Trends everywhere? The case of hedge fund styles[*]

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February 28, 2018

Preliminary version. Do not distribute.

[*]We thank Pedro Barroso, Paul Karehnke and the people at KeyQuant, for various useful comments and suggestions.

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Abstract

This paper demonstrates that returns of Managed Futures, Global Macro, Multistrategies and Fund of Hedge Funds strategies can be partly explained by a Trend exposure, whereas other hedge fund styles do not exhibit significant results. Following the practice of trend-followers, a volatility-adjusted time-series momentum signal is applied on a daily basis across a large set of futures, covering the major asset classes. We find that a Trend exposure is a significant determinant of hedge funds returns at the aggregate level, as well as at the fund level. Another contribution of this study is related to the understanding of the CTA space, composed of pure Trend funds as well as funds that do not exhibit any Trend exposure.

1 Introduction

During the 2008-2009 Global Financial Crisis (GFC), alternative strategies suffered heavy losses, raising doubt about their ability to deliver absolute and uncorrelated returns. Indeed, the "arbitrage" funds such as market neutral, relative value and long/short equity, mainly hedge traditional risk exposures but bet on liquidity asymmetries. Credit crunch and loss of confidence between major institutions made liquidity evaporate, hurting these funds. However, hedge funds were not all equal when it comes to the consequences of the crisis. Indeed, liquidity sellers should have benefited from this environment. Following the crisis, there was a strong desire for all parties involved to better understand hedge funds, in terms of transparency and in terms of sources of returns. Researchers from academia as well as from industry analyse time series to extract such information. The standard way to decipher them is through a linear factor model, where past returns of a strategy are projected on a series of known factors.

In this paper, we build a new factor, harvesting the trends in the financial markets, and look at their presence in the cross-section of alternative strategies. First, we want to check whether our factor is strongly priced among Managed Futures funds, also called Commodity Trading Advisors (CTAs). Indeed, most of them are systematic and apply a trend-following strategy. Secondly, we want to know what are the other hedge funds strategies that have a trend exposure, to possibly confirm what we saw during the GFC. With the same objective in mind, Fung and Hsieh (2001) created options factors, monthly-reshuffled lookback straddles written on the following five common asset classes : Bonds, Foreign exchange, Commodities, Equities and Interest Rates [14].

Our main contribution lies in the construction: our factor is dynamic, diversified, can go long and short, and harvest all types of trends: from short term to long term ones. Despite these demanding features, our construction remains transparent and realistic. We tested several specifications to check if some hedge funds were more exposed to a specific type of trends. We find that CTAs have a statistically and economically significant exposure on our trend factor, both at the index and fund levels. Also, this result holds when adjusting for the standard risk factors, and for different index providers. Despite good results for monthly and equity-only specifications, the improvement in R-squared for this strategy is the highest for our central specification, confirming our initial assumptions. Not surprisingly, Fund of funds and Multi-strategies are exposed to our factor. Both are diversified in terms of variety of strategies, so it makes sense part of their assets is allocated to trend following. The second main result is that Global Macro funds have a strong exposure to our factor, perhaps due to their cross-asset feature and to their objective to time markets or trends. Betas are not significant in the rest of the alternative space, confirming this could be the missing factor that causes the difference in performances observed during the 2008 crisis.

The remainder of the paper is organized as follows. Section 2 describes the relevant literature. Data and factor construction are presented in Section 3. Our empirical methodology and the results are provided in Section 4. In Section 5 we examine the robustness of our results and extensions of the analysis. Section 6 reviews our arguments and concludes the paper.

2 Literature review

Since our research is mainly related to understanding hedge funds performances, we focus on the alternative space and more specifically, the relevant factor models. The Efficient Market Hypothesis (EMH) described by Fama (1969) [12] based on Samuelson's work (1965) [28], and what Markowitz (1952) [21] and Sharpe (1964) [29] derived in terms of portfolio construction is the corner stone of the Modern Portfolio Theory. A huge number of publications were related to testing whether prices did move randomly and funds can or cannot outperform the market without leveraging. This question has been central for decades, especially concerning the equity markets. Indeed, many researchers were able to prove the existence of a significant alpha, thus contradicting the Capital Asset Pricing Model (CAPM), but all attempts were nipped in the bud with the apparition of risk factors. Fama and French (1996) extended the CAPM with two new factors: size and value [13]. CAPM and Fama-French models can be used to assess the risk exposures of a portfolio. The beta is the exposure of the portfolio to this risk factor. In the equity market, the risk factors were designed as portfolios replicating a way of investing, a style (growth, value, small cap focus . . .). Hedge funds are different than mutual funds: they can short sell, use leverage, use options and have access to alternative asset classes. Thus, the equivalent of the CAPM for alternative investments would be a model where all asset classes are put as covariables. Still, such a static model won't capture neither the ability to leverage nor the volatility exposure. Moreover, hedge fund managers trade more frequently than traditional managers: the investment process is no longer a buy-and-hold one.

Return-based style analysis refers to the technique of linear factor models. Seminal contributions on this matter came from Fung and Hsieh (2001, 2004) [14, 15], Glosten and Jagannathan (1994) [16], Agarwal and Naik (2001,2004) [2, 3] and Ben Dor and Jagannathan (2003) [10], all trying to understand hedge fund performances by analysing the cross-variation between their returns and other strategies' returns. To solve this issue, Fung and Hsieh (2004) proposed seven (even nine in further work) risk factors to explain the hedge funds performances. They include the main asset classes: equity (equity market, size), fixed income (bond, credit) and emerging markets to account for the cross-asset dimension of hedge funds and three proxies of trend-following strategies on bonds, currencies and commodities (lookback options) to account for their dynamic exposures. They first focus on trend-following funds and then extend their scope to all alternative strategies [14, 15]. Similarly to the Fung and Hsieh (2004) contribution but more focusing on volatility, Agarwal and Naik (2004) included volatility exposure through put options, written on the S&P500 index to explain the differences in returns across the alternative styles [3]. Hasanhodzic and Lo (2007) use observed factors, such as the S&P 500 index, the USD return index, the Bond Index, etc., to model the returns of individual hedge funds [17].

Despite their strong economic support, these papers did not do particularly well in explaining hedge fund strategies. Firstly, these hedge fund factor models can be doubted on the assumptions side of the model. Indeed, these models have one main drawback: the estimations of the betas can be biased. Despite their convexity, the option-based factors of Fung and Hsieh cannot capture all the non-linearities in the hedge funds payoffs, resulting in wrong estimations of betas. De Roon and Karehnke (2017) confirm it: "However, we show that this approach in general does not suffice because option-like payoffs can still generate a positive alpha at the expense of negative skewness". They focus on a solution including a skewness integration to alleviate it [25]. Another bias is the time-varying dimension of the loadings. Indeed, as stated before, hedge funds can dynamically allocate to different risk factors and fixing ex ante a specification does not permit to capture this. A more dynamic model, which would allow betas to vary, might be needed. Indeed, Patton and Ramadorai (2010) showed that hedge funds exposures vary across and within months, confirming the relative high frequency behaviour [24]. However, due to the fact hedge funds reports only monthly net asset values (NAVs), this model can't be applied in practice. Also, time-varying beta estimation would require very long sample, which is not exactly the case for monthly returns. Betas could vary but more generally, the set of risk factors that some hedge fund might decide to expose to might change. Darolles and Mero (2011) propose a selection algorithm to keep only the most relevant risk factors in a time-varying setup [9]. Secondly, the Fung and Hsieh (2004) factor model does very well at explaining the equity-related alternative strategies, such as Long/Short Equity and Market Neutral but results are somewhat less robust on fixed income-related ones and to a larger extent, cross-asset strategies such as Macro ones. Focusing on CTA strategy, Elaut and Erdos (2016) confirm it: "The performance of these models in explaining Managed Futures funds return is, however, lackluster" [11].

Alternative models or procedures were suggested with very interesting insights in their area, and contributed a lot to the comprehension of mutual funds. However, these factors are not all relevant to our issue of demystifying hedge funds returns. At the same time, there were some interesting papers proposing additional factors, with a strong economic rationale, aiming at demystifying hedge funds performances. Mitchell and Pulvino (2001) focused on risk arbitrage, Sadka (2009, 2011) on a liquidity factor, Bali (2014) on an uncertainty indicator while Buraschi (2013), Arisoy, Agarwal and Naik (2015) worked on volatility and correlation risks [1, 8, 22, 26, 27]. Even more recently, a strong interest rose about a cross-asset carry factor, with works from Koijen et al. (2016) and Baltas (2017) [4, 20]. Most of these factors are the result of an economic rationale, either by a pure risk argument, or by means of institutional constraints. They rely on being long some assets and short some others, hoping for a reduction in the spread, which is the essence of arbitrage. The famous adage qualifies them perfectly: it's like "picking pennies in front of a steamroller". On the contrary, the trend following strategy has a rather different profile, with a right convexity (many small losses and few large gains), taking advantage of an anomaly, the trends in the markets, caused by the behavioural biases of investors. Thus, all these factors are very helpful understanding the cross-section of hedge funds but not specifically on macro strategies.

Finally, we turned to papers from industry, though often the results of joint work with academic researchers, to find interesting answers to our problem. There are some attempts at building trend following benchmarks in the industrial side of the academic literature. Indeed, Moskowitz, Ooi and Pedersen (2012), with AQR, published a seminal article on what they call time-series momentum; UBS, RPM and Aspect Capital were also connected to academic researchers' work on this matter. Moskowitz, Ooi and Pedersen (2012) documented serial correlation in the risk-adjusted returns across the major asset classes, and showed that a simple "time-series momentum" (hereafter named TSMOM) could harvest this alpha [23]. Their construction is similar to ours, except that they focus on the 1-year lookback with a monthly rebalancing. Hurst, Ooi and Pedersen (2015) [18] worked on the economic intuition behind the presence of such trends in the financial markets. Their discovery is major: the random walk hypothesis and the related EMH are strongly challenged. Based on the recent field of behavioural finance, Barberis, Shleifer and Vishny (1998) show investors are not perfectly rational, suffer from multiple behavioural biases which create market inefficiencies [7]. The most famous are herding, anchoring, confirmation biases. For further information, refer to Hurst, Ooi and Pedersen (2013) who propose a very thorough review of such biases and the associated mechanisms that create trends [18]. In addition, they show TSMOM helps understanding Managed Futures indexes and individual funds. Simultaneously, Baltas and Kosowski (2012) also document a time-series momentum as a benchmark for Trend Following funds [5]. The construction methodology is similar to the one used by Moskowitz and his co-authors, as well as the proof of autocorrelation in the risk-adjusted returns. In addition, they study fund flows in the CTA industry and assess whether they suffer from capacity constraint or not, despite only trading futures contracts. Baltas and Kosowski (2015) focus on the impact of the volatility and correlations on the performances of the time-series momentum factor [6]. Hutchinson and O'Brien (2015) [19] relate Trend-Following returns to the periods of crisis and show that post-crisis returns are usually weak/below average. Elaut and Erdos (2016) [11] build a trend-following benchmark mixing the diversified TSMOM across a large set of lookback horizons and show it improves the understanding of individual CTAs in comparison to the standard Trend Following benchmarks [5, 23]. Industry also did its part in this benchmarking mission when Societe Generale (formerly NewEdge) published CTA and Trend indexes, which are baskets of actual funds, as well as a factor, the Trend Indicator. However, objectives of industrial research are different than pure academic ones, with the latter more concerned about returns than economic understanding. Our paper aims at filling this gap: use industrial and academic ideas to build a new risk factor synonym of Trend and to better understand the cross-section of hedge funds strategies. Do we detect trend everywhere in the hedge fund space?

3 Data and methodology

3.1 Data

In this section, we briefly describe the various datasets we use in the paper, namely, futures prices, standard hedge fund factors from the literature, as well as hedge funds indices and individual funds' returns.

3.1.1 Futures. Our sample consists of 50 futures, across five asset classes: 19 commodities, 12 equity indices, 9 bonds, 7 currencies and 3 short-term interest rates. These instruments are among the most traded and liquid contracts in the world. This is important since our benchmark construction will be on a daily frequency, so we want to remove any illiquidity issue (price impact and price significativity) as much as possible. For each of them, we record 4pm UTC and closing prices across all the front-month contracts that are rolled over to build the continuous time series. The roll calendar is based on liquidity, and a forward ratio price adjustment is performed to avoid any gap in the series due to Backwardation or Contango structure. In accordance with Moskowitz et al. (2012), and the observed daily volume, the front-month contract is always the most liquid. All contracts were not traded during the full sample, making the universe of tradable contracts for our strategies start from 38 contracts in 1990 to reach the 50 contracts in 2007. See details of the futures sample in Appendix A. The list of contracts we use is similar to what can be found in the trend following literature [5, 23].

[Insert here Table 1]

Table 1 presents univariate statistics of the returns of our futures contracts. Our database of futures is highly heterogeneous, and in many aspects: annualized return spans from -22% for the natural gas to almost 8% for the soybean meal, whereas annualized volatility reaches 46% for the natural gas and is as low as 0.37% for Euribor. Also, the return distributions of some futures are highly assymmetric with fat tails when others have a distribution similar to a bell curve. First-order autocorrelation is also presented, and remains low across futures, except for some of them such as Live Cattle, Euribor.

3.1.2 Asset pricing benchmark. We use in our analysis the nine-factor model from Fung and Hsieh [14]. In their seminal paper, they show these factors have strong explanatory power for hedge fund indexes returns. Specifically, they contain four asset class factors, being Buy-and-Hold (B&H) portfolios of major indexes, two equity-oriented and two qualified as fixed-income. The first factor is the S&P500 index returns (now referred as Equity), a second is its spread with the Russell 2000 index (now referred as the Size risk factor). Another is constructed using the 10-year T-Bond yield, standing for the Bond exposure, and the last one is the Credit exposure, based on the spread with Moodys BAA bonds and the previously cited Treasury index. To account for the optionality and the dynamics of hedge funds exposures, they added trend following risk factors, built as portfolios of lookback straddle options. Initially, there were only three of them, for these three underlyings: currencies (PTFSFX), commodities (PTFSCOM) and bonds (PTFSBD). They further added similar versions on interest rates (PTFSIR) and equity market (PTFSSTK). All these data were taken from Fung and Hsieh website.[1]

3.1.3 Hedge fund data. Our dataset comprises eleven HFR indexes, spanning from Equity Market Neutral to Global Macro. The full list, along some description of the indexes, is available in Appendix A. For each of them, we have all the monthly returns from January 1990 until December 2016. For robustness check purpose, we also have a selection of Credit Suisse First Boston (CSFB) indices, available from January 1994 to October 2016. The selection was done to have a similar set of strategies as in our HFR database. In both cases, returns in excess of cash were calculated, by deducing the returns of the Euribor 3M.

To analyse the commonality of returns between our Trend factor and CTA performances, we collected individual funds returns from the EuroHedge Database. Our original dataset contains 3696 funds across various alternative strategies. Some fund characteristics are available such as fee structure, assets under management, inception date and some informations related to the management firm. As common for all hedge funds databases, reported returns are net-of-fees and monthly. The Managed Futures Category contains 362 funds, and 137 of them are in USD currency. Cleaning was performed and additional data (fees information) from Bloomberg was retrieved. Monthly gross-of-fees returns were calculated based on the fee schedule and a quarterly crystallization, unless otherwise stated. Management fee was increased by 0.25% annually to include expense fees. Our dataset starts in December 1993 and ends in June 2017. At least 50% of the funds actively traded past January 2011, which will stand for the start of the sample used in the analysis.

3.2 Factor construction

We construct our Trend risk factor based on the practice of trend followers and the momentum anomaly. This portfolio is cross-section-diversified since invested across asset classes, and time-diversified due to its dynamic trend timing nature. We expect its returns to be correlated with hedge funds indices as well as individual CTAs performances. Indeed, many CTA employ trend following strategies over different horizons: from short-term (around 1 month holding period), some medium-term (from 6 months to 1 year) and some long-term (more than one year). Specialized CTAs trade only commodity markets, or focus on one horizon, but we hope to understand returns of all kinds of CTAs thanks to our sub-Trend factors. The risk factor is in fact an equal-weight basket of five time-series momentums, each diversified across futures, with daily rebalancing, with a lookback horizon: 20, 65, 130, 260 and 520 trading days respectively. These windows were chosen as to fit standard calendar splits (one month, three months, six months, one year and two years) to keep it simple and assuming trend signals used by actual CTAs might be set up that way. Despite showing serial correlation over different lookbacks, Moskowitz, Ooi and Pedersen (MOP, 2012) focus on the 1-year lookback to build their time-series momentum (TSMOM). Baltas and Kosowski (BK, 2012), as well as Elaut and Erdos (EE, 2016), mix different time horizons when constructing their trend following benchmark [5, 11]. The first mix monthly, weekly and daily rebalanced portfolios, each with a different lookback, to construct their Futures-based Trend Following benchmark (FTB). Like us, the latter proposes a more dynamic one, due to a daily rebalancing, but with as much as 251 different lookbacks (ranging from 10 to 260 days). In an ad hoc analysis, we studied the relationships between trend following strategies which differ by the lookback they use and we found the loss of information, as measured by the correlation, is proportional with the log-difference in lookback. Thus, to avoid over-fitting, we selected the five most informative lookbacks, being the one mentioned earlier.

We assumed daily rebalancing as the futures in our dataset are ones of the most liquid contracts in the world, thus reducing any potential friction costs. For the same reason, CTAs are known to be agile and can switch their position from one day to the other, and monthly rebalanced portfolios would not have been able to capture their returns.

The construction of our factor is standard in the trend following literature, represented by MOP (2012), BK (2012) and EE (2016):

$$r_t^P = \frac{1}{N_t} \sum_{i=1}^{N_t} \mathrm{S}_{t-1,i} \frac{\kappa}{\sigma_{t-1,i}} r_{t,i} \tag{1}$$

where:

- $S_{t-1,i}$ is the average $\overline{\mathrm{sign}(p_{t-1} - p_{t-1-h})}$, where each component is the momentum signal on the past h trading days, for h in $\{20, 65, 130, 260, 520\}$.
- $\sigma_{t-1,i}$ is the realized volatility of future i
- N_t is the number of actively traded contracts at date t
- $r_{t,i}$ is the return of future i at date t
- κ is the individual target volatility

Note that this strategy can be applied to a different set of futures, for example, if we were to select only the $N_{t,Equity}$ equity futures, we would get a version of Trend on the Equity asset class. Finally, Trend is only an allocation of the "sub"-Trend factors built on the different asset classes. This property also applies when decomposing across lookbacks. This feature will be tested in the robustness analysis, where we will analyze the comparative explanatory power of these sub-Trend factors.

As explained in the data section, not all futures trade for the whole period, making the number of contracts available for trading time-varying. Signals and volatility, constituting the position, are just lagged one day since we use 4 pm UTC prices, making instantaneous execution possible. Indeed, with closing prices, one would wait for the settlement to calculate signals, pushing the trading on the next day. We assume signals are calculated at 4 pm and execution is done simultaneously. The individual target volatility κ is set to target a 10% annual volatility per future. Note the diversification between futures reduces the portfolio volatility. Since most CTAs offer products with a specified volatility, we further add a target volatility step in the construction process to make our factors closer to real-life CTAs. MOP (2012), BK (2012) and EE (2016) all use a fast volatility, which is the standard RiskMetrics exponentially weighted moving average estimator with a 94% decay. However, due to the inclusion of a long-term component in our trend index, and to reduce the turnover, we use a 99% decay to be consistent in terms of weights with a 1-year rolling volatility. Indeed, a slowest volatility is more stable, thus reducing the turnover.

[Insert here Table 2]

Trend strategy on average earned 2.34% per month during the period running from January 2010 to March 2016 (on which HFR indices are available). Over the full sample, the average monthly return is 2.69%. We then split this period into two periods, pre- and post-GFC crisis: from December 1993 to March 2009 for the pre-crisis subperiod and April 2009 to July 2017 for the post-crisis subperiod [2]. Average monthly return goes from 3.21% to 1.73%, being almost divided twofold. As we can see on the Figure 1, we notice good performances during the GFC, which allows to keep our factor as a potential candidate for understanding the then performances.

[Insert here Figure 1]

[Insert here Table 3]

Table 3 shows the main performance and risk measures of our Trend factor, along with CTA and Global Macro HFR indices. As said before, volatility is a parameter which can be fixed at whatever level without loss of generality, so here we set it at the same of the CTA index for comparison purposes. Performances of our factor are gross of fees (management, performance and expense fees) as well as gross of transaction costs.

[Insert here Table 4]

Table 4 presents its correlation with Fung and Hsieh factors. Concerning the standard asset class benchmarks, correlations with Trend are close to zero except for the 10 Year T-Bond. Indeed, the steady decrease in the US rates due to the quantitative easing by the U.S. Federal Reserve Bank (FED) made trend followers maintain their position during the whole period, thus explaining the relatively high correlation with bonds. As for the PTFS option factors, correlations evolve between 0.10 for interest rates to 0.52 for foreign exchange. This confirms the work of Fung and Hsieh, their lookback straddle portfolios capturing part of the variation due to a trend exposure. As a robustness check, correlations were also calculated for the Trend index built on a selection of six futures and results were not economically different (refer to Table 15 in appendix A).

We saw relatively high correlations between our trend factor and the selected HFR indexes, being Global Macro and Systematic Diversified, as well as with Fung and Hsieh options factors.

The performances of our factor are indeed strongly related to the ones of CTA-related indexes. In addition, we calculated the correlations with Newedge CTA and Trend indexes and they were also high. This result is encouraging, but needs to be checked for robustness. To do so, we need to adjust the correlation by the other known risk factors, by calculating the beta on our factor in a multivariate regression. This is the goal of the following section.

4 Empirical results

We are going to use standard time-series regressions, where the dependant variable will be one of the HFRI indices and the explanatory variables the selected risk factors. There will be several specifications, each corresponding to a set of factors and aiming at answering a specific question.

The first specification, corresponding to Equation (2), is equivalent to the univariate analysis we did in the previous section, analyzing the correlation between our trend factor and relevant indexes. It consists of regressing one HFR index against our factor:

$$r^{index} = \alpha + \beta_{Trend} * \text{Trend} + \epsilon \tag{2}$$

The equity market being a strong driver of the financial markets in general, we add the S&P500 index to the model, resulting in the following equation:

$$r^{index} = \alpha + \beta_{Trend} * \text{Trend} + \beta_{Equity} * \text{Equity} + \epsilon \tag{3}$$

We call this specification the "augmented CAPM". Indeed, most market participants have in mind the Capital Asset Pricing Model when they think of asset pricing, having a strong bias towards equities in their way of reasoning [29]. This specification enables us to understand equity strategies in particular. Indeed, their correlation to Trend index could be "biased" due to the equity positioning of our cross-asset momentum.

Fama and French (1996) started from the CAPM and added two orthogonal factors they thought should explain part of the cross-variation of stock returns, size and value [13]. Understanding of equity mutual funds was highly improved. This reasoning can be extended to long-only cross-asset traditional funds, which perform a strategic allocation between the major asset classes. To do so, we further add the major asset classes, the size factor in the equity market, and bond and credit markets:

$$r^{index} = \alpha + \beta_{Trend} * \text{Trend} + \beta_{Equity} * \text{Equity} + \beta_{Size} * \text{Size} + \beta_{Bond} * \text{Bond} + \beta_{Credit} * \text{Credit} + \epsilon \quad (4)$$

This "augmented asset class factor model" allows us to detect any trend exposure in the traditional investment world, whose members tend to be static in their allocation.

The last two specifications are designed for hedge funds, since they incorporate the famous Fung and Hsieh ABS factors. The "augmented FH model" comprises the B&H asset class factors, the options factors written on the same indexes, and our Trend factor.

$$r^{index} = \alpha + \beta_{Trend} * \text{Trend} + \beta_{\mathbf{AssetClass}} * \mathbf{AssetClass} + \beta_{\mathbf{PTFS}} * \mathbf{PTFS} + \epsilon \quad (5)$$

For brevity, we gather some loadings and factors in vectors and matrices, written in bold. We note $\beta_{\mathbf{AssetClass}}$ the vector containing $\{\beta_{Equity}, \beta_{Size}, \beta_{Bond}, \beta_{Credit}\}$, **AssetClass** is the matrix containing the following factor returns $\{\text{Equity}, \text{Size}, \text{Bond}, \text{Credit}\}$. Similarly, $\beta_{\mathbf{PTFS}}$ the vector containing $\{\beta_{PTFSFX}, \beta_{PTFSCOM}, \beta_{PTFSBD}, \beta_{PTFSIR}, \beta_{PTFSSTK}\}$ and **PTFS** is the matrix of the associated factor returns.

This specification helps measuring the additional information in our factor relative to the attempt of Fung and Hsieh creating trend following benchmarks. The last model is the "FH model", which is defined as model (4) without our Trend factor:

$$r^{index} = \alpha + \beta_{\mathbf{AssetClass}} * \mathbf{AssetClass} + \beta_{\mathbf{PTFS}} * \mathbf{PTFS} + \epsilon \quad (6)$$

Models (3) and (5) can be compared to see whether our Trend factor or Fung and Hsieh factors best explain the trend exposure of hedge funds.

Our starting benchmark only includes the Trend factor as a regressor, but is augmented step-by-step with the nine factors of Fung and Hsieh (2004) model [15]. The same models will be computed with alternative versions of the trend factor: monthly and sector-only trend factors for robustness check and horizon trend factors to observe if exposures to trend vary with the lookback (main characteristic of the time series momentum). Moreover, the Fama-McBeth two-step approach will be used to evaluate the premium associated with the anomaly: in the first step we regress each fund on the trend factor, to get its trend beta (time-series dimension) and the second step consists in the regression of the mean performance of funds against the vector of betas (cross-section dimension).

Another standard approach in the literature consists in forming quantile portfolios and test for the difference in alpha: low trend beta and high trend beta portfolios are formed on a rolling basis and risk-adjusted returns (alpha) of both quantiles are compared to test for the significativity of the premium.

The first analysis will focus on confirming our factor has a strong explanatory power of the Systematic Diversified HFR index, which is the one closest to CTA/Managed Futures strategy, to validate our construction. In a second step, the other HFR indexes will be regressed in the various specifications to detect any trend exposure in the rest of the alternative space.

4.1 Validation on the systematic diversified style

First, we start by analysing the returns of the Systematic Diversified HFR index and its exposure to Trend, in multiple specifications. The first one is the one where our factor is the only regressor, and step by step we add other risk factors.

[Insert here Table 5]

Over the whole period that runs from January 2010 to March 2016, the R-squared of our 1-factor model is 63% for the Systematic Diversified index, and its exposure to Trend is 0.29 with a t-statistic of 11.17. Adding the asset classes factors does not change the results: beta stays at 0.29 when the equity market is added, and reaches 0.28 when Size, Bond and Credit are added, while t-statistics remain around 11. R-squared reaches 66% in the latter specification. The final addition consists in the five options factors of Fung and Hsieh: PTFSBD, PTFSFX, PTFSCOM, PTFSIR and PTFSSTK. In that case, exposure of the HFRMTI index is 0.26, with a t-statistic of 8.84, and the R-squared slightly improves to 72%. Despite adjusting for factors that have been designed to represent trend following returns, exposure of the Systematic Diversified to our Trend factor remains highly significant. We then compare these results to the standard specification, the 9-factor Fung-Hsieh model, to properly assess our contribution. Without our Trend index, R-squared is at 38% and is almost doubled when adding it (72%). Exposures to the PTFS factors are all reduced except for the equity one, confirming these options factors do capture part of a trend exposure. Specifications (3) and (5) can be put side by side to see which model does better at explaining the Systematic Diversified index. 66% of the variance of the returns are explained by the asset classes and the Trend factor, whereas this proportion is only 38% when PTFS options factors replace our Trend factor. The advantage of the Fung Hsieh specification is that we can decompose the exposures on the different asset classes, whereas the Trend factor is unidimensional. However, as described in the factor construction section, sub-Trend factors can be built and a full specification containing four of them (one for each asset class) can be tested. Robustness checks will ensure results hold for the sector-only versions of Trend.

4.2 Extension to the other hedge fund styles

In this section, we apply the models (4) and (5) to all the HFR indices in the sample, and compare the R-squared.

[Insert here Figure 2]

As we can see on Figure 2, the Systematic Diversified Index is the index that exhibits the largest improvement in R-squared due to the addition of Trend to the model (with an increase as large as 34 points). In second position comes the Global Macro index. Fund of funds and to a lesser extent, Multistrategy, show an improvement as well.

[Insert here Table 6]

Table 6 contains the results of the model (5). First,we look at the standard asset class factor loadings in the cross-section of hedge fund styles. As expected, Equity and Size factors are highly significant in the equity-related strategies. Confirming the CAPM, all styles exhibit a significant loading on the equity market. Short-selling evidently exhibits a strong negative beta. Surprisingly, bond exposure is only significant in the Market Neutral strategy.

Among the eleven HFR indexes, four of them exhibit significant Trend exposure, at a 5% level: by decreasing t-statistic, Systematic Diversified, Macro, Fund of Funds and Quantitative Directional. Loadings on Fung-Hsieh PTFS factors can point towards a substitution effect between these asset class options factors and our Trend factor. Indeed, out of the four previously mentioned strategies, only the latter, Quantitative Directional (HFRIENHI) has a remaining significant exposure, but only one, on the PTFSBD factor. For the other seven hedge fund styles, only Market

Neutral, Short Selling and Equity Hedge display at least a significant exposure on one of the PTFS factors. However, only one asset class is concerned each time, and the significancy never reaches the 1% threshold. When there is no significant exposure on our cross-asset Trend factor, loadings on the various PTFS factors are very often non significant.

The substitution effect we detect can be checked by a before/after analysis, comparing t-statistics of the loadings in model (4) versus the ones in model (5), that is before/after adding our Trend factor to the Fung-Hsieh 9-factor model.

In addition, a stepwise procedure was used to see for which indexes the Trend factor will remain selected, as shown in Table 7. It confirms the previous results: Systematic Diversified, Macro, Fund of Funds and the two Equity Market Neutral and Quantitative Directional are the strategies where Trend is kept. Is is the case for 45% of the indexes whereas this proportion is lower for PTFS factors, except the Commodity one. This is not surprising since commodities themselves are not present in the four asset classes also present in the factor model, making it logical to select it despite a dynamic exposure. Overall, our results show our trend risk factor is an important determinant of hedge funds indexes returns.

[Insert here Table 7]

5 Robustness checks

5.1 Specification

[Insert here Tables 8 and 9]

In order to check the contribution of our factor, we ran the same analyses with the equity-only version of the Trend index. In this case, the universe of futures is reduced to 12 indices. For all specifications, results are far worse than with the full version of Trend, with lower R-squared, and lower t-statistics. Indeed, the t-statistics are between 3 and 4, comparing to 11 in the standard case. R-squared only reaches 56% in the most complete specification (4), compared to 72% before. Results are similar (even larger R-squared reductions) for the other sub-versions of Trend, built on only one asset class. Indeed, selecting futures of a particular asset class (then using a non-diversified Trend index) greatly reduces the explanatory power of the regression. That confirms a big part of our contribution lies in the diversified feature of our factor.

[Insert here Table 10]

We saw there are five option factors in Fung-Hsieh model, each written on an index representing an asset class. Since our factor trades 50 futures, one could argue our model has a higher R-squared due to the diversity of underlyings and not due to the actual construction of the factor. To test it, we created a factor trading only a selection of futures. Six were selected, one for each sector: S&P500, US10Y T-note, EUR/USD, Corn, Gold and Crude Oil. R-squared of all specifications are indeed lower to their counterparts in the benchmark model, reaching 50% in the full specification (4). However, trend loading remains significant with t-statistic around 6 in specifications (1)-(3). In (4), beta is 0.38 and t-statistic is 3.93. Moreover, it is at the expense of the PTFS factors, since only the FX one is still significant after adding the reduced trend factor. These results are not surprising: one of the major characteristics and advantages of the trend following strategy is its diversification and the fact it trades several futures from all asset classes. Trading six out of of fifty futures does not change the transparency and replicability of our factor, so one cannot argue the factor is a sophisticated strategy.

[Insert here Table 11]

Decomposing the Trend index into five sub-versions of it allows to increase the R-squared of the HFRI indexes, but only marginally, which suggests the indexes that do not show any exposure on the aggregate level do not show exposure on the sub-versions either. Fund of Funds, Equity Market Neutral, Quantitative Directional and Equity Hedge have significant exposures only on the long-term sub-Trend factor, whereas this is the one showing the lowest t-statistic for Systematic Diversified and Macro indexes. All other significant exposures are the results of an arbitrage effect: Trend 65 and 130 displaying a high correlation (67%), some indexes exhibit a long exposure on the first one and a short on the 130-days factor.

[Insert here Table 12]

Table 12 contains the variable selection results associated to the full specification. As the t-statistics announced, the very short and very long horizon Trend factors are not selected when explaining the Systematic Diversified style. Also, all sub-Trend factors are kept when explaining the Macro index. On an aggregate level, the 20-days Trend factor is not very present in the cross-section of hedge fund styles, suggesting there might be no reward in following such short trends. Medium-term to long-term Trend indices are more often selected, confirming many results from the literature regarding the length of the trends in the markets [18, 23]. All this relies on the assumption actual hedge funds are efficient in their way of selecting strategies.

5.2 Cross-sectional analysis

[Insert here Table 13]

Table 13 presents summary statistics of the Managed Futures funds labelled in US dollars. One thing noteworthy is the difference between mean and median AUM, with the first being much higher than the latter, meaning the distribution is right-skewed, with a few very large funds. Also, despite the recent decrease in fees in the alternative industry, it seems more than 75% of the selected funds still have a 20% incentive fee. However, management fee seems lower than the traditional 2% in the industry with a median at 1.20%. Concerning performances, USD Managed Futures funds offer on average 23 basis points per month.

In this section, we look at the loadings on Trend of various hedge funds and examine the relationship between their performances and their exposure.

[TO BE COMPLETED]

6 Conclusion

We introduce a transparent cross-asset factor, based on the time series momentum methodology [23, 5] that shows good performances during the 2008 crisis, thus making him a potential candidate for explaining the differences in performance within the hedge funds industry during this period.

This article investigates the presence of a trend following exposure across the various hedge funds styles. We first confirm it in the CTA/Managed Futures style, but more surprisingly, we also detect it in other strategies such as Global Macro, Fund of Funds and Multistrategies. The significant improvement in the explanatory power of the factor model we propose is the confirmation that Trend is a strong driver of the alternative space returns.

We look at the contribution of our Trend relative to the Fung-Hsieh options factors and we confirm the cross-asset and dynamic characteristics are decisive. Thanks to the transparency feature of our construction, we are able to dig into the Trend exposure and understand where it comes from. Indeed, indexes as well as individual funds are not all equal in terms of the type of trends they are exposed to, hereby differentiating trends on the different asset classes, or trends on different lookback windows.

We retrieve returns data as well as fund characteristics from the EuroHedge database and analyze in the cross-section the variation of the Trend loading. Some funds do not exhibit any Trend exposure, whereas some funds are very well explained by this factor.

An interesting and natural extension of our analysis would be to study the relationship between the Trend loading (or the R-squared of the regression) and the actual performances of the fund. Also, stability through time of the Trend beta could be analyzed to check if funds change their strategy allocation, and if there is a typical profile for this kind of behaviour.

References

[1] V. Agarwal, E. Arisoy, and N. Y. Naik. Volatility of Aggregate Volatility and Hedge Fund Returns. *Journal of Financial Economics*, 2015.

[2] V. Agarwal and N. Y. Naik. Characterizing Hedge Fund Risks with Buy-and-Hold and Option-Based Strategies. 2001.

[3] V. Agarwal and N. Y. Naik. Risks and portfolio decisions involving hedge funds. *Review of Financial Studies*, 17(1):63–98, 2004.

[4] N. Baltas. Optimising Cross-Asset Carry. In *Factor Investing*, pages 1–29. 2017.

[5] N. Baltas and R. Kosowski. Momentum Strategies in Futures Markets and Trend-following Funds. 2012.

[6] N. Baltas and R. Kosowski. Demystifying Time-Series Momentum Strategies: Volatility Estimators, Trading Rules and Pairwise Correlations. 2015.

[7] N. Barberis, A. Shleifer, and R. Vishny. A model of investor sentiment. *Journal of Financial Economics*, 49(3):307–343, 1998.

[8] A. Buraschi, R. Kosowski, and F. Trojani. When There Is No Place to Hide : Correlation Risk and the Cross-Section of Hedge Fund Returns. *Review of Financial Studies*, 27(2):581–616, 2014.

[9] S. Darolles and G. Mero. Hedge Fund Returns and Factor Models : A Cross-Sectional Approach. *Bankers, Markets & Investors*, pages 1–42, 2011.

[10] A. B. Dor, R. Jagannathan, and I. Meier. Understanding Mutual Fund and Hedge Fund Styles Using Returns-Based Style Analysis. *Journal of Investment Management*, 1(1):94–134, 2003.

[11] G. Elaut and P. Erdos. Adaptive time series momentum: an objective benchmarket for systematic trend-following strategies. 2016.

[12] E. F. Fama. American Finance Association Efficient Capital Markets : A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2):28–30, 1969.

[13] E. F. Fama and K. French. Mutlifactor explanations of Asset Pricing Anomalies. *Journal of Finance*, 21(1):55–84, 1996.

[14] W. Fung and D. A. Hsieh. The Risk in Hedge Fund Strategies: Theory and Evidence from Rrend Followers. *The Review of Financial Studies*, 18(4):313–341, 2001.

[15] W. Fung and D. A. Hsieh. Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, 60(5):65–80, 2004.

[16] L. R. Glosten and R. Jagannathan. A contingent performance claim approach evaluation. *Journal of Empirical Finance*, 1(1):133–160, 1994.

[17] J. Hasanhodzic and A. W. Lo. Can Hedge-Fund Returns Be Replicated ?: The Linear Case. *Journal of Investment Management*, 5(2), 2007.

[18] B. Hurst, Y. H. Ooi, and L. H. Pedersen. De-mystifying managed futures. *Journal of Investment Management*, 11(3):42–58, 2013.

[19] M. C. Hutchinson and J. O. Brien. Time Series Momentum and Macroeconomic Risk Time Series Momentum and Macroeconomic Risk. pages 1–45, 2015.

[20] R. S. J. Koijen, T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt. Carry. 2016.

[21] H. Markowitz. Portfolio Selection. *The Journal of Finance*, 7(1):77–91, 1952.

[22] M. Mitchell and T. Pulvino. Characteristics of Risk and Return in Risk Arbitrage. *Journal of Finance*, 56(6):2135–217, 2001.

[23] T. J. Moskowitz, Y. H. Ooi, and L. H. Pedersen. Time series momentum. *Journal of Financial Economics*, 104(2):228–250, 2012.

[24] A. J. Patton. On the Dynamics of Hedge Fund Risk Exposures On the Dynamics of Hedge Fund Risk Exposures. *Quantitative Finance*, LXVIII(2), 2010.

[25] F. D. Roon, P. Karehnke, N. Atreya, P. Barroso, O. Chuprinin, J. Driessen, and R. Edelen. Spanning tests for assets with option-like payoffs : the case of hedge funds. 2017.

[26] R. Sadka. Liquidity Risk and the Cross-Section of Hedge-Fund Returns. *Journal of Financial Economics*, 98(1):54–71, 2009.

[27] R. Sadka. Hedge-Fund Performance and Liquidity Risk. *Journal of Investment Management*, 2012.

[28] P. A. Samuelson. Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, 2:41, 1965.

[29] W. F. Sharpe. Capital asset prices: A theroy of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442, 1964.

Figure 1. Track record of our Trend Index.

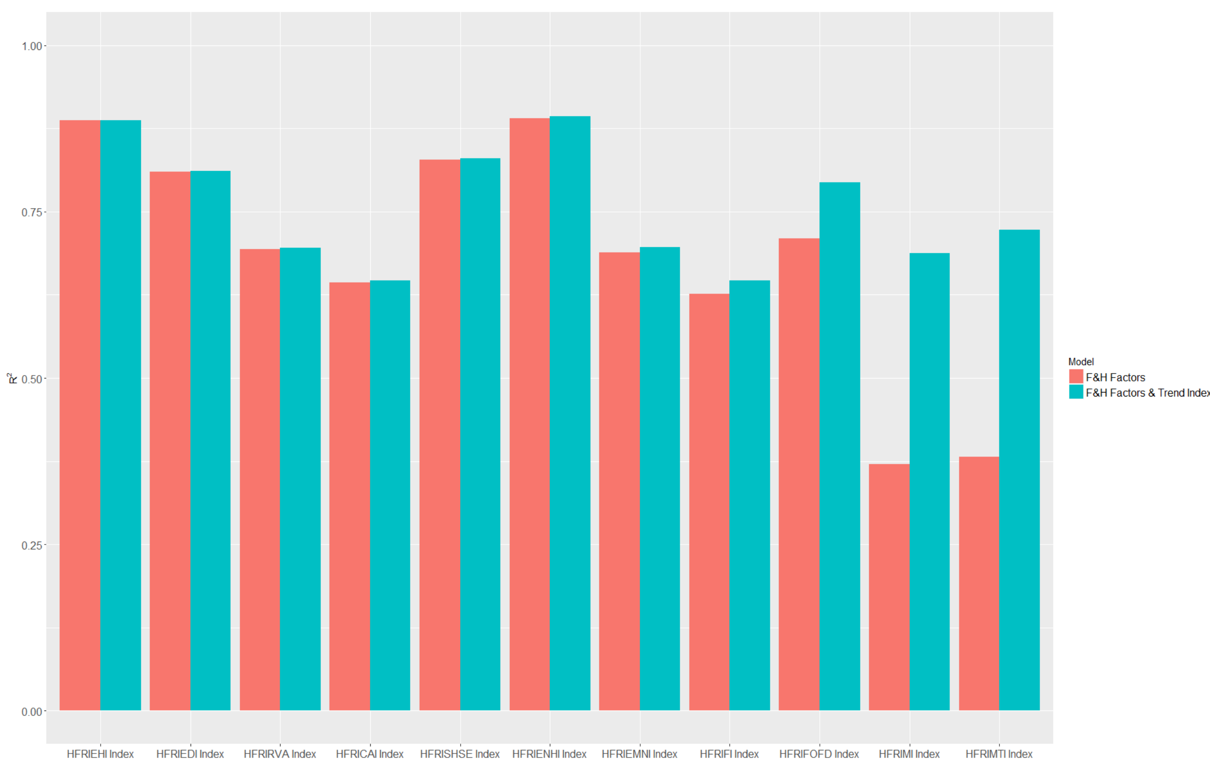

Figure 2. R^2 of two factor models (specifications 4 and 5) on selected HFR indexes.

	Ann. Return	Volatility	VaR (95%)	MDD	S	K	ρ
R.CBOT.Emini_DJIndex	6.13	16.35	1.49	-53.65	-0.06	15.06	-0.02
R.CME.Emini_Midcap	7.70	20.12	1.84	-57.27	-0.23	13.36	-0.01
R.CME.Emini_Nasdaq	3.43	26.97	2.52	-86.50	-0.02	9.83	-0.05
R.CME.Emini_SP500	4.22	18.26	1.71	-63.47	-0.24	11.59	-0.02
R.MX.SPCanada	4.10	18.15	1.69	-55.95	-0.61	12.67	-0.04
R.Eurex.Eurostoxx50	1.40	22.79	2.27	-68.16	-0.15	7.19	0.02
R.Eurex.DAX	4.79	21.80	2.13	-75.30	-0.30	8.71	0.03
R.Eurex.SMI	3.28	17.82	1.69	-57.06	-0.34	10.57	0.06
R.ICE.Emini_Russel	7.43	23.44	2.19	-58.38	-0.09	10.67	-0.01
R.NELLondon.Footsie	2.50	17.05	1.68	-57.17	-0.17	7.37	0.02
R.NELParis.CAC40	3.08	21.20	2.09	-67.20	-0.09	7.15	0.02
R.NELAmst.AEX	4.83	20.20	1.97	-73.27	-0.24	8.76	0.03
R.CBOT.US10YTnote	3.46	5.84	0.59	-14.06	-0.14	6.01	0.02
R.CBOT.US2YTnote	1.35	1.58	0.16	-4.46	0.06	7.76	0.02
R.CBOT.US5YTnote	2.57	17.80	0.40	-46.07	0.01	2340.24	-0.48
R.CBOT.USTBond	4.06	9.33	0.95	-19.28	-0.11	4.94	0.02
R.MX.CGB	3.32	5.96	0.60	-15.86	-0.23	5.65	0.03
R.Eurex.Bobl	2.69	3.06	0.31	-8.29	-0.24	5.22	0.01
R.Eurex.BundDTB	3.97	5.12	0.52	-11.58	-0.21	4.92	0.02
R.Eurex.Schatz	0.82	1.16	0.12	-4.63	-0.31	7.49	0.05
R.CME.EuroDollar	0.52	0.64	0.06	-2.47	0.49	21.58	0.08
R.NELLondon.Euribor	0.23	0.37	0.03	-2.28	0.88	20.33	0.16
R.NELLondon.Gilt	3.00	6.67	0.66	-17.44	0.01	6.73	0.01
R.NELLondon.ShortSterling	0.31	1.01	0.07	-4.20	14.16	629.03	0.02
R.CME.AUD_USD	2.11	11.34	1.10	-41.39	-0.32	10.41	-0.01
R.CME.CAD_USD	0.23	7.80	0.77	-34.79	0.05	9.01	0.01
R.CME.CHF_USD	0.67	11.36	1.12	-51.01	0.94	27.62	0.01
R.CME.EUR_USD	-0.06	9.69	0.99	-35.54	0.17	5.39	0.02
R.CME.GBP_USD	0.84	9.51	0.92	-40.61	-0.30	9.84	0.04
R.CME.JPY_USD	-0.97	10.71	1.05	-62.81	0.57	9.63	0.00
R.CME.MEP_USD	3.46	11.61	1.04	-39.90	-1.28	21.24	-0.02
R.CBOT.Corn	-6.92	24.84	2.48	-90.09	0.05	7.85	-0.02
R.CBOT.SoybeanMeal	7.94	24.72	2.49	-49.07	0.03	6.02	-0.01
R.CBOT.SoybeanOil	-2.91	22.00	2.25	-76.00	0.06	5.45	0.03
R.CBOT.Soybeans	2.56	22.17	2.18	-51.62	-0.20	6.65	-0.02
R.CBOT.Wheat	-10.54	27.42	2.73	-97.47	0.16	6.13	-0.04
R.CME.LiveCattle	3.89	14.17	1.49	-43.16	-0.07	4.91	0.07
R.ICE.Cocoa	-3.84	28.34	2.88	-91.04	0.13	6.09	0.01
R.ICE.Coffee	-8.16	34.60	3.41	-96.22	0.24	10.22	0.02
R.ICE.Cotton	-2.70	25.44	2.54	-93.31	0.03	6.10	-0.00
R.ICE.Sugar11	-1.22	30.38	3.09	-73.76	-0.19	5.56	-0.01
R.ComEx.Copper	4.65	24.56	2.44	-67.60	-0.19	6.97	-0.01
R.ComEx.Gold	1.37	15.64	1.50	-62.76	-0.28	10.48	0.01
R.ComEx.Silver	0.63	27.43	2.68	-73.66	-0.34	9.71	0.01
R.Nymex.Palladium	6.38	31.22	2.97	-87.43	-0.35	9.68	0.04
R.Nymex.Platinum	2.35	20.33	1.99	-67.23	-0.47	7.93	0.05
R.Nymex.CrudeOil	-0.08	34.25	3.34	-93.34	-0.86	19.56	0.01
R.Nymex.HeatingOil	1.80	32.59	3.24	-84.56	-0.90	23.29	0.02
R.Nymex.NaturalGas	-22.48	46.45	4.68	-99.86	0.07	6.02	-0.01
R.Nymex.RBOBGasoline	-4.02	33.23	3.34	-76.35	-0.11	5.50	0.02

Table 1. Summary statistics of our continuous futures. *Note: Ann. return refers to the annualized return in %, volatility, value-at-risk (VaR) and maximum drawdown (MDD) are also expressed in %, S and K stand for skewness and kurtosis, whereas ρ is the first-order autocorrelation.*

	Period 1	Period 2	Period 3	Period 4
Mean	0.0234	0.0269	0.0321	0.0173
Std. Dev.	0.0613	0.0604	0.0613	0.0576
Q25	-0.0201	-0.0174	-0.0136	-0.0247
Median	0.0210	0.0212	0.0250	0.0122
Q75	0.0734	0.0674	0.0692	0.0577
Skewness	0.2485	0.5327	0.5624	0.4279
Kurtosis	2.6732	3.3506	3.4448	2.8980

Table 2. Summary statistics of our (monthly) Trend Index (TI), on the HFR sub-period running from January 2010 to March 2016 (period 1), from December 1993 to July 2017 (period 2), from December 1993 to March 2009 (period 3) and from April 2009 to July 2017 (period 4).

	Trend Index	CTA	Global Macro
Expected Return (in %)	7.51	9.41	10.23
Volatility (in %)	7.35	7.35	7.18
Sharpe Ratio ($r_f = 0\%$)	1.02	1.28	1.43
VaR (95%, in %)	0.75	3.41	3.71
Maximum Drawdown (in %)	-13.15	-11.77	-10.70
Calmar Ratio	0.57	0.80	0.96

Table 3. Main statistics of our Trend Index (gross of fees), compared against HFR indexes (net of fees).

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	Trend Index
PTFSBD	1									
PTFSFX	0.5	1								
PTFSCOM	0.19	0.31	1							
PTFSIR	0.35	0.19	0.14	1						
PTFSSTK	0.31	0.28	0.23	0.23	1					
Equity	-0.51	-0.3	-0.22	-0.17	-0.25	1				
Size	-0.13	-0.03	-0.15	0.05	-0.02	0.36	1			
Bond	-0.34	-0.24	-0.25	-0.26	-0.17	0.4	0.37	1		
Credit	0.35	0.32	0.21	0.23	0.25	-0.38	-0.17	-0.55	1	
Trend Index	0.34	0.52	0.12	0.1	0.23	-0.04	-0.08	-0.19	0.08	1

Table 4. Pearson Correlation of F&H factors and our Trend Index (TI), on the HFR sub-period running from January 2010 to March 2016.

	(1)	(2)	(3)	(4)	(5)
Alpha	-0.47%	-0.53%	-0.58%	-0.53%	0.09%
	(2.89)	(3.24)	(-3.45)	(-2.54)	(0.30)
Equity		0.06	0.10	0.12	0.24
		(1.60)	(2.17)	(2.54)	(3.43)
Size			-0.08	-0.09	-0.16
			(-1.09)	(-1.33)	(-1.56)
Bond			-0.02	-0.01	-0.04
			(-0.69)	(-0.42)	(-1.14)
Credit			0.01	0.00	-0.05
			(0.26)	(0.02)	(-0.88)
PTFSBD				0.01	0.03
				(0.70)	(1.94)
PTFSFX				0.02	0.05
				(1.88)	(3.84)
PTFSCOM				0.01	0.01
				(1.32)	(0.86)
PTFSIR				0.01	0.01
				(0.81)	(0.33)
PTFSSTK				-0.03	-0.02
				(-2.84)	(-1.14)
Trend	0.29	0.29	0.28	0.26	
	(11.17)	(11.34)	(10.86)	(8.84)	
R^2	0.63	0.64	0.66	0.72	0.38
ΔR^2 vs (5)	//	//	//	0.34	//

Table 5. Regressions of Systematic Diversified HFR index on the Fung-Hsieh factors, combined with our Trend Index for the various specifications. T-statistic is displayed below the coefficients.

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	Trend	R^2
HFRIEMNI Index	0.00	-0.01	0.00	-0.01	-0.00	-0.00	0.11	0.00	0.02	0.01	0.01	0.70
	[0.84]	[-1.54]	[0.38]	[-2.53]	[-0.23]	[-0.25]	[6.59]	[0.19]	[2.42]	[0.52]	[1.80]	
HFRIENHI Index	-0.00	-0.02	0.01	-0.01	0.00	-0.02	0.41	0.07	0.02	0.03	0.03	0.89
	[-1.89]	[-2.37]	[1.49]	[-0.95]	[0.87]	[-3.12]	[15.11]	[1.84]	[1.36]	[1.23]	[2.16]	
HFRISHSE Index	-0.00	0.03	-0.00	-0.00	-0.01	-0.00	-0.52	-0.28	-0.01	0.05	-0.01	0.83
	[-1.44]	[2.00]	[-0.27]	[-0.42]	[-0.70]	[-0.12]	[-10.23]	[-3.78]	[-0.38]	[1.26]	[-0.10]	
HFRIFOFD Index	-0.00	-0.00	0.00	-0.00	-0.00	-0.01	0.18	0.04	0.02	-0.04	0.06	0.79
	[-1.19]	[-0.49]	[0.64]	[-0.16]	[-0.09]	[-1.02]	[8.31]	[1.05]	[1.60]	[-2.27]	[4.22]	
HFRIMTI Index	-0.00	0.02	0.02	0.02	0.01	-0.04	0.12	-0.07	-0.01	0.01	0.26	0.75
	[-2.52]	[1.11]	[1.19]	[1.95]	[1.05]	[-3.04]	[2.81]	[-1.34]	[-0.25]	[0.15]	[9.63]	
HFRICAI Index	0.00	-0.00	0.00	-0.01	-0.00	-0.01	0.21	0.04	-0.00	-0.05	0.01	0.65
	[0.21]	[-0.18]	[0.35]	[-1.42]	[-0.56]	[-0.77]	[6.40]	[0.73]	[-0.28]	[-2.03]	[0.14]	
HFRIFI Index	0.00	-0.01	0.01	-0.00	0.00	-0.01	0.13	0.03	-0.02	-0.07	0.02	0.64
	[2.05]	[-1.70]	[1.31]	[-0.83]	[0.57]	[-1.03]	[5.35]	[0.80]	[-1.51]	[-3.92]	[0.55]	
HFRIEDI Index	-0.00	-0.01	0.00	-0.01	-0.00	-0.00	0.27	0.09	0.00	-0.08	0.01	0.81
	[0.01]	[-0.73]	[0.62]	[-1.85]	[-0.78]	[-0.08]	[9.12]	[1.92]	[0.13]	[-3.55]	[-0.27]	
HFRIEHI Index	-0.00	-0.01	0.01	-0.01	-0.00	-0.00	0.45	0.15	0.01	-0.04	0.00	0.89
	[-1.24]	[-1.18]	[1.33]	[-2.23]	[-0.09]	[-0.44]	[14.05]	[3.27]	[0.39]	[-1.49]	[-0.33]	
HFRIMI Index	-0.00	0.00	0.01	0.01	0.01	-0.02	0.12	-0.01	-0.00	0.00	0.15	0.73
	[-2.66]	[0.32]	[0.82]	[1.23]	[1.38]	[-3.00]	[4.50]	[-0.52]	[0.20]	[-0.06]	[9.03]	
HFRIRVA Index	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.14	0.02	-0.02	-0.07	0.00	0.70
	[1.89]	[-1.27]	[0.36]	[-1.17]	[0.08]	[-1.95]	[6.08]	[0.68]	[-1.49]	[-3.71]	[-0.28]	

Table 6. Regressions of the HFR indexes on the Fung-Hsieh factors, combined with Trend. T-statistic is displayed below the coefficients.

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	Trend	Total
HFRIEMNI Index	1	0	1	0	0	1	0	1	0	1	5
HFRIENHI Index	1	1	0	0	1	1	1	0	0	1	6
HFRISHSE Index	1	0	0	0	0	1	1	0	1	0	4
HFRIFOFD Index	0	0	0	0	0	1	0	1	1	1	4
HFRIMTI Index	0	1	1	1	1	1	1	0	0	1	7
HFRICAI Index	0	0	1	0	0	1	0	0	1	0	3
HFRIFI Index	1	1	0	0	0	1	0	1	1	0	5
HFRIEDI Index	0	0	1	0	0	1	1	0	1	0	4
HFRIEHI Index	0	0	1	0	0	1	1	0	1	0	4
HFRIMI Index	0	1	1	0	1	1	0	0	0	1	5
HFRIRVA Index	0	0	0	0	1	1	0	0	1	0	3
% Selected	36.36	36.36	54.55	9.09	36.36	100.00	45.45	27.27	63.64	45.45	

Table 7. Variable Selection with Stepwise procedure, in the small factor model (FH+TI). *Note: 1 means the factor is selected, whereas 0 means the factor has not been selected.*

	(1)		(2)		(3)		(4)	
	GM	CTA	GM	CTA	GM	CTA	GM	CTA
Alpha	0.08%	0.13%	0.02%	0.17%	-0.04%	0.03%	0.00%	0.06%
	(0.57)	(0.55)	(0.15)	(0.72)	(-0.26)	(0.12)	(0.03)	(0.26)
Equity			0.08	-0.05	0.09	0.03	0.11	0.09
			(2.52)	(-0.72)	(1.97)	(0.34)	(2.64)	(1.35)
Size					-0.00	-0.05	-0.02	-0.08
					(-0.02)	(-0.42)	(-0.38)	(-0.93)
Bond					-0.03	-0.07	-0.02	-0.04
					(-1.45)	(-1.80)	(-1.08)	-(1.49)
Credit					0.00	0.02	-0.01	-0.01
					(0.10)	(0.38)	(-0.41)	(-0.24)
PTFSBD							0.01	0.02
							(0.97)	(1.65)
PTFSFX							0.03	0.06
							(4.31)	(4.73)
PTFSCOM							0.01	0.02
							(1.21)	(1.83)
PTFSIR							0.01	0.01
							(1.08)	(0.86)
PTFSSTK							-0.03	-0.05
							(-3.17)	(-3.31)
Trend	0.10	0.14	0.09	0.15	0.09	0.16	0.12	0.20
	(4.30)	(3.38)	(3.31)	(3.36)	(3.38)	(3.52)	(4.75)	(5.13)
R^2	0.20	0.14	0.23	0.14	0.26	0.21	0.53	0.56

Table 8. Regressions of Global Macro (GM) and CTA indexes on the Fung-Hsieh factors, combined with our Equity-only Trend Index. T-statistic is displayed below the coefficients.

	(Commodities)		(Currencies)		(Equities)		(Bonds)	
	GM	CTA	GM	CTA	GM	CTA	GM	CTA
Alpha	-0.18%	-0.24%	-0.17%	-0.24%	-0.01%	0.06%	-0.12%	-0.16%
	(-1.06)	(-0.88)	(-1.02)	(-0.88)	(0.03)	(0.26)	(-0.66)	(-0.58)
Equity	0.19	0.23	0.21	0.26	0.11	0.09	0.20	0.25
	(4.92)	(3.66)	(5.29)	(4.10)	(2.64)	(1.35)	(4.90)	(3.76)
Size	-0.04	-0.11	-0.04	-0.12	-0.02	-0.08	-0.07	-0.16
	(-0.66)	(-1.22)	(-0.75)	(-1.30)	(-0.38)	(-0.93)	(-1.10)	(-1.65)
Bond	-0.04	-0.07	-0.03	-0.07	-0.02	-0.04	0.01	0.02
	(-1.87)	(-2.25)	(-1.67)	(-2.09)	(-1.08)	(0.58)	(-1.97)	(0.43)
Credit	-0.02	-0.03	-0.02	-0.03	-0.01	-0.03	-0.03	-0.05
	(-0.76)	(-0.62)	(-0.78)	(-0.65)	(-0.41)	(-0.97)	(-0.96)	(-0.84)
PTFSBD	0.01	0.03	0.02	0.05	0.01	0.02	0.00	0.01
	(1.04)	(1.70)	(2.17)	(2.88)	(0.97)	(1.65)	(0.14)	(0.58)
PTFSFX	0.02	0.04	0.01	0.02	0.03	0.06	0.03	0.05
	(3.03)	(3.33)	(0.99)	(1.12)	(4.31)	(4.73)	(3.18)	(3.45)
PTFSCOM	-0.01	-0.01	0.00	0.01	0.01	0.02	0.01	0.02
	(-1.00)	(-0.55)	(0.06)	(0.57)	(1.21)	(1.83)	(0.77)	(1.30)
PTFSIR	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00
	(0.60)	(0.35)	(0.29)	(0.02)	(1.08)	(0.86)	(0.41)	(0.16)
PTFSSTK	-0.01	-0.02	-0.01	-0.02	-0.03	-0.05	-0.01	-0.01
	(-1.39)	(-1.36)	(-1.71)	(-1.72)	(-3.17)	(-3.31)	(-0.57)	(-0.47)
Trend	0.07	0.13	0.08	0.14	0.16	0.20	0.08	0.14
	(4.05)	(4.19)	(3.62)	(3.89)	(4.75)	(5.13)	(2.29)	(2.53)
R^2	0.50	0.51	0.48	0.50	0.53	0.56	0.42	0.44

Table 9. Regression (specification (4)) of GM and CTA indexes with a Sector-only Trend Index. T-statistic is displayed below the coefficients.

	(1)		(2)		(3)		(4)	
	GM	CTA	GM	CTA	GM	CTA	GM	CTA
Alpha	-0.01%	-0.17%	-0.24%	-0.30%	-0.26%	-0.37%	-0.26%	-0.39%
	(-0.38)	(-0.80)	(-1.84)	(-1.41)	(-1.96)	(-1.71)	(-1.43)	(-1.34)
Equity			0.14	0.11	0.15	0.14	0.17	0.20
			(4.60)	(2.04)	(4.22)	(2.41)	(4.37)	(3.13)
Size					-0.04	-0.11	-0.05	-0.13
					(-0.67)	(-1.18)	(-0.82)	(-1.38)
Bond					-0.02	-0.04	-0.02	-0.04
					(-0.93)	(-1.31)	(-0.85)	(-1.21)
Credit					-0.04	-0.05	-0.04	-0.06
					(-1.21)	(-1.01)	(-1.32)	(-1.23)
PTFSBD							0.01	0.02
							(0.77)	(1.38)
PTFSFX							0.02	0.03
							(2.07)	(2.28)
PTFSCOM							0.00	0.01
							(0.25)	(0.77)
PTFSIR							-0.00	-0.01
							(-0.17)	(-0.46)
PTFSSTK							-0.01	-0.02
							(-1.53)	(-1.53)
Trend	0.24	0.49	0.28	0.52	0.28	0.52	0.22	0.38
	(4.47)	(6.05)	(5.80)	(6.45)	(5.70)	(6.26)	(3.66)	(3.93)
R^2	0.21	0.33	0.39	0.37	0.41	0.41	0.48	0.50

Table 10. Regressions of GM and CTA HFR indexes with a Trend Index built on a selection of futures. T-statistic is displayed below the coefficients.

	Trend 20	Trend 65	Trend 130	Trend 260	Trend 520	R^2
HFRIEMNI Index	0.02	-0.01	-0.04	0.03	0.04	0.74
	[0.79]	[-0.24]	[-1.71]	[1.49]	[2.1]	
HFRIENHI Index	0.03	0.05	-0.03	-0.02	0.08	0.90
	[0.61]	[1.07]	[-0.72]	[-0.45]	[2.5]	
HFRISHSE Index	-0.01	-0.17	0.09	0.02	0.01	0.84
	[-0.14]	[-1.99]	[1.11]	[0.26]	[0.24]	
HFRIFOFD Index	-0.01	0.06	0	0.04	0.05	0.78
	[-0.25]	[1.55]	[-0.03]	[1.19]	[1.98]	
HFRIMTI Index	0.08	0.29	0.15	0.18	0.02	0.79
	[1.15]	[4.02]	[2.12]	[3.09]	[0.44]	
HFRICAI Index	0.03	0.14	-0.1	-0.05	0.03	0.69
	[0.57]	[2.71]	[-1.98]	[-1.1]	[0.89]	
HFRIFI Index	-0.01	0.1	-0.04	-0.01	0.01	0.66
	[-0.35]	[2.39]	[-1.05]	[-0.31]	[0.24]	
HFRIEDI Index	0	0.07	-0.07	-0.03	0.03	0.82
	[-0.04]	[1.48]	[-1.41]	[-0.69]	[0.89]	
HFRIEHI Index	0	0.13	-0.12	-0.07	0.07	0.90
	[-0.07]	[2.66]	[-2.38]	[-1.57]	[2.01]	
HFRIMI Index	0.07	0.19	0.06	0.08	0.05	0.76
	[1.49]	[4.11]	[1.29]	[1.98]	[1.41]	
HFRIRVA Index	0	0.08	-0.07	-0.02	0.03	0.73
	[-0.11]	[2.13]	[-2.1]	[-0.78]	[1.19]	

Table 11. Regressions of the HFR indexes on the Fung-Hsieh factors, combined with our Trend Indices.T-statistic is displayed below the coefficients. *Note: Only sub-Trend horizon factors are displayed but the model used is the full one, with Fung-Hsieh nine factors.*

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	Trend 20	Trend 65	Trend 130	Trend 260	Trend 520	Total
HFRIEMNI Index	0	0	1	0	0	1	0	1	0	0	0	1	1	1	6
HFRIENHI Index	1	1	0	0	1	1	1	0	0	0	0	0	0	1	6
HFRISHSE Index	1	0	0	0	0	1	1	0	1	0	1	0	0	0	5
HFRIFOFD Index	0	0	0	0	0	1	0	1	1	0	1	0	1	1	6
HFRIMTI Index	1	1	1	1	1	1	1	0	0	0	1	1	1	0	10
HFRICAI Index	0	0	1	0	1	1	0	0	1	0	1	1	0	0	6
HFRIFI Index	0	0	0	0	1	1	0	0	1	0	1	1	0	0	5
HFRIEDI Index	0	0	1	1	0	1	1	0	1	0	1	1	0	0	7
HFRIEHI Index	0	0	1	0	0	1	1	0	1	0	1	1	0	1	7
HFRIMI Index	0	0	0	1	1	1	0	0	0	1	1	1	1	1	8
HFRIRVA Index	0	0	0	0	1	1	0	0	1	0	1	1	0	0	5
% Selected	27.27	18.18	45.45	27.27	54.55	100.00	45.45	18.18	63.64	9.09	81.82	72.73	36.36	45.45	

Table 12. Variable Selection with Stepwise procedure, in the large factor model (Fung-Hsieh factors and our sub-Trend horizon indices).*Note: 1 means the factor is selected, whereas 0 means the factor has not been selected.*

Fund Characteristic	Mean	Std. Dev.	P25	Median	P75
Return (% per month)	0.23	0.35	0.00	0.23	0.38
Mgt. Fee (in %)	1.38	0.84	1.00	1.20	2.00
Incentive Fee (in %)	18.02	6.62	20.00	20.00	20.00
Age (years)	8.87	6.63	3.38	7.59	13.14
AUM (US$M)	1 454.66	4 335.61	30.00	179.93	792.00

Table 13. Summary statistics of the EuroHedge database of Managed Futures (N=91 funds).

A Appendix

HFRI Names	Short Name	Strategies included
HFRI Macro: Systematic Diversified Index (HFRIMTI Index)	Systematic Diversified	Managed Futures, Trend Following
HFRI EH: Equity Market Neutral Index (HFRIEMNI Index)	Equity Market Neutral	Quantitative Equity Market Neutral Strategies
HFRI EH: Quantitative Directional (HFRIENHI Index)	Quantitative Directional	Factor-Based and Statistical Arbitrage Trading Strategies
HFRI FOF: Diversified Index (HFRIFOFD Index)	Fund of Funds	Investment in a variety of strategies among multiple managers
HFRI RV: Fixed Income-Convertible Arbitrage Index (HFRICAI Index)	Fixed Income-Convertible Arbitrage	Relative Value Strategies limited to Fixed Income and Convertible Instruments
HFRI RV: Multi-Strategy Index (HFRIFI Index)	Multi-Strategy	Relative Value Strategies on Fixed Income, derivatives, Equity, Real Estate and/or MLP Assets
HFRI Event-Driven (Total) Index (HFRIEDI Index)	Event-Driven	Event Driven Strategies
HFRI Equity Hedge (Total) Index (HFRIEHI Index)	Equity Hedge	Long-Short Equity Strategies
HFRI Macro (Total) Index (HFRIMI Index)	Global Macro	Global Macro Strategies
HFRI Relative Value (Total) Index (HFRIRVA Index)	Relative Value	Relative Value Strategies

Table 14. Description of the HFRI database.

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	Trend Index
PTFSBD	1									
PTFSFX	0.5	1								
PTFSCOM	0.19	0.31	1							
PTFSIR	0.35	0.19	0.14	1						
PTFSSTK	0.31	0.28	0.23	0.23	1					
Equity	-0.51	-0.3	-0.22	-0.17	-0.25	1				
Size	-0.13	-0.03	-0.15	0.05	-0.02	0.36	1			
Bond	-0.34	-0.24	-0.25	-0.26	-0.17	0.4	0.37	1		
Credit	0.35	0.32	0.21	0.23	0.25	-0.38	-0.17	-0.55	1	
Trend Index	0.43	0.52	0.23	0.32	0.25	-0.13	0	-0.3	0.34	1

Table 15. Pearson Correlation of F&H factors and our Trend Index on a selection of 6 futures (S&P500, US10Y T-note, EUR/USD, Corn, Gold and Crude Oil), on the HFR sub-period running from January 2010 to March 2016.

Notes

[1]http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls

[2]Our definition of sub-periods is based on Edelman et al. (2012), who identify March 2009 as a structural break point associated with the end of credit crisis.