	3.95	6.75	7.04
Minimum (%)	-6.07	-2.57	-3.13	-3.31
Std.Dev. (%)	2.70	1.07	1.64	1.43
Skewness	0.42	0.56	0.58	0.63
Kurtosis	3.54	3.81	3.94	4.66
Sharpe	0.23	0.24	0.23	0.28
Max DD (%)	-10.51	-5.27	-8.73	-7.08
Sortino	0.46	0.48	0.48	0.57

Table 2

This table shows descriptive statistics for AUM-weighted and equal-risk-weighted BarclayHedge index and BarclayHedge contrarian index.

Panel A - Static Benchmarks by Baltas & Kosowski															
	M	M Com	M Fixed	M FX	M Stock	W	W Com	W Fixed	W FX	W Stock	D	D Com	D Fixed	D FX	D Stock
M	1.00	0.65	0.42	0.62	0.74	**0.50**	0.37	0.16	0.34	0.35	**0.25**	0.21	0.07	0.24	0.13
M Com	0.65	1.00	0.03	0.38	0.24	0.32	**0.50**	0.00	0.18	0.10	0.19	**0.31**	0.02	0.10	0.04
M Fixed	0.42	0.03	1.00	0.07	0.02	0.28	-0.03	**0.56**	0.12	0.08	0.30	0.10	**0.37**	0.18	0.10
M FX	0.62	0.38	0.07	1.00	0.33	0.24	0.15	-0.04	**0.39**	0.16	0.14	0.11	-0.02	**0.21**	0.08
M Stock	0.74	0.24	0.02	0.33	1.00	0.36	0.25	-0.07	0.21	**0.43**	0.04	0.03	-0.13	0.13	**0.08**
W	**0.50**	0.32	0.28	0.24	0.36	1.00	0.61	0.51	0.56	0.72	**0.54**	0.39	0.20	0.37	0.33
W Com	0.37	**0.50**	-0.03	0.15	0.25	0.61	1.00	0.04	0.24	0.16	0.31	**0.56**	-0.06	0.14	0.10
W Fixed	0.16	0.00	**0.56**	-0.04	-0.07	0.51	0.04	1.00	0.07	0.13	0.35	0.11	**0.54**	0.12	0.07
W FX	0.34	0.18	0.12	**0.39**	0.21	0.56	0.24	0.07	1.00	0.30	0.35	0.24	0.03	**0.59**	0.12
W Stock	0.35	0.10	0.08	0.16	**0.43**	0.72	0.16	0.13	0.30	1.00	0.33	0.05	0.00	0.20	**0.45**
D	**0.25**	0.19	0.30	0.14	0.04	**0.54**	0.31	0.35	0.35	0.33	1.00	0.58	0.50	0.49	0.68
D Com	0.21	**0.31**	0.10	0.11	0.03	0.39	**0.56**	0.11	0.24	0.05	0.58	1.00	0.03	0.27	0.11
D Fixed	0.07	0.02	**0.37**	-0.02	-0.13	0.20	-0.06	**0.54**	0.03	0.00	0.50	0.03	1.00	0.09	0.06
D FX	0.24	0.10	0.18	**0.21**	0.13	0.37	0.14	0.12	**0.59**	0.20	0.49	0.27	0.09	1.00	0.10
D Stock	0.13	0.04	0.10	0.08	**0.08**	0.33	0.10	0.07	0.12	**0.45**	0.68	0.11	0.06	0.10	1.00
Ave. Corr.	0.61	0.22	0.04	0.26	0.20	0.58	0.15	0.08	0.21	0.20	0.56	0.13	0.06	0.15	0.09
SR 95-14	1.18	0.80	0.77	0.27	0.73	0.57	0.57	0.29	0.37	0.41	0.64	0.64	0.56	0.28	0.26
SR 95-04	2.25	1.50	0.98	1.02	1.05	0.77	0.55	0.39	0.69	0.57	1.11	0.75	0.66	0.92	0.50
SR 05-14	0.64	0.43	0.60	-0.55	0.53	0.43	0.63	0.19	0.07	0.25	0.33	0.66	0.45	-0.30	-0.04
Panel B - Selected Static Benchmarks															
	M	M Com	M Fixed	M FX	M Stock	W	W Com	W Fixed	W FX	W Stock	D	D Com	D Fixed	D FX	D Stock
M	1.00	0.60	0.44	0.58	0.73	**0.56**	0.39	0.18	0.36	0.42	**0.33**	0.32	0.01	0.26	0.21
M Com	0.60	1.00	0.00	0.31	0.18	0.34	**0.57**	0.00	0.13	0.11	0.16	**0.44**	-0.11	0.00	0.03
M Fixed	0.44	0.00	1.00	0.10	0.04	0.30	-0.03	**0.59**	0.10	0.10	0.24	0.00	**0.39**	0.14	0.09
M FX	0.58	0.31	0.10	1.00	0.27	0.28	0.17	0.03	**0.50**	0.12	0.23	0.22	-0.05	**0.34**	0.10
M Stock	0.73	0.18	0.04	0.27	1.00	0.39	0.21	-0.10	0.24	**0.54**	0.18	0.13	-0.14	0.21	**0.23**
W	**0.56**	0.34	0.30	0.28	0.39	1.00	0.63	0.49	0.52	0.75	**0.51**	0.37	0.22	0.28	0.35
W Com	0.39	**0.57**	-0.03	0.17	0.21	0.63	1.00	0.00	0.23	0.27	0.32	**0.62**	-0.06	0.10	0.08
W Fixed	0.18	0.00	**0.59**	0.03	-0.10	0.49	0.00	1.00	0.10	0.12	0.32	0.03	**0.59**	0.07	0.08
W FX	0.36	0.13	0.10	**0.50**	0.24	0.52	0.23	0.10	1.00	0.25	0.32	0.22	-0.01	**0.53**	0.15
W Stock	0.42	0.11	0.10	0.12	**0.54**	0.75	0.27	0.12	0.25	1.00	0.32	0.06	0.03	0.14	**0.46**
D	**0.33**	0.16	0.24	0.23	0.18	**0.51**	0.32	0.32	0.32	0.32	1.00	0.57	0.50	0.57	0.70
D Com	0.32	**0.44**	0.00	0.22	0.13	0.37	**0.62**	0.03	0.22	0.06	0.57	1.00	-0.03	0.28	0.10
D Fixed	0.01	-0.11	**0.39**	-0.05	-0.14	0.22	-0.06	**0.59**	-0.01	0.03	0.50	-0.03	1.00	0.08	0.14
D FX	0.26	0.00	0.14	**0.34**	0.21	0.28	0.10	0.07	**0.53**	0.14	0.57	0.28	0.08	1.00	0.24
D Stock	0.21	0.03	0.09	0.10	**0.23**	0.35	0.08	0.08	0.15	**0.46**	0.70	0.10	0.14	0.24	1.00
Ave. Corr.	0.59	0.16	0.05	0.23	0.17	0.57	0.17	0.07	0.19	0.21	0.58	0.12	0.06	0.20	0.16
SR 95-14	1.42	0.96	0.84	0.45	0.76	1.16	0.68	0.55	0.75	0.88	0.99	0.72	0.96	0.62	0.49
SR 95-04	2.55	1.44	1.04	1.04	1.09	1.91	0.93	0.85	0.97	1.02	1.82	1.27	1.28	1.35	0.72
SR 05-14	0.91	0.70	0.69	-0.16	0.55	0.79	0.61	0.33	0.50	0.74	0.62	0.62	0.69	0.09	0.26

Table 3

This table reports the correlations, annualized Sharpe ratios, and average correlations for the static benchmarks proposed by Baltas and Kosowski (2012) in Panel A and for our selected static benchmarks in Panel B. The BK benchmarks are *M(12,1)*, *W(8,1)* and *D(15,1)* strategies where *M/W/D(j,k)* stands for monthly, weekly, and daily strategies with lookback j and holding period k. The benchmarks in Panel B are *M(11,1)*, *W(14,1)*, and *D(21,1)*. Below the correlation matrix, the average correlations refer to the average correlation between the given strategy and the strategies with the same evaluation period excluding the diversified benchmark from the single asset class average correlation. The Sharpe ratios have been calculated for three periods, for the full sample period and for the periods between 1995 and 2004 and between 2005 and July 2014. The Sharpe ratios are adjusted for autocorrelation as suggested by Lo (2002). In particular, the reported Sharpe ratios are calculated as $SR(q) = \eta(q) * SR$ with

$$\eta(q) = \frac{q}{\sqrt{q + 2\sum_{k=1}^{q-1}(q-k)\rho_k}}$$

Where SR is the regular Sharpe ratio on a monthly basis and ρ_k is the k-th order autocorrelation. $\eta(q) * SR$ is then the annualized autocorrelation adjusted Sharpe ratio with $q = 12$.

Panel A - Dynamic Benchmarks															
	M	M Com	M Fixed	M FX	M Stock	W	W Com	W Fixed	W FX	W Stock	D	D Com	D Fixed	D FX	D Stock
M	1.00	0.57	0.39	0.50	0.72	**0.76**	0.52	0.23	0.47	0.59	**0.34**	0.28	0.05	0.20	0.29
M Com	0.57	1.00	0.03	0.32	0.20	0.48	**0.77**	-0.01	0.25	0.18	0.22	**0.44**	-0.01	0.11	0.11
M Fixed	0.39	0.03	1.00	0.11	0.01	0.46	0.03	**0.79**	0.14	0.16	0.38	0.15	**0.45**	0.22	0.10
M FX	0.50	0.32	0.11	1.00	0.26	0.47	0.29	0.08	**0.74**	0.18	0.24	0.20	0.03	**0.33**	0.16
M Stock	0.72	0.20	0.01	0.26	1.00	0.52	0.22	-0.08	0.23	**0.73**	0.15	0.09	-0.11	0.07	**0.33**
W	**0.76**	0.48	0.46	0.47	0.52	1.00	0.61	0.46	0.55	0.71	**0.58**	0.44	0.22	0.36	0.44
W Com	0.52	**0.77**	0.03	0.29	0.22	0.61	1.00	0.04	0.32	0.21	0.32	**0.56**	-0.01	0.21	0.13
W Fixed	0.23	-0.01	**0.79**	0.08	-0.08	0.46	0.04	1.00	0.08	0.12	0.39	0.15	**0.59**	0.16	0.08
W FX	0.47	0.25	0.14	**0.74**	0.23	0.55	0.32	0.08	1.00	0.23	0.31	0.24	0.00	**0.52**	0.20
W Stock	0.59	0.18	0.16	0.18	**0.73**	0.71	0.21	0.12	0.23	1.00	0.41	0.20	0.02	0.14	**0.58**
D	**0.34**	0.22	0.38	0.24	0.15	**0.58**	0.32	0.39	0.31	0.41	1.00	0.57	0.47	0.52	0.61
D Com	0.28	**0.44**	0.15	0.20	0.09	0.44	**0.56**	0.15	0.24	0.20	0.57	1.00	0.07	0.32	0.16
D Fixed	0.05	-0.01	**0.45**	0.03	-0.11	0.22	-0.01	**0.59**	0.00	0.02	0.47	0.07	1.00	0.17	0.03
D FX	0.20	0.11	0.22	**0.33**	0.07	0.36	0.21	0.16	**0.52**	0.14	0.52	0.32	0.17	1.00	0.19
D Stock	0.29	0.11	0.10	0.16	**0.33**	0.44	0.13	0.08	0.20	**0.58**	0.61	0.16	0.03	0.19	1.00
Ave. Corr.	0.55	0.18	0.05	0.23	0.15	0.57	0.19	0.08	0.21	0.19	0.54	0.18	0.09	0.23	0.12
SR 96-14	1.12	0.69	0.74	0.71	1.02	0.77	0.61	0.49	0.45	0.62	0.91	0.72	0.63	0.51	0.06
SR 96-04	2.18	1.04	1.12	1.07	1.10	1.67	1.20	0.73	0.79	1.07	1.26	0.79	0.98	1.39	0.33
SR 05-14	0.66	0.50	0.47	0.33	0.94	0.39	0.45	0.29	0.09	0.31	0.69	0.75	0.34	-0.09	-0.18
Panel B - Enhanced Dynamic Benchmarks															
	M	M Com	M Fixed	M FX	M Stock	W	W Com	W Fixed	W FX	W Stock	D	D Com	D Fixed	D FX	D Stock
M	1.00	0.55	0.25	0.51	0.54	**0.67**	0.50	0.23	0.46	0.44	**0.27**	0.28	0.08	0.28	0.18
M Com	0.55	1.00	0.00	0.26	0.17	0.43	**0.76**	-0.01	0.18	0.12	0.23	**0.44**	-0.01	0.12	0.10
M Fixed	0.25	0.00	1.00	0.01	0.06	0.30	0.02	**0.66**	0.08	0.15	0.30	0.11	**0.37**	0.27	0.06
M FX	0.51	0.26	0.01	1.00	0.21	0.33	0.22	-0.01	**0.75**	0.12	0.09	0.10	-0.05	**0.28**	0.03
M Stock	0.54	0.17	0.06	0.21	1.00	0.29	0.13	0.03	0.14	**0.57**	0.11	0.09	-0.06	0.05	**0.16**
W	**0.67**	0.43	0.30	0.33	0.29	1.00	0.49	0.41	0.43	0.55	**0.63**	0.44	0.29	0.35	0.33
W Com	0.50	**0.76**	0.02	0.22	0.13	0.49	1.00	-0.05	0.27	0.14	0.29	**0.54**	0.02	0.18	0.08
W Fixed	0.23	-0.01	**0.66**	-0.01	0.03	0.41	-0.05	1.00	0.01	0.22	0.39	0.14	**0.60**	0.22	0.14
W FX	0.46	0.18	0.08	**0.75**	0.14	0.43	0.27	0.01	1.00	0.12	0.17	0.18	-0.03	**0.48**	0.04
W Stock	0.44	0.12	0.15	0.12	**0.57**	0.55	0.14	0.22	0.12	1.00	0.39	0.15	0.13	0.16	**0.40**
D	**0.27**	0.23	0.30	0.09	0.11	**0.63**	0.29	0.39	0.17	0.39	1.00	0.55	0.44	0.38	0.37
D Com	0.28	**0.44**	0.11	0.10	0.09	0.44	**0.54**	0.14	0.18	0.15	0.55	1.00	0.12	0.20	0.10
D Fixed	0.08	-0.01	**0.37**	-0.05	-0.06	0.29	0.02	**0.60**	-0.03	0.13	0.44	0.12	1.00	0.13	0.07
D FX	0.28	0.12	0.27	**0.28**	0.05	0.35	0.18	0.22	**0.48**	0.16	0.38	0.20	0.13	1.00	0.10
D Stock	0.18	0.10	0.06	0.03	**0.16**	0.33	0.08	0.14	0.04	**0.40**	0.37	0.10	0.07	0.10	1.00
Ave. Corr.	0.46	0.14	0.02	0.16	0.15	0.51	0.12	0.06	0.13	0.16	0.44	0.14	0.11	0.14	0.09
SR 96-14	1.41	1.16	0.95	0.91	1.04	1.29	0.98	1.13	1.35	1.30	1.56	1.31	1.41	1.35	1.73
SR 96-04	2.24	1.50	0.93	1.04	0.98	1.74	1.34	0.92	1.25	1.52	1.68	1.75	1.61	1.72	1.49
SR 05-14	0.99	0.98	1.05	0.78	1.11	1.00	0.88	1.58	1.53	1.13	1.45	1.22	1.34	1.15	2.07

Table 4

This table shows correlations, annualized Sharpe ratios and average correlations for dynamic and enhanced dynamic benchmarks in Panel A, and Panel B, respectively. Below the correlation matrix, the average correlations are in reference to the average correlation between the given strategy and the strategies with the same evaluation period excluding the diversified benchmark from the single asset class average correlation. The Sharpe ratios have been calculated for three periods, for the full sample period and for the periods between 1995 and 2004 and between 2005 and July 2014. The Sharpe ratios are adjusted for autocorrelation as suggested by Lo (2002). In particular, the reported Sharpe ratios are calculated as $SR(q) = \eta(q) * SR$ with

$$\eta(q) = \frac{q}{\sqrt{q + 2\sum_{k=1}^{q-1}(q-k)\rho_k}}$$

Where SR is the regular Sharpe ratio on a monthly basis and ρ_k is the k-th order autocorrelation. $\eta(q) * SR$ is then the annualized autocorrelation adjusted Sharpe ratio with $q = 12$.

	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Panel A - Static Benchmarks															
Mean (%)	0.89	0.79	1.34	1.01	0.70	1.02	0.81	1.08	1.15	1.21	1.35	1.06	1.61	1.00	1.79
Median (%)	0.58	0.25	0.22	0.28	-0.17	0.97	0.60	0.58	0.64	0.53	1.48	0.96	1.82	0.77	2.29
Maximum (%)	14.44	18.22	22.74	21.31	28.33	18.08	21.39	25.40	26.65	31.88	13.57	21.80	25.04	23.21	29.77
Minimum (%)	-6.09	-7.76	-12.88	-14.20	-11.05	-8.19	-8.93	-17.18	-10.55	-22.33	-8.88	-11.16	-18.58	-21.70	-22.83
Std.Dev. (%)	3.25	3.64	6.77	6.37	6.56	3.62	3.93	7.22	6.26	7.20	3.75	3.95	7.24	6.89	8.05
Skewness	0.84	1.08	0.55	0.50	1.07	0.60	0.96	0.44	0.79	0.47	0.19	0.64	0.32	0.43	0.00
Kurtosis	4.91	6.34	3.12	3.20	4.71	4.81	6.27	3.70	4.33	4.37	3.37	6.51	3.93	4.17	3.73
Sharpe	0.27	0.22	0.20	0.16	0.11	0.28	0.21	0.15	0.18	0.17	0.36	0.27	0.22	0.15	0.22
Max DD (%)	-24.77	-25.25	-38.66	-51.57	-45.00	-20.51	-19.48	-62.58	-23.55	-34.32	-22.08	-26.16	-29.31	-52.14	-55.99
Sortino	0.57	0.47	0.44	0.32	0.27	0.57	0.43	0.27	0.40	0.32	0.71	0.46	0.39	0.27	0.36
Panel B - Static Benchmarks - Baltas & Kosowski															
	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.57	0.73	0.77	0.62	0.30	0.65	0.67	0.49	0.73	0.68	1.15	0.83	1.50	0.58	1.70
Median (%)	0.29	0.71	-0.10	-0.17	-0.89	0.52	0.14	-0.10	0.31	0.35	1.04	0.66	1.22	0.18	1.68
Maximum (%)	13.93	17.63	22.39	20.88	28.03	17.69	20.45	22.64	27.23	29.95	14.46	21.78	29.28	26.20	29.77
Minimum (%)	-8.39	-7.87	-14.30	-10.55	-16.17	-8.20	-9.58	-17.49	-18.19	-16.34	-10.92	-14.16	-18.58	-21.70	-22.83
Std.Dev. (%)	3.27	3.58	7.05	6.22	7.10	3.62	4.07	7.21	6.54	7.07	3.93	4.04	7.49	7.13	8.06
Skewness	0.85	0.87	0.56	0.73	0.91	0.75	1.09	0.46	0.90	0.63	0.20	0.48	0.37	0.35	0.00
Kurtosis	4.93	6.24	3.17	3.33	4.63	5.27	6.22	2.91	4.82	4.08	3.82	6.61	4.15	4.57	3.79
Sharpe	0.17	0.20	0.11	0.10	0.04	0.18	0.17	0.07	0.11	0.10	0.29	0.20	0.20	0.08	0.21
Max DD (%)	-28.84	-16.78	-42.36	-71.06	-49.92	-27.99	-22.20	-53.12	-40.67	-40.13	-22.98	-29.51	-33.50	-74.31	-53.69
Sortino	0.36	0.39	0.23	0.22	0.09	0.36	0.36	0.15	0.23	0.20	0.52	0.33	0.35	0.13	0.35
Panel C - Dynamic Benchmarks															
	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.65	0.62	0.74	0.74	0.07	0.75	0.65	0.84	0.74	0.90	1.03	0.78	1.43	1.25	1.69
Median (%)	0.41	0.44	-0.19	0.34	-0.92	0.48	0.43	-0.25	0.12	-0.13	1.08	0.46	1.09	1.00	1.98
Maximum (%)	12.96	14.91	21.18	19.44	27.59	17.06	20.27	23.50	25.52	27.82	14.32	19.20	25.99	27.30	24.24
Minimum (%)	-5.38	-5.99	-12.21	-12.96	-8.89	-6.43	-7.66	-14.12	-11.08	-18.78	-8.20	-8.50	-16.20	-15.53	-22.74
Std.Dev. (%)	2.71	2.92	5.33	5.38	5.58	3.20	3.48	6.40	5.67	6.69	3.44	3.86	6.76	6.29	7.04
Skewness	0.90	1.02	0.65	0.58	1.33	0.74	1.19	0.76	0.89	0.61	0.12	1.02	0.56	0.63	-0.11
Kurtosis	5.20	6.27	3.71	3.68	5.93	5.55	7.78	3.96	5.14	4.47	3.64	6.81	4.54	4.94	3.68
Sharpe	0.24	0.21	0.14	0.14	0.01	0.23	0.19	0.13	0.13	0.13	0.30	0.20	0.21	0.20	0.24
Max DD (%)	-17.55	-15.70	-35.69	-45.26	-54.91	-23.40	-25.19	-49.19	-48.03	-38.49	-23.12	-25.45	-33.75	-38.55	-26.83
Sortino	0.49	0.46	0.30	0.29	0.03	0.46	0.40	0.29	0.27	0.26	0.54	0.39	0.37	0.37	0.38
Panel D - Enhanced Dynamic Benchmarks															
	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.92	0.89	1.37	1.37	1.39	0.91	0.87	1.38	1.60	1.34	1.12	1.05	1.60	1.36	1.79
Median (%)	0.62	0.57	0.77	0.77	0.47	0.45	0.56	0.31	1.24	0.70	1.07	0.68	0.89	1.38	1.37
Maximum (%)	12.94	15.05	21.11	16.77	26.14	17.06	20.27	23.38	25.52	27.87	14.32	19.20	25.99	27.30	24.35
Minimum (%)	-5.37	-4.40	-8.96	-10.34	-9.87	-5.84	-7.66	-12.98	-11.08	-16.16	-9.64	-8.14	-15.90	-15.53	-22.74
Std.Dev. (%)	2.58	2.75	4.65	4.28	4.60	2.93	3.15	5.62	4.89	5.48	3.23	3.50	6.21	5.79	6.55
Skewness	1.41	1.46	1.01	0.80	1.37	1.19	1.45	1.03	1.21	0.82	0.17	1.38	0.76	0.55	0.03
Kurtosis	7.27	8.31	4.95	3.96	7.63	6.87	10.55	4.85	7.04	5.84	4.33	8.94	5.03	5.87	4.32
Sharpe	0.36	0.32	0.30	0.32	0.30	0.31	0.28	0.24	0.33	0.25	0.35	0.30	0.26	0.24	0.27
Max DD (%)	-9.36	-8.58	-14.85	-16.72	-14.42	-9.73	-13.14	-23.49	-16.70	-23.06	-14.13	-17.54	-32.73	-32.21	-25.60
Sortino	0.78	0.76	0.68	0.76	0.68	0.74	0.54	0.56	0.67	0.46	0.59	0.59	0.48	0.38	0.42

Table 5 This table shows monthly descriptive statistics for our static benchmarks, static benchmarks suggested by Baltas and Kosowski (2012), dynamic, and enhanced dynamic benchmarks in Panel A, B, C, and D, respectively.

Alpha (%)	D Com	D Fixed	D FX	D Stock	W Com	W Fixed	W FX	W Stock	M Com	M Fixed	M FX	M Stock	Adj. R^2
Panel A - Static Benchmarks													
-0.01	0.15***	0.12***	0.10***	0.06**									0.28
-0.11					0.11***	0.18***	0.11***	0.09***					0.52
-0.22*									0.11***	0.19***	0.06***	0.09***	0.45
-0.4***	0.06	0.05**	0.04	0.01	0.05	0.11***	0.07***	0.05**	0.07**	0.10***	0.02	0.06***	0.64
-0.39***	0.09**	0.09***	0.06**	0.03					0.10***	0.15***	0.04	0.08***	0.55
Panel B - Static Benchmarks - Baltas & Kosowski													
Alpha (%)	D Com	D Fixed	D FX	D Stock	W Com	W Fixed	W FX	W Stock	M Com	M Fixed	M FX	M Stock	Adj. R^2
0.17	0.12***	0.10***	0.11***	0.03*									0.22
0.12					0.14***	0.16***	0.11***	0.07***					0.44
-0.14									0.13***	0.18***	0.04*	0.09***	0.45
-0.17	0.01	0.03*	0.02	-0.01	0.09**	0.09***	0.06**	0.04**	0.07**	0.11***	0.03	0.07***	0.58
-0.21**	0.08**	0.07***	0.06***	0.02					0.10***	0.14***	0.03	0.09***	0.51
Panel C - Dynamic Benchmarks													
Alpha (%)	D Com	D Fixed	D FX	D Stock	W Com	W Fixed	W FX	W Stock	M Com	M Fixed	M FX	M Stock	Adj. R^2
0.16	0.11**	0.12***	0.11***	0.11***									0.24
-0.05					0.14***	0.19***	0.13***	0.12***					0.57
-0.28***									0.12***	0.22***	0.08***	0.11***	0.55
-0.22**	-0.09*	0.02	0.04	0.01	0.14***	0.09***	0.09***	0.06	0.05	0.13***	0.01	0.07**	0.63
-0.29***	-0.02	0.04*	0.07**	0.04					0.12***	0.20***	0.06**	0.11***	0.58
Panel D - Enhanced Dynamic Benchmarks													
Alpha (%)	D Com	D Fixed	D FX	D Stock	W Com	W Fixed	W FX	W Stock	M Com	M Fixed	M FX	M Stock	Adj. R^2
-0.23*	0.14***	0.14***	0.18***	0.06**									0.21
-0.39***					0.18***	0.23***	0.14***	0.08***					0.43
-0.29**									0.13***	0.2***	0.08***	0.08***	0.34
-0.53***	-0.02	0.02	0.05	0.01	0.15*	0.17***	0.10*	0.02	0.03	0.07**	0.01	0.07**	0.45
-0.53***	0.06	0.09**	0.10**	0.04					0.10**	0.15***	0.07**	0.08***	0.39

Table 6

This table reports estimates of performance evaluation equations. The independent variable is the excess return of the systematic AUM-weighted BarclayHedge index and the risk factors are single the asset class time series momentum benchmarks. In particular, the refer to the M(11,1), W(14,1), D(21,1) static benchmarks, the M(12,1), W(8,1), D(15,1) static benchmarks, and the dynamic and enhanced dynamic benchmarks in Panel A, B, C, and D, respectively. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

Panel A - Static Benchmarks				
Alpha (%)	D	W	M	Adj. R²
0.05	0.41***			0.25
-0.09		0.49***		0.43
-0.17			0.43***	0.36
-0.34***	0.17***	0.27***	0.24***	0.54
-0.31***	0.28***		0.35***	0.46
Panel B - Static Benchmarks - Baltas & Kosowski				
Alpha (%)	D	W	M	Adj. R²
0.22**	0.34***			0.17
0.11		0.46***		0.39
-0.06			0.41***	0.36
-0.12	0.10*	0.27***	0.27***	0.51
-0.13	0.23***		0.36***	0.44
Panel C - Dynamic Benchmarks				
Alpha (%)	D	W	M	Adj. R²
0.11	0.46***			0.22
-0.03		0.6***		0.51
-0.11			0.51***	0.42
-0.16	0.12**	0.36***	0.22***	0.54
-0.21*	0.28***		0.43***	0.48
Panel D - Enhanced Dynamic Benchmarks				
Alpha (%)	D	W	M	Adj. R²
0.02	0.43***			0.17
-0.08		0.54***		0.35
-0.16			0.51***	0.38
-0.33***	0.19***	0.16	0.37***	0.45
-0.35***	0.28***		0.45***	0.44

Table 7

This table shows estimates of the performance evaluation equations. The independent variable is the excess return on the systematic AUM-weighted BarclayHedge index and the risk factors are diversified time series momentum benchmarks. In particular, results for M(11,1), W(14,1), D(21,1) static benchmarks, M(12,1), W(8,1), D(15,1) static benchmarks, and dynamic and enhanced dynamic benchmarks are reported in Panel A, B, C, and D, respectively. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

	AUM Weighted		Equal-Risk-Weighted	
	Market	Contrarian	Market	Contrarian
Eq.	(1)	(2)	(3)	(4)
Alpha (%)	-0.40***	-0.06	-0.23***	0.01
Dyn M Fixed	0.35***		0.15***	
Dyn M Stock	0.24***	0.05***		0.07***
Dyn W Com		0.05**		0.11***
Dyn W Fixed		0.09***		0.15***
Dyn W Stock			0.13***	
Dyn D Stock	0.11***			
Stat M FX			0.10***	
Stat W FX	0.20***			
Stat D Com	0.12***			
Stat D Fixed	0.16***		0.10***	
BK M Com	0.06*			
BK W Com			0.15***	
BK D Stock				-0.02*
PTFSFX		0.09***	0.13***	0.18***
Citi Bond		0.05**	0.04*	0.06**
GSCI	0.19***		0.10***	0.07***
MSCI WI		-0.04**		
MSCI EM			0.03*	0.04**
Adj. R^2	0.64	0.37	0.70	0.54

Table 8

This table shows the estimates of stepwise least squares regressions. The Market Index (Contrarian Index) refers to the AUM-weighted, equally weighted, and equal risk weighted BarclayHedge (contrarian BarclayHedge) CTA index. Standard forward stepwise least squares methodology has been applied to select the most important uncorrelated regressors of 64 possible factors that include 48 single asset class time series momentum benchmarks, the 5 lookback straddle options based primitive trend-following factors (PTF) of Fung and Hsieh (2001 and 2004) for bonds, commodities, FX, interest rates and stocks, the remaining Fung-Hsieh factors like the S&P 500 total return index returns, the monthly change in the 10-year T-note yield, the monthly change in the credit spread (the BAA bond yield over the 10-year T-note yield) and finally the small firm factor that is defined as the difference between Russell 2000 and S&P 500 returns. We also consider the returns of the following total return indices over the risk-free rate: Goldman Sachs Commodity Index (GSCI), MSCI All Countries World Index, MSCI All Countries World Index excluding the US, MSCI Europe, Australasia and Far East (EAFE) Index, MSCI Emerging Market (EM) Index, MSCI World Index (WI). The independent variables are adjusted to 10% annual volatility. The correlations between these variables are sometimes high, thus the stepwise iteration process employs constraints that circumvent inclusion of highly correlated variables, i.e., correlation above 0.4. The restrictions have been calibrated in such a way that if a factor comes in in an earlier step, the factor with which it highly correlates cannot come in in a later step. The iteration stops if no factor can be added that produces a significant t-statistic at 10% level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

	D	W	M
Eq.	(1)	(2)	(3)
Alpha (%)	0.94***	0.31**	0.21*
Dyn M Com			0.30***
Dyn M Fixed		0.27***	0.41***
Dyn M FX		0.20***	
Dyn M Stock			0.51***
Dyn W Com		0.26***	
Dyn W FX			0.18***
Dyn W Stock		0.32***	
Dyn D Com	0.21***		
Dyn D Fixed	0.20***		-0.11**
Dyn D FX	0.14***		
BK M Stock	0.10**		
PTFSFX		0.11***	
PTFSSTK	0.25***		
Citi Bond	0.08***		
MSCI EM		-0.14***	
S&P 500	-0.14***		
Adj. R^2	0.50	0.57	0.68

Table 9

This table shows the estimates of stepwise least squares regressions for the daily, weekly, and monthly enhanced dynamic strategies. Standard forward stepwise least squares methodology has been applied to select the most important uncorrelated regressors of 52 possible factors that include 36 single asset class time series momentum benchmarks (M(12,1), M(11,1), W(14,1), W(8,1), D(15,1), D(21,1) static strategies and dynamic strategies), the 5 lookback straddle options based primitive trend-following factors (PTF) of Fung and Hsieh (2001 and 2004) for bonds, commodities, FX, interest rates and stocks, the remaining Fung-Hsieh factors like the S&P 500 total return index returns, the monthly change in the 10-year T-note yield, the monthly change in the credit spread (the BAA bond yield over the 10-year T-note yield) and finally the small firm factor that is defined as the difference between Russell 2000 and S&P 500 returns. We also consider the returns of the following total return indices over the risk-free rate: Goldman Sachs Commodity Index (GSCI), MSCI All Countries World Index, MSCI All Countries World Index excluding the US, MSCI Europe, Australasia and Far East (EAFE) Index, MSCI Emerging Market (EM) Index, MSCI World Index (WI). The independent variables are adjusted to 10% annual volatility. The correlations between these variables are sometimes high, thus the stepwise iteration process employs constraints that circumvent inclusion of highly correlated variables, i.e., correlation above 0.4. The restrictions have been calibrated in such a way that if a factor comes in in an earlier step, the factor with which it highly correlates cannot come in in a later step. The iteration stops if no factor can be added that produces a significant t-statistic at 10% level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

Appendix

	Barclay CTA	Barclay Syst.	BTOP50	Newedge CTA	Newedge Trend
Eq.	(1)	(2)	(3)	(4)	(5)
Alpha (%)	-0.31***	-0.41***	-0.45***	-0.47***	-0.86***
Dyn M Fixed	0.19***	0.23***	0.29***	0.33***	0.59***
Dyn M Stock			0.23***	0.28***	0.53***
Dyn W Stock	0.14***	0.18***			
Dyn D Stock			0.03	0.04	0.07
Stat M FX	0.13***	0.16***			
Stat W FX			0.19***	0.21***	0.30***
Stat D Com			0.09**	0.08**	0.09
Stat D Fixed	0.12***	0.15***	0.13***	0.11**	0.19**
BK M Com			0.07**	0.05*	0.12**
BK W Com	0.19***	0.24***			
PTFSFX	0.16***	0.19***			
Citi Bond	0.01	0.01			
GSCI	0.13***	0.14***	0.16***	0.20***	0.38***
MSCI EM	0.08***	0.06*			
Adj. R^2	0.66	0.67	0.56	0.61	0.62
Sample	97-14	97-14	97-14	00-14	00-14

Table A1

This table shows the robustness checks for the stepwise least squares regressions for various manager based CTA indices. Note that the Newedge indices are available from only 2000, the other are reported from 1997. Standard forward stepwise least squares methodology has been applied to select the most important uncorrelated regressors of 64 possible factors that include 48 single asset class time series momentum benchmarks, the 5 lookback straddle options based primitive trend-following factors (PTFS) of Fung and Hsieh (2001 and 2004) for bonds, commodities, FX, interest rates and stocks, the remaining Fung-Hsieh factors like the S&P 500 total return index returns, the monthly change in the 10-year T-note yield, the monthly change in the credit spread (the BAA bond yield over the 10-year T-note yield) and finally the small firm factor that is defined as the difference between Russell 2000 and S&P 500 returns. We also consider the returns of the following total return indices over the risk-free rate: Goldman Sachs Commodity Index (GSCI), MSCI All Countries World Index, MSCI All Countries World Index excluding the US, MSCI Europe, Australasia and Far East (EAFE) Index, MSCI Emerging Market (EM) Index, MSCI World Index (WI). The independent variables are adjusted to 10% annual volatility. The correlations between these variables are sometimes high, thus the stepwise iteration process employs constraints that circumvent inclusion of highly correlated variables, i.e., correlation above 0.4. The restrictions have been calibrated in such a way that if a factor comes in in an earlier step, the factor with which it highly correlates cannot come in in a later step. The iteration stops if no factor can be added that produces a significant t-statistic at 10% level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

Panel A - Dynamic Benchmarks - SR=0.2

	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.63	0.67	0.75	0.68	-0.05	0.75	0.59	0.83	0.76	0.90	1.02	0.73	1.37	1.25	1.51
Median (%)	0.45	0.45	-0.16	0.04	-1.01	0.48	0.42	-0.25	0.30	-0.15	1.08	0.32	1.00	0.98	1.96
Maximum (%)	12.96	14.90	21.18	19.44	27.36	17.06	20.27	23.50	25.52	27.84	14.32	19.20	25.98	27.30	24.27
Minimum (%)	-5.37	-5.17	-12.25	-12.93	-8.66	-6.43	-7.66	-14.12	-11.08	-18.78	-8.20	-8.34	-16.12	-15.53	-22.74
Std.Dev. (%)	2.68	2.89	5.30	5.34	5.50	3.18	3.46	6.38	5.63	6.68	3.43	3.83	6.73	6.27	7.09
Skewness	0.90	1.04	0.67	0.59	1.35	0.76	1.21	0.76	0.92	0.62	0.13	1.08	0.57	0.65	-0.19
Kurtosis	5.34	6.28	3.74	3.66	6.13	5.65	7.98	3.98	5.19	4.47	3.67	7.02	4.55	4.96	3.78
Sharpe	0.24	0.23	0.14	0.13	-0.01	0.23	0.17	0.13	0.13	0.13	0.30	0.19	0.20	0.20	0.21
Max DD (%)	-17.19	-13.50	-34.15	-47.96	-61.93	-21.80	-24.93	-49.22	-46.88	-38.26	-23.15	-29.76	-33.69	-35.04	-31.03
Sortino	0.48	0.53	0.31	0.26	-0.02	0.47	0.36	0.28	0.28	0.26	0.54	0.38	0.36	0.37	0.33

Panel B - Enhanced Dynamic Benchmarks - SR=0.2

	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.92	0.88	1.38	1.36	1.35	0.91	0.86	1.38	1.60	1.34	1.13	1.05	1.53	1.46	1.78
Median (%)	0.62	0.54	0.76	0.81	0.44	0.45	0.56	0.29	1.16	0.56	1.05	0.66	0.46	1.36	1.39
Maximum (%)	12.94	15.05	21.11	16.55	26.04	17.06	20.27	22.96	25.52	27.89	14.32	19.20	25.98	27.30	24.38
Minimum (%)	-5.35	-4.39	-8.96	-10.34	-9.98	-5.84	-7.66	-12.98	-11.08	-16.15	-9.57	-8.14	-15.90	-15.29	-22.74
Std.Dev. (%)	2.57	2.74	4.60	4.28	4.50	2.92	3.14	5.60	4.84	5.46	3.22	3.48	6.20	5.65	6.55
Skewness	1.42	1.47	1.03	0.81	1.34	1.19	1.45	1.03	1.26	0.80	0.18	1.40	0.76	0.66	0.03
Kurtosis	7.33	8.39	5.06	3.93	7.70	6.92	10.65	4.84	7.15	5.86	4.35	9.07	5.04	6.07	4.32
Sharpe	0.36	0.32	0.30	0.32	0.30	0.31	0.27	0.25	0.33	0.25	0.35	0.30	0.25	0.26	0.27
Max DD (%)	-9.34	-8.57	-13.56	-15.85	-14.28	-9.73	-13.10	-23.19	-14.85	-23.26	-14.01	-16.80	-32.78	-27.63	-26.25
Sortino	0.78	0.76	0.69	0.76	0.66	0.73	0.53	0.57	0.70	0.46	0.59	0.59	0.45	0.44	0.42

Panel C - Dynamic Benchmarks - SR=0.4

	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.63	0.62	0.76	0.75	0.04	0.78	0.65	0.82	0.74	0.79	1.04	0.83	1.49	1.29	1.65
Median (%)	0.45	0.46	-0.19	0.34	-0.98	0.46	0.42	-0.25	0.05	-0.14	1.14	0.51	1.09	1.10	1.98
Maximum (%)	12.97	14.94	21.18	19.44	27.91	17.06	20.27	23.49	25.52	27.75	14.32	19.20	25.99	27.66	24.24
Minimum (%)	-5.90	-5.99	-12.30	-12.90	-8.89	-6.43	-7.66	-14.27	-11.08	-18.77	-8.20	-8.47	-16.20	-15.39	-22.74
Std.Dev. (%)	2.73	2.93	5.34	5.41	5.63	3.23	3.46	6.39	5.69	6.76	3.44	3.84	6.81	6.28	7.04
Skewness	0.82	1.01	0.64	0.59	1.30	0.74	1.24	0.76	0.90	0.58	0.11	1.01	0.54	0.66	-0.10
Kurtosis	5.20	6.28	3.70	3.67	5.87	5.38	8.04	3.97	5.11	4.41	3.63	6.85	4.48	5.00	3.68
Sharpe	0.23	0.21	0.14	0.14	0.01	0.24	0.19	0.13	0.13	0.12	0.30	0.22	0.22	0.21	0.23
Max DD (%)	-23.76	-14.21	-35.22	-43.28	-58.58	-19.85	-23.11	-50.37	-46.95	-38.72	-22.74	-25.64	-34.36	-40.35	-27.04
Sortino	0.46	0.46	0.30	0.29	0.02	0.49	0.40	0.28	0.26	0.22	0.55	0.42	0.38	0.39	0.37

Panel D - Enhanced Dynamic Benchmarks - SR=0.4

	D	D Com	D Fixed	D FX	D Stock	W	W Com	W Fixed	W FX	W Stock	M	M Com	M Fixed	M FX	M Stock
Mean (%)	0.94	0.88	1.36	1.36	1.43	0.91	0.87	1.37	1.59	1.36	1.13	1.06	1.66	1.40	1.79
Median (%)	0.61	0.53	0.82	0.77	0.43	0.44	0.56	0.34	1.29	0.62	1.03	0.72	0.89	1.36	1.39
Maximum (%)	12.97	15.05	21.11	16.17	26.11	17.06	20.27	23.40	25.52	27.80	14.32	19.20	25.99	27.66	24.35
Minimum (%)	-5.38	-4.74	-8.96	-9.91	-9.66	-5.84	-7.66	-12.98	-11.08	-16.16	-10.03	-8.14	-15.90	-15.39	-22.74
Std.Dev. (%)	2.58	2.76	4.69	4.29	4.76	2.95	3.17	5.65	4.96	5.50	3.25	3.52	6.32	5.79	6.59
Skewness	1.45	1.46	0.97	0.78	1.53	1.18	1.43	1.02	1.15	0.83	0.15	1.33	0.73	0.59	0.03
Kurtosis	7.30	8.30	4.82	3.85	8.28	6.78	10.36	4.80	6.76	5.73	4.32	8.71	4.85	5.86	4.28
Sharpe	0.36	0.32	0.29	0.32	0.30	0.31	0.27	0.24	0.32	0.25	0.35	0.30	0.26	0.24	0.27
Max DD (%)	-9.45	-8.91	-15.64	-17.48	-14.30	-9.76	-13.19	-23.88	-20.52	-23.13	-14.77	-18.71	-32.98	-33.12	-26.69
Sortino	0.83	0.74	0.66	0.75	0.71	0.73	0.54	0.56	0.65	0.48	0.58	0.59	0.49	0.40	0.42

Table A2

This table shows monthly descriptive statistics for dynamic benchmarks with minimum required Sharpe Ratio (SR) of 0.2 and 0.4, and enhanced dynamic benchmarks with SR of 0.2 and 0.4 in Panel A, B, C, and D, respectively.

	SR=0.2				SR=0.4			
	AUM Weighted		Equal-Risk-Weighted		AUM Weighted		Equal-Risk-Weighted	
	Market	Contrarian	Market	Contrarian	Market	Contrarian	Market	Contrarian
Eq.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha (%)	-0.35***	-0.05	-0.23***	0.02	-0.39***	-0.05	-0.22***	-0.01
Dyn M Fixed	0.35***		0.16***		0.35***		0.15***	
Dyn M Stock	0.22***	0.05***		0.06***	0.24***	0.04**		0.05**
Dyn W Com		0.05**		0.11***		0.05**		0.11***
Dyn W Fixed		0.09***		0.15***		0.09***		0.15***
Dyn W Stock			0.13***				0.12***	
Dyn D Stock	0.10***				0.12***			
Stat M FX			0.10***				0.11***	
Stat W FX	0.20***				0.20***			
Stat D Com	0.11***				0.12***			
Stat D Fixed	0.15***		0.10***		0.16***		0.10***	
BK M Com	0.07*				0.06*			
BK W Com			0.15***				0.15***	
BK D Stock				-0.02				-0.02
PTFSFX		0.09***	0.13***	0.18***		0.09***	0.13***	0.18***
Citi Bond		0.05**	0.04*	0.06**		0.05*	0.04*	0.05**
GSCI	0.20***		0.10***	0.08***	0.19***		0.10***	0.07***
MSCI WI		-0.05**				-0.04**		
MSCI EM			0.04*	0.04*			0.03	0.04**
Adj. R^2	0.62	0.37	0.70	0.54	0.64	0.36	0.69	0.53

Table A3

This table reports the robustness checks for the stepwise least squares regressions. The dynamic momentum benchmarks are constructed with a minimum required Sharpe Ratio of 0.2 and 0.4 instead of the baseline 0.3. The Market Index (Contrarian Index) refers to the AUM-weighted, equally weighted, and equal-risk weighted BarclayHedge (contrarian BarclayHedge) CTA index. Standard forward stepwise least-squares methodology has been applied to select the most important uncorrelated regressors of 64 possible factors that include 48 single asset class time series momentum benchmarks, the 5 lookback straddle options based primitive trend-following factors (PTFS) of Fung and Hsieh (2001 and 2004) for bonds, commodities, FX, interest rates and stocks, the remaining Fung-Hsieh factors like the S&P 500 Total Return index returns, the monthly change in the 10-year T-note yield, the monthly change in the credit spread (the BAA bond yield over the 10-year T-note yield) and finally the small firm factor that is defined as the difference between Russell 2000 and S&P 500 total returns. We also consider the returns of the following total return indices over the risk-free rate: Goldman Sachs Commodity Index (GSCI), MSCI All Countries World Index, MSCI All Countries World Index excluding the US, MSCI Europe, Australasia and Far East (EAFE) Index, MSCI Emerging Market (EM) Index, MSCI World Index (WI). The independent variables are adjusted to 10% annual volatility. The correlations between these variables are sometimes high, thus the stepwise iteration process employs constraints that circumvent inclusion of highly correlated variables, i.e., correlation above 0.4. The restrictions have been calibrated in such a way that if a factor comes in in an earlier step, the factor with which it highly correlates cannot come in in a later step. The iteration stops if no factor can be added that produces a significant t-statistic at 10% level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

		Panel A - VIX			Panel B - TED			Panel C - SP500			Panel D - Tbill		
		Daily	Monthly	Daily & Monthly	Daily	Monthly	Daily & Monthly	Daily	Monthly	Daily & Monthly	Daily	Monthly	Daily & Monthly
	Alpha (%)	-0.45***	-0.44***	-0.43***	-0.39***	-0.38***	-0.37***	-0.40***	-0.42***	-0.43***	-0.37***	-0.39***	-0.38***
	Dyn M Fixed	0.34***	0.33***	0.32***	0.36***	0.37***	0.37***	0.36***	0.33***	0.33***	0.35***	0.35***	0.37***
	Dyn M Stock	0.25***	0.25***	0.23***	0.25***	0.26***	0.26***	0.25***	0.22***	0.23***	0.23***	0.24***	0.24***
	Dyn D Stock	0.10***	0.11***	0.08**	0.11***	0.10**	0.10***	0.12***	0.11***	0.11***	0.11***	0.10**	0.10**
	Stat W FX	0.20***	0.21***	0.21***	0.21***	0.21***	0.20***	0.19***	0.24***	0.23***	0.19***	0.20***	0.20***
	Stat D Com	0.13***	0.14***	0.14***	0.13***	0.13***	0.13***	0.12***	0.13***	0.13***	0.12***	0.12***	0.12***
	Stat D Fixed	0.16***	0.16***	0.16***	0.16***	0.15***	0.16***	0.17***	0.13***	0.15***	0.15***	0.15***	0.12**
	BK M Com	0.06*	0.08**	0.09**	0.06	0.05	0.06	0.06*	0.09**	0.10***	0.06	0.06	0.05
	GSCI	0.19***	0.18***	0.20***	0.18***	0.19***	0.18***	0.19***	0.19***	0.19***	0.18***	0.18***	0.18***
Daily Factors	Dyn M Fixed*C	0.01		0.04			0.01	-0.06**		-0.08***	0.00		-0.01
	Dyn M Stock*C	-0.04		-0.04			-0.02	0.00		-0.01	0.01		0.03
	Dyn D Stock*C	0.03		0.07**			0.04	-0.04		-0.04	-0.01		-0.07**
	Stat W FX*C	-0.02		-0.01			0.01	0.02		0.03	-0.02		0.07
	Stat D Com*C	0.06**		0.10*			-0.04	0.00		0.00	0.01		0.00
	Stat D Fixed*C	0.04		0.01			-0.04	0.05		0.08**	-0.01		0.06
	BK M Com*C	-0.06**		-0.01			-0.02	0.00		0.00	-0.03		0.02
	GSCI*C	0.03		0.06			0.02	-0.06*		-0.03	-0.04		-0.02
Monthly Factors	Dyn M Fixed*C		0.00	-0.02	-0.04	-0.05	-0.06		-0.02	-0.01		-0.01	0.02
	Dyn M Stock*C		-0.02	0.00	-0.06*	-0.06	-0.05		0.00	0.01		0.02	-0.01
	Dyn D Stock*C		-0.01	-0.07**	0.01	0.00	-0.02		-0.05	-0.05		-0.05*	0.03
	Stat W FX*C		-0.02	-0.02	-0.01	0.00	0.00		0.06***	0.07***		0.01	-0.06
	Stat D Com*C		0.04	-0.04	0.02	0.04	0.06		-0.03	-0.02		0.01	0.01
	Stat D Fixed*C		0.04	0.03	-0.02	-0.02	0.00		-0.06*	-0.06*		0.01	-0.07
	BK M Com*C		-0.05**	-0.02	-0.04	-0.03	-0.02		0.04	0.04*		-0.02	-0.05
	GSCI*C		0.00	-0.03	0.01	0.00	-0.02		0.02	0.03*		-0.05**	-0.02
	Adj. R^2	0.66	0.65	0.66	0.66	0.66	0.66		0.67	0.67	0.64	0.64	0.64

Table A4

This table shows style analysis regression results allowing for time-variation in factor loadings through conditioning variables which are the VIX, TED spread, S&P 500 returns, and 3-month T-bill yield in Panel A, B, C, D, respectively. The models consider conditioning variable – risk factor interactions both at daily and monthly frequencies similarly as in Patton and Ramadorai (2013). The conditioning variables are standardized using a 4-year window and avoiding lookahead bias they are lagged by one period. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

Panel A - AUM-Weighted Market Index

	S&P 500 Returns			Realized Volatility			VIX			TED Spread		
	Low	High	Wald p	Low	High	Wald p	Low	High	Wald p	Low	High	Wald p
Alpha (%)	-0.41	-0.41***	0.99	-0.33***	-0.58**	0.34	-0.47***	0.12	0.09	-0.39***	-0.62**	0.39
Dyn M Fixed	0.35*	0.35***	0.97	0.34***	0.32***	0.85	0.33***	0.28**	0.23	0.37***	0.41***	0.60
Dyn M Stock	0.34***	0.21***	0.24	0.22***	0.33***	0.41	0.24***	0.27**	0.06	0.32***	-0.02	0.00
Dyn D Stock	0.11	0.10***	0.97	0.09**	0.14*	0.53	0.11***	0.11	0.81	0.09**	0.24***	0.11
Stat W FX	0.19***	0.21***	0.73	0.23***	0.07	0.03	0.23***	0.11*	0.01	0.21***	0.23***	0.74
Stat D Com	0.05	0.15***	0.53	0.10***	0.28*	0.22	0.12***	0.24**	0.28	0.12***	0.13	0.92
Stat D Fixed	0.26	0.15***	0.58	0.12***	0.25***	0.11	0.12***	0.25**	0.03	0.16***	0.05	0.27
BK M Com	0.06	0.05	0.97	0.05	0.09	0.74	0.04	0.19	0.56	0.07*	0.02	0.61
GSCI	0.26*	0.17***	0.57	0.20***	0.22***	0.80	0.17***	0.33***	0.04	0.17***	0.27***	0.19
Adj. R^2		0.64			0.65			0.66			0.66	

Panel B - Equal Risk-Weighted Contrarian Index

	S&P 500 Returns			Realized Volatility			VIX			TED Spread		
	Low	High	Wald p	Low	High	Wald p	Low	High	Wald p	Low	High	Wald p
Alpha (%)	0.54	-0.02	0.31	0.06	-0.31*	0.05	-0.01	-0.02	0.95	0.06	0.01	0.84
Dyn M Stock	0.11**	0.06**	0.30	0.04*	0.13*	0.19	0.05**	0.06	0.83	0.08**	0.02	0.29
Dyn W Com	0.02	0.13***	0.34	0.13***	-0.05	0.03	0.12***	0.07	0.48	0.13***	0.08**	0.28
Dyn W Fixed	0.23***	0.13***	0.11	0.13***	0.24***	0.15	0.10***	0.32***	0.06	0.16***	0.03	0.15
PTFSFX	0.15***	0.17***	0.77	0.16***	0.23***	0.47	0.18***	0.07	0.07	0.20***	0.10**	0.04
Citi Bond	0.01	0.08***	0.26	0.08***	0.01	0.28	0.08***	-0.07	0.14	0.08**	0.11	0.74
MSCI WI	0.12	0.03	0.50	0.04*	0.00	0.55	0.03	0.05	0.63	0.02	0.01	0.82
Adj. R^2		0.50			0.52			0.52			0.52	

Table A5

This table shows style analysis regression results allowing for regime switching through S&P500 returns, realized S&P 500 volatility, VIX index and TED spread. As in Patton and Ramadorai (2013), in each month the daily values of conditioning variables are cumulated and if the sum reaches the 90th percentile (10th percentile for the S&P 500) of the distribution of past monthly values then the model switches to the high (low) regime. The only exception is the VIX index which is not cumulated, but the daily values are compared to monthly past realizations. The columns labeled ‘Wald p’ show the p-values for the Wald F-statistic testing the difference between the low and high regime estimates. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors are based on the Newey-West (1994) autocorrelation and heteroskedasticity consistent covariance matrix estimator.

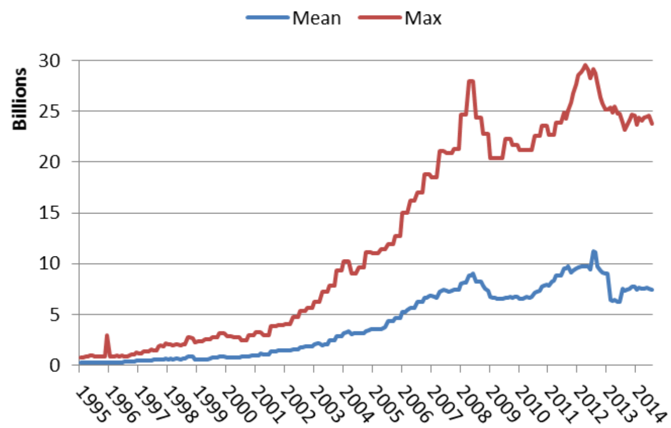

Figure 1

This figure shows the weighted average AUM and the largest CTA's AUM included in the systematic BarclayHedge index.

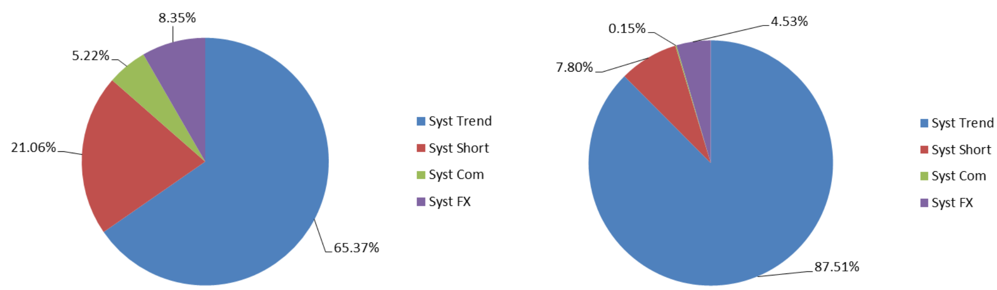

Figure 2

This figure shows the average composition of the systematic BarclayHedge index in terms of number of CTAs and in terms of weighted AUM in the left and right pie chart, respectively.

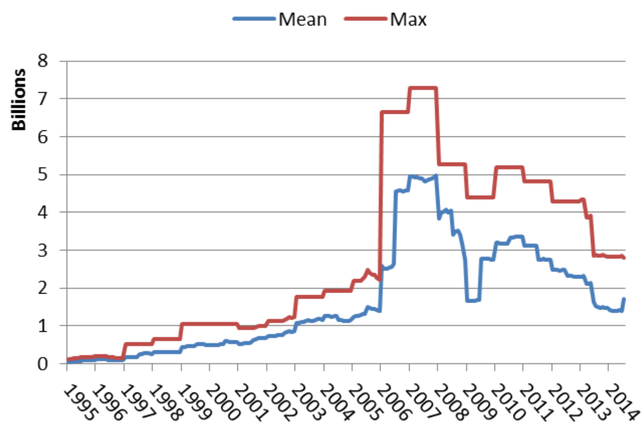

Figure 3

This figure shows the weighted average AUM and the largest CTA's AUM included in the systematic contrarian BarclayHedge index.

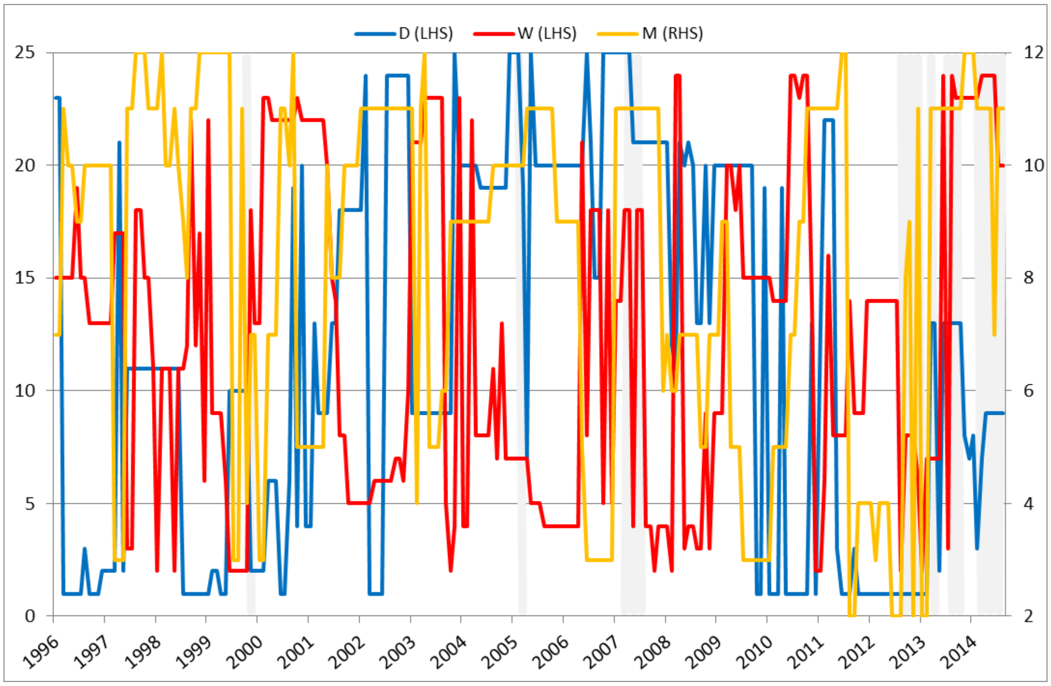

Figure 4

This figure shows the lookback length that corresponds to the best performing daily, weekly, and monthly momentum strategies. At each month-end Sharpe ratios on 1 year rolling data are calculated for all the strategies and the lookback of the best-performing is selected. The holding period is fixed at 1 month, 1 week, and 1 day for monthly, weekly, and daily strategies respectively. The lookback varies between 2 and 12 months, between 2 weeks and 24 weeks, and between 1 and 25 day(s) for monthly, weekly, and daily strategies, respectively. The grey highlighted area indicates that at least one of the competing strategies has produced an annualized Sharpe ratio of less than 0.3.

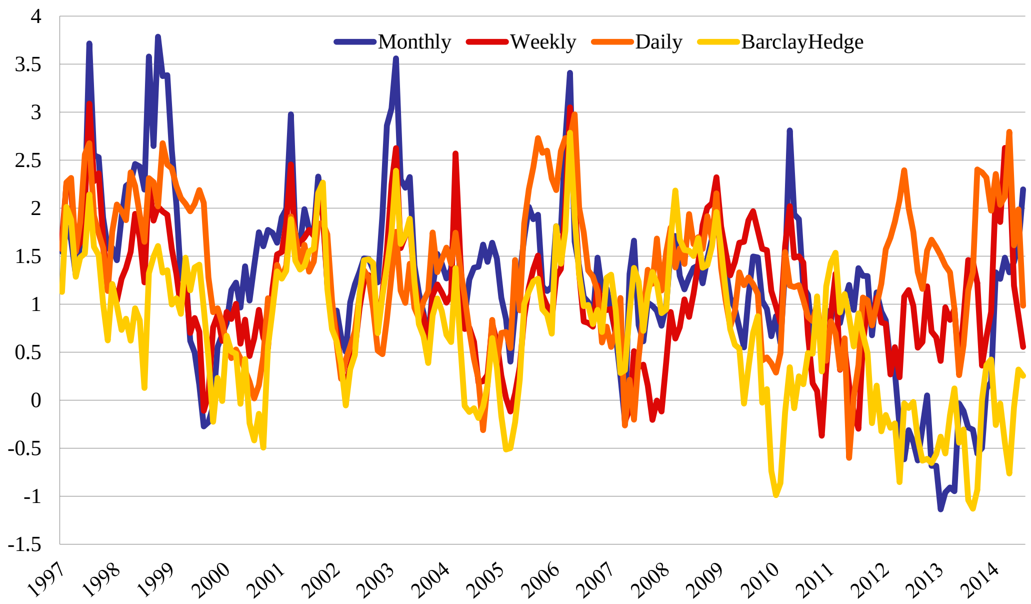

Figure 5

This figure shows the one-year rolling Sharpe ratios for monthly, weekly, daily enhanced dynamic benchmarks and for the AUM-weighted systematic BarclayHedge index.

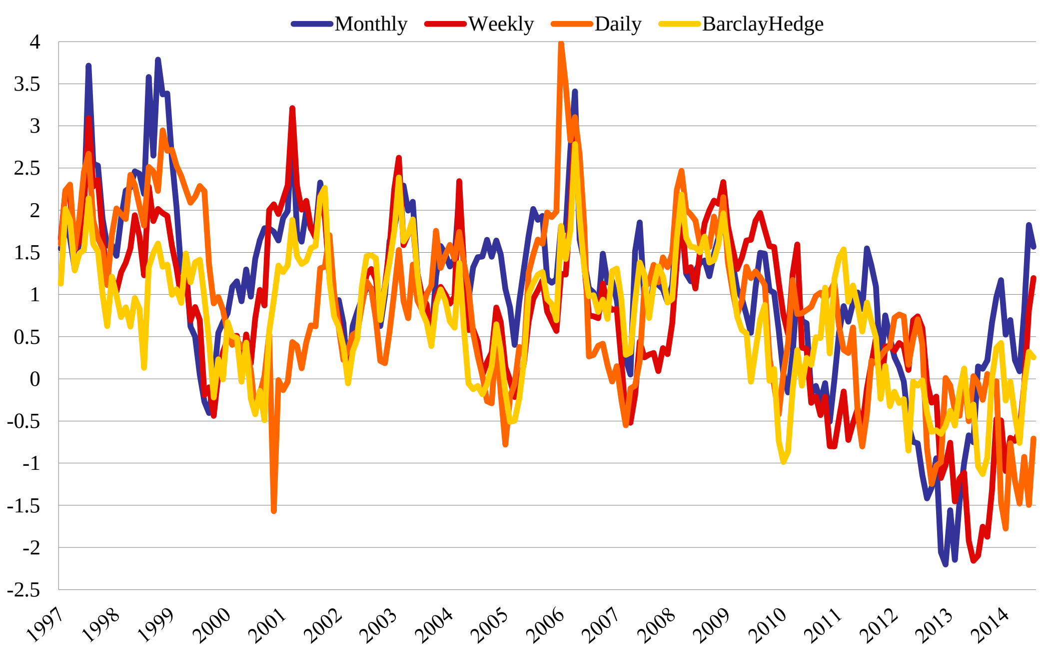

Figure A1

This figure shows the one-year rolling Sharpe ratios for monthly, weekly, daily dynamic benchmarks and for the AUM-weighted systematic BarclayHedge index.

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