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

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Abstract

This paper investigates empirically whether time-series momentum returns can explain the performance of hedge funds in the cross-section. Following the trend following literature, 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 build a hierarchical set of trend factors: the full version TREND can be split in summable factors across two dimensions, the horizon of the signals and the traded asset class. We show that Managed Futures, Global Macro and Fund of Hedge Funds strategies can be partly explained by a TREND exposure, whereas Equity Market Neutral and Quantitative Directional are only exposed to long term trend factors. Moreover, a TREND exposure is a significant determinant of hedge funds returns at the aggregate level, as well as at the fund level. Finally, funds with high TREND beta outperform by 41 basis points of alpha the funds with low Trend beta. These results prove useful when managing the risk of a portfolio of hedge funds strategies, since assessment of the Trend exposure is easier. 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), hedge funds suffered heavy losses, raising doubt about their ability to deliver absolute and uncorrelated returns. However, some strategies such as trend following did particularly well. The questions are: what differentiates these funds from the ones that went down ? Are these funds exposed to specific trend risk premia ? Can this strategy be used to build diversified portfolios ? 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. Up to now, there has been attempts to explain the hedge funds performances but results were not convincing for Managed Futures. This is all the more surprising since the first dynamic factors included in a factor model were specifically designed to understand trend following funds. Indeed, its systematic feature should make it easily replicable but empirical tests do not confirm it.

In this paper, we build a new hierarchical set of factors, harvesting the trends in the financial markets, and look at their presence in the cross-section of alternative strategies. We define a hierarchical framework in which the global factor TREND can be derived into an allocation of sub-versions of the factor. Therefore, our construction remains transparent. The standard way to decipher hedge fund strategies is through a linear factor model, where past returns of a strategy are projected on a series of known factors. First, we check whether our TREND 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 test if other hedge funds strategies have a trend exposure, to confirm what we observe during the GFC. The standard factor model in the literature comes from Fung and Hsieh (2001) [18] who created options factors, monthly-reshuffled lookback straddles written on the following five common asset classes : Bonds, Foreign exchange, Commodities, Equities and Interest Rates. What sets us apart lies in the construction of dynamic, diversified factors, that can go long and short, and harvest all types of trends: from short term to long term ones. We tested several specifications to check if some hedge funds were more exposed to a specific type of trends. We confirm that CTAs have a statistically and economically significant exposure on our TREND factor, both at the index and fund levels. 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 with our global factor, confirming our initial intuitions. Not surprisingly, Fund of funds and Multi-strategies are also exposed to the trend factor. Both are diversified in terms of variety of strategies, so it makes sense that a portion of their assets is allocated to trend following. The second main result is that Global Macro funds have a strong exposure to our TREND 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 reason for their low performance during the GFC.

Firstly, our paper helps understanding the difference in performance during the 2008 crisis by showing a TREND factor is strongly priced in some but not all hedge funds styles. Our hierarchical approach enables to dig deeper in the strategies and see what are the hidden trend exposures across styles. Finally, funds are rewarded on risk-adjusted terms by exposing to trends.

Our paper helps demystifying the CTA space. By differentiating funds according to their Trend(s) exposure, one can better understand the contribution of each constituent of a Managed Futures funds' portfolio. Indeed, thanks to this model, a trend exposure can be computed for each constituent and then linearly aggregated to get the result at the portfolio level. This risk management benefit holds when going one step higher in terms of allocation of capital. Indeed, the trend exposure of a portfolio of hedge funds can be better monitored: hidden trend exposures in Macro strategies and even Multistrategies can now be taken into account when doing the allocation between hedge fund styles.

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 Sections 4 and 5. In Section 6 we examine the robustness of our results and provide extensions of the analysis. Section 7 reviews our arguments and concludes the paper.

2 Literature review

Our research is firstly related to hedge funds performances literature. Let us then focus on the alternative space and more specifically, the relevant factor models developed to understand these alternative returns. Thanks to the Capital Asset Pricing Model (CAPM), Sharpe (1964) [32] performs the first style analysis of mutual funds. Mutual funds returns are divided into systematic returns coming from the market exposure and idiosyncratic returns, related to the ability to select stocks. Indeed, many researchers were able to prove the existence of a significant alpha, thus contradicting the CAPM, but all attempts were nipped in the bud with the apparition of risk factors. Fama and French (1996) [17] extend the CAPM with two new factors: size and value. 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 are generally designed as portfolios replicating a philosophy of investing, a style: for example growth, value, small cap and momentum. Contrary to the first cited, the latter takes advantage of an anomaly in the equity market discovered by Jegadeesh and Titman (1993) [24]: going long the winners and short the losers delivers alpha. Carhart (1997) [12] adds this cross-section momentum factor into the standard risk model.

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 in this space refers to the technique of linear factor models. First, seminal contributions on this matter came from Fung and Hsieh (2001, 2004) [18, 19], Agarwal and Naik (2001,2004) [3, 4] and Ben Dor and Jagannathan (2003) [15], all trying to understand hedge fund performances by analysing the cross-variation between their returns and other strategies' returns. Fung and Hsieh (2001, 2004) [18, 19] propose 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 . Focusing on volatility, Agarwal and Naik (2004) [4] include volatility exposure through put options, written on the S&P500 index to explain the differences in returns across the alternative styles. Later, Hasanhodzic and

Lo (2007) [21] use observed factors, such as the S&P 500 index, the USD return index, the Bond Index, to model the returns of individual hedge funds in order to build clones with an out-of-sample focus.

Despite their strong economic support, these papers do not perform particularly well in explaining some hedge fund styles, and in particular trend-following strategies. Firstly, these hedge fund factor models can be doubted on their assumptions. Indeed, these models have one main drawback: the estimations of the betas can lead to wrong interpretations. 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) [14] confirm 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. 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 (2013) [28] showed that hedge funds exposures vary across and within months, confirming the relative high frequency behaviour. They have access to daily returns of some HFR indexes. However, hedge funds report only monthly net asset values (NAVs), making the model not applicable in practice. Also, time-varying beta estimation would require very long sample, which is not 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) [13] propose a selection algorithm to keep only the most relevant risk factors in a time-varying setup. 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) [16] confirm that "the performance of these models in explaining Managed Futures funds' return is, however, lackluster". In addition, there are some interesting papers proposing additional factors, with a strong economic rationale, aiming at demystifying hedge funds performances. Mitchell and Pulvino (2001) [26] focused on risk arbitrage, Sadka (2009, 2011) [30, 31] on a liquidity factor, Bali (2014) [6] on an uncertainty indicator while Buraschi (2013) [11], Arisoy, Agarwal and Naik (2015) [1] worked on volatility and correlation risks. Agarwal et al. (2009) [2] and Agarwal et al. (2016) [5] form factors based on higher moments of the distributions, with a respective focus on stocks and holdings, and show it is priced in the cross-section of hedge funds. Hedge funds are not only exposed to these risk factors but also to the standard market, as shown by Patton et al. (2009) [29]. Thus, the asset class factors of Fung and Hsieh are necessary in the factor model. Even more recently, a strong interest rose about a cross-asset carry factor, with works from Koijen et al. (2016) [25] and Baltas (2017) [7]. 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, from the book "When Genius failed" by Roger Lowenstein qualifies them perfectly: it's like "picking up pennies in front of a steamroller". On the contrary, the trend following strategy has a rather different profile, with a right skewness (many small losses and few large gains), taking advantage of the trends in the markets, caused by the behavioural biases of investors. Thus, all these factors are very helpful to understand the cross-section of hedge funds but not specifically on directional strategies.

Finally, we turn to papers from industry, though often the results of joint work with academic researchers. 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) [27] 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. Their construction is similar to ours, except that they focus on the 1-year lookback with a monthly rebalancing. The cross-sectional version is applied within the equity asset class and is market neutral, the portfolio being long the winners and short the losers. Conversely, the time-series momentum is applied on futures of different asset classes, and is long or short each of them regardless of the asset class. No cross-section comparison is done to determine the position.

Hurst, Ooi and Pedersen (2013) [22] worked on the economic intuition behind the presence of such trends in the financial markets. It is a major breakthrough: the random walk hypothesis and the related Efficient Market Hypothesis are strongly challenged. Based on the recent field of behavioural finance, Barberis, Shleifer and Vishny (1998) [10] show investors are not perfectly rational, suffer from multiple behavioural biases which create market inefficiencies. The most famous are herding, anchoring and confirmation biases. For further information, refer to Hurst, Ooi and Pedersen (2013) [22] who propose a very thorough review of such biases and the associated mechanisms that create trends. In addition, they show TSMOM helps to understand Managed Futures indexes and individual funds. Simultaneously, Baltas and Kosowski (2012) [8] also document a time-series momentum as a benchmark for Trend Following funds. 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) [9] focus on the impact of the volatility and correlations on the performances of the time-series momentum factor. Hutchinson and O'Brien (2015) [23] relate Trend-Following returns to the periods of crisis and show that post-crisis returns are usually weak/below average. Elaut and Erdos (2016) [16] 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 [8, 27]. 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. 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

In this section, we first describe the various datasets involved in the empirical illustration, namely, futures prices, standard hedge fund factors from the literature, as well as hedge funds indices and individual funds' returns. Secondly, we document the construction methodology of our hierarchical set of factors.

3.1 Data

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. Since our benchmark construction will be on a daily frequency, we want to remove any illiquidity issue (price impact and price significativity) as much as possible by applying the following procedure. 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. Indeed, futures have an expiry date so need to be put together to form a continuous time series, that represents the returns of a static exposure. 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.[1] 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. All futures starting date are shown in Table 1. The list of contracts we use is similar to what can be found in the trend following literature [8, 27].

[Insert here Table 1]

Table 1 also presents univariate statistics for futures contracts returns. The results are highly heterogeneous 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. Thus, 1 $ invested in an interest rate market is not as risky as 1$ invested in a commodity market. We need to correct by the differences in volatility to have a similar risk contribution by market. According to Getmansky, Lo and Makarov [20], presence of auto-correlation in hedge funds monthly returns indicates illiquidity, or even a smoothing behavior. Indeed, funds that invest in illiquid assets such as Private Equity can be forced to use mark to model valuations instead of mark to market, resulting in smoothed net asset values. Here, the first-order autocorrelation is low and not significant across all futures, which confirms the liquidity of this type of contract. Futures markets have a fundamental role in the price discovery process. Thus, it is possible to implement a dynamic strategy, which can switch position on a day-to-day basis. Also, the return distributions of some futures are highly assymmetric with fat tails when others have a distribution similar to a bell curve.

3.1.2 Asset pricing benchmark. We use in our analysis the nine-factor model from Fung and Hsieh (2001) [18]. In their seminal paper, they show these factors have strong explanatory power for most hedge fund indexes. 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.[2]

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 Table 21 in Appendix A. For each of them, we have all the monthly returns from January 1990 until December 2016. As a robustness check, 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 the risk-free rate, set as the Euribor 3M, were calculated.

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 521 funds, and 425 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.

Table 2 presents the average monthly return of the HFR indexes. We split the complete 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 [3]. Systematic Diversified and Macro indexes were among the most performing ones before March 2009, but also the ones that suffered the most after GFC. Conversely, non-directional strategies such as Convertible Arbitrage, Relative Value, Equity Market Neutral experienced a lower performance variation, which was even positive for the first mentioned.

[Insert here Table 2]

Table 3 contains the main statistics of the HFR indexes computed over the period when Fung and Hsieh factors are available (hereafter called "FH period"), that is from January 2010 to March 2016. There is strong cross-section variation in the returns and sharpe ratios in the hedge fund space, highlighting the different risk profiles of these strategies. Assuming Systematic Diversified and Global Macro strategies can be leveraged, they would exhibit a lower maximum drawdown compared to the rest of the hedge fund space, which in particular results from their GFC behavior.

[Insert here Table 3]

3.2 Factor construction

Two main principles drive the construction of our factors, concerning two different types of trends. First, the major trends between asset classes need to be captured, thus we build a TREND factor (similar to a top-down approach) that represents them. Secondly, the trends within a given asset class as well (similar to a bottom-up approach) are harvested through the *sector*-TREND factors. Another aspect concerns the timeframe of the trends: short-term (ST) as well as long-term (LT) trends need to be taken into account. The global TREND portfolio is positioned according to the mean of individual signals, and the *horizon*-TREND portfolios focus on one timeframe each. To reach these objectives, we construct our trend risk factor based on the practice of hedge funds and especially systematic CTAs. The construction 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) [27] focus on the 1-year lookback to build their time-series momentum (TSMOM). Baltas and Kosowski (BK, 2012) [8], as well as Elaut and Erdos (EE, 2016) [16], mix different time horizons when constructing their trend following benchmark. 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 above.

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. Let us introduce two signal notations. The first one is s_{i,t,h_j}, and refers to a momentum signal at date t for a market i over a period h_j. s_{i,t,h_j} is worth 1 if price on date t is higher than the price h_j days before, and -1 otherwise. In the global TREND construction, we take the average of five signals with the respective lookbacks

$h_j \in \{20, 65, 130, 260, 520\}$ to build the global signal $S_{i,t}$. The mathematics are the following:

$$S_{i,t} = \overline{\text{sign}(p_{i,t} - p_{i,t-h})} = \frac{1}{n_s}\sum_{j=1}^{n_s}\text{sign}(p_{i,t} - p_{i,t-h_j}) = \frac{1}{n_s}\sum_{j=1}^{n_s} s_{i,t,h_j} \tag{1}$$

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

$$r_t^P = \frac{\kappa}{N_t}\sum_{i=1}^{N_t}\mathrm{S}_{i,t-1}\frac{r_{i,t}}{\sigma_{i,t-1}} \tag{2}$$

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

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, but the diversification between futures reduces the portfolio volatility.

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. Let's look at the mathematics of such decompositions.

First, we note Ω_t the universe of tradable futures at date t, and N_t its corresponding cardinality. We can partition it into *sectors*, which are essentially asset classes:

$$\Omega_t = \{\Psi_{j,t}, j = 1..n_\Psi\} \tag{3}$$

Each sector j has its own time-varying cardinality : $N_{\Psi_{j,t}}$. At all dates t, we have the following relation between cardinalities, due to the property of partition of the universe:

$$N_t = \sum_{j=1}^{n_\Psi} N_{\Psi_{j,t}} \tag{4}$$

Let's start from the market level formulation:

$$\begin{aligned} r_t^{\Omega_t} &= \frac{1}{N_t}\sum_{i=1}^{N_t} \mathrm{S}_{i,t-1}\frac{\kappa}{\sigma_{i,t-1}} r_{i,t} = \frac{1}{N_t}\sum_{j=1}^{n_\Psi}\sum_{i\in\Psi_{j,t}} \mathrm{S}_{i,t-1}\frac{\kappa}{\sigma_{i,t-1}} r_{i,t} \\ &= \sum_{j=1}^{n_\Psi}\frac{N_{\Psi_{j,t}}}{N_t}\frac{1}{N_{\Psi_{j,t}}}\sum_{i\in\Psi_{j,t}} \mathrm{S}_{i,t-1}\frac{\kappa}{\sigma_{i,t-1}} r_{t,i} = \sum_{j=1}^{n_\Psi}\frac{N_{\Psi_{j,t}}}{N_t} r_t^{\Psi_{j,t}} \end{aligned} \tag{5}$$

The TREND portfolio is an allocation of the sector-TREND portfolios, with the weights being the fraction of the number of futures per sector divided by the total number of futures available at date t. Figure 1 presents the decomposition. In our case, sectors are asset classes, resulting in the five following factors: TRENDFX on Currencies, TRENDBD on Bonds and Interest Rates, TRENDSTK on Equity indices, TRENDCOM on Commodities.

Hence, the importance of a given asset class is proportional to the number of available liquid futures. The underlying assumption is that, once risk-adjusted, all the markets are viewed as equal, their asset class is foregone. A consequence is that more money is allocated to sectors with a large number of futures, assuming more capacity. This assumption is not problematic for two reasons: all selected futures are among the most liquid and our factor is gross of transaction costs, so there is no impact of the hypothetical AUM on the factor returns.

After seeing the market decomposition, let's focus on the signal decomposition.

$$\begin{aligned} r_t^{\Omega_t} &= \frac{1}{N_t}\sum_{i=1}^{N_t} \mathrm{S}_{i,t-1}\frac{\kappa}{\sigma_{i,t-1}} r_{i,t} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{1}{n_s}\sum_{j=1}^{n_s} s_{i,t-1,h_j}\right)\frac{\kappa}{\sigma_{i,t-1}} r_{i,t} \\ &= \frac{1}{n_s}\sum_{j=1}^{n_s}\frac{1}{N_t}\sum_{i=1}^{N_t} s_{i,t-1,h_j}\frac{\kappa}{\sigma_{i,t-1}} r_{i,t} = \frac{1}{n_s}\sum_{j=1}^{n_s} r_{t,h_j}^{\Omega_t} \end{aligned} \tag{6}$$

The TREND portfolio is in fact an equal-weight allocation of the horizon-Trend portfolios, portfolios whose signal is based on only one lookback each. The five factors will be noted: TREND1M, TREND3M, TREND6M, TREND1Y and TREND2Y. Figure 2 shows the structure of the signal decomposition, with an additional layer corresponding to the following partition:

$$\{20, 65, 130, 260, 520\} = ST \cup LT = \{20, 65\} \cup \{130, 260, 520\} \tag{7}$$

This property of decomposition, across sectors and lookback windows, allows to satisfy both the macro and the market dimensions objective and to better understand the types of trends present in the hedge fund space.

[Insert here Table 4]

Table 4 exhibits the statistics of the factors over several periods. TREND factor on average earned 0.85% per month during the period running from January 2010 to March 2016 with a 2.72% monthly standard deviation. Over the full sample, the average monthly return is 0.98%, close to sub-sample value. The other distribution metrics are similar as well, suggesting the sub period is similar to the full one in terms of the trend factor returns. Average monthly return goes from 1.15% in the pre-GFC period to 0.60% post-GFC, being almost divided twofold.

As we can see on the Figure 3, we notice good performances during the GFC, which allows to keep our factor as a potential candidate for understanding the performances of that time.

[Insert here Figure 3]

[Insert here Table 5]

Table 5 shows the main performance and risk measures of TREND factors. As said before, volatility is a parameter which can be fixed at whatever level without loss of generality, so here we set it at 10% annual daily volatility for comparison purposes [4]. The global TREND factor exhibits Sharpe and Calmar ratios slightly higher than 1, which is similar to the results on time-series momentum factors from MOP (2012) [27] and BK (2012) [8]. When decomposing this factor into the four *sector*-TREND factors, the risk-adjusted performances are lower and vary depending on the traded asset class. For example, TRENDCOM and TRENDFX suffer from large drawdowns, whereas TRENDBD has statistics closer to the full version ones. Though with a lower dispersion, same conclusions can apply when decomposing TREND by signal horizon: Calmar Ratio varies from 0.42 to 0.96. The most-performing factor is the one with a 1-year momentum, confirming the findings of Hurst, Ooi and Pedersen (2013) [22].

[Insert here Table 6]

Table 6 presents the correlation of all our TREND factors 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 0.18 for PTFSCOM to 0.51 for PTFSFX. This confirms the work of Fung and Hsieh, their lookback straddle portfolios capturing part of the variation due to a trend exposure. Unsurprisingly, correlation between the *sector*-TREND factors and the PTFS factors are lower on average, with the highest correlation often reached when the asset class. For example, TRENDFX has a 0.59 correlation with PTFSFX. However, TRENDCOM exhibits a 0.31 correlation with PTFSFX, whereas its correlation with PTFSCOM is 0.29. Still, these intra-asset class correlations between Fung and Hsieh and our specifications remain quite low. Let's now look at the relations between Fung and Hsieh factors and the signal horizon. For each asset class, the correlation decreases when the horizon of our factor increases. For instance, PTFSBD has a 0.5 correlation with TREND1M, 0.38 with TREND3M and a very low 0.09 correlation with TREND2Y. In their construction, Fung and Hsieh (2001) [18] use options with quarterly expirations, thus capturing trends over this timeframe. A momentum signal with a lookback inferior to three months is needed to capture such trends, confirming the previous finding. As a robustness check, correlations were also calculated for the factors built on a selection of six futures and results were not economically different (refer to Table 22 in appendix A).

[Insert here Table 7]

As we can see on Table 7, correlations are relatively low between TREND and the HFR indexes, except for Global Macro and Systematic Diversified, and Fund of Funds to a lower extent. The pattern is very similar for both TRENDCOM and TRENDFX factors. TRENDSTK correlations are high with all hedge funds indexes except for Equity Short Selling, suggesting trends on this asset class are essentially long since hedge funds are usually positively exposed to the equity risk premium, even for the Equity Market Neutral style. TRENDBD is positively correlated to both Systematic Diversified and Global Macro, but relations with other styles are in opposite direction as the ones of the TRENDSTK factor. In addition, TRENDSTK and TRENDBD are negatively correlated, with -0.17 correlation. Despite the quantitative easing, which results in upward trends in both rates and equities, thre is still dispersion in the trends in these asset classes. In terms of lookback horizon of the signals, six month and one year display the largest correlation to the two directional strategies that are Systematic Diversified and Global Macro. All these findings are encouraging, but need 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 Hedge funds exposure

We start with time-series analysis of returns of hedge funds indices, and examine their exposure on our Trend factor. Our benchmark model is the standard Fung and Hsieh (2001) [18] nine factor model. A hedge fund series of excess returns $r_{i,t}$ can be decomposed into a risk-adjusted performance, α_i and a systematic performance coming from the exposures β_i^k to the k factors. The unexplained variation is the residuals ϵ_i, that are supposed to follow a normal distribution in the Ordinary Least Squares model.

4.1 Trends everywhere?

In order to understand the relation between the hedge funds index and trends, we add our TREND factor to the model, making a 10-factor risk model :

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_i^1 \text{Equity} + \beta_i^2 \text{Size} + \beta_i^3 \text{Bond} + \beta_i^4 \text{Credit} + \beta_i^5 \text{PTFSBD} + \beta_i^6 \text{PTFSFX} + \beta_i^7 \text{PTFSCOM} \\ + \beta_i^8 \text{PTFSIR} + \beta_i^9 \text{PTFSSTK} + \beta_i^{10} \text{TREND} + \epsilon_i \quad (8) \end{aligned}$$

where $r_{i,t}$ denotes the monthly return of the hedge fund index i in excess of the 3-month Euribor, and the regressors are described in the data section.

We want to test whether our factor improves the understanding of the two directional "macro" strategies, as represented by the Systematic Diversified and Global Macro indexes. If the beta on our factor is significant and the R-squared increases (in comparison to the nine factor model, without TREND), we can conclude that our trend following specification contains something related to the macro strategies than isn't present in the Fung-Hsieh factors. If not, it means that trends harvested as in our specification are either the same as the ones with lookback straddles or that the macro strategies do not capture them.

Results presented in Table 8 show our factor greatly improves the understanding of the Systematic Diversified index, with a 0.80 beta associated with a t-statistic of 12.30. The R-squared increases from 38% for the benchmark model to 82% for the full model. Thus, we can conclude the Systematic Diversified index contains trend following, as implemented in our construction.

[Insert here Table 8]

Table 8 also presents the results of the factor model for the Global Macro index. Again, the beta is highly significant (t-statistic of 11.43) and the R-squared drastically increases from 37% to 79%. We can conclude the Global Macro index returns are related to trend following ones.

As expected, Systematic Diversified and Global Macro strategies are exposed to this trend-following strategy. The first is systematic and both are invested across asset classes, and these features also correspond to our factor. However, exposures to different asset classes could have been captured thanks to the factors in the benchmark model. Indeed, the major equity and fixed income benchmarks are present as well as systematic portfolios of options, also written on currencies and commodities. We can then conclude a significant exposure on Trend is not simply the result of a cross-asset dimension but is truly an indicator of an exposure to trends.

The natural question that comes up concerns the hedge funds strategies that are not cross-asset in essence. For example, could a long/short equity portfolio be in fact exposed to macro trends despite investing only on cash equities ? The same interrogation applies to the other alternative strategies. To answer this question, we apply our ten-factor model to the rest of the alternative space. Again, a significant and positive beta indicates the presence of a trend strategy in the analyzed index. By definition, Multi-Strategy and Fund of Funds are strong candidates to have an exposure on Trend, since they invest internally or externally in a set of alternative strategies. The rest of the strategies are often the result of capturing a given fundamental premium on an asset class, resulting in different positions than the momentum ones. Results of the regressions can be found in Table 9.

[Insert here Table 9]

Fund of funds index displays a positive beta with a t-statistic of 4.88, confirming these funds allocate part of their capital to diversified trend following strategies. Surprisingly, the Equity Hedge Quantitative Directional exhibits a low positive beta but significant at a 5% level (t-statistic of 2.18). Indeed, some statistical arbitrage strategies present in this index might position themselves according to past price momentum, since such phenomenon has been shown to be significant in some markets. All remaining HFR indexes do not exhibit a significant loading on TREND, confirming their focus on one asset class and a different premium than momentum.

4.2 Asset Class-Trends everywhere?

We now want to dig deeper in understanding the hedge funds styles, and a way to do that is to use the decomposition feature of our construction and replace our TREND factor by its four *sector*-TREND components. We want to test whether some strategies exhibit some exposure to Trends in specific asset classes. To do so, we use again a factor model, where the TREND factor is replaced by four asset class TREND components : TRENDSTK, TRENDBD, TRENDFX and TRENDCOM. We split the test into two parts, depending on the previous results. For the alternative indexes that do not show any exposure on the macro level, we test if they are not at all exposed to any trends or if they do on the sector level but the exposure gets erased during the aggregation step of the construction, where some diversification comes into play. Secondly, for the ones that show an exposure to the global TREND factor, we test if this exposure comes from all asset classes or if it is related to a specific one.

[Insert here Table 10]

As we can see on Table 10, the Systematic Diversified index exhibits positive and significant exposures across all *sector*-TRENDs, Equities being the strongest and Currencies the weakest. The result is similar for the Global Macro index with slightly lower t-statistics. We know the significant exposure at a macro level for these strategies does not necessarily come from their cross-asset dimension, since Fung-Hsieh factors are here to control for that, but in addition we know they are harvesting trends everywhere. Fund of Funds index showed a high exposure to TREND and we interpreted that as a capital allocation to trend followers, which should result in an exposure to TREND across asset classes, as per the results on the Systematic Diversified style. Unexpectedly, beta is only significant to TRENDSTK. Fund of Funds allocate capital between many strategies and diversify between managers among each of them. Recall that any long-only static exposure has been controlled for with Fung and Hsieh factors. A possibility is that there is capital invested in strategies with opposite positions on these asset classes, thus reducing the net exposure we observe. For example, contrarian strategies such as mean reverting might be exploited on commodities. The Equity Hedge Quantitative Directional low but significant macro exposure disappeared when zooming into asset classes.

Finally, among the strategies not showing a global TREND exposure, none exhibits an asset class specific TREND exposure. Inversely, among the ones that exhibited a global TREND exposure, all show significant results across asset classes except the Fund of Funds index. The trends harvested on the macro level are the same trends that can be harvested per asset class.

4.3 Horizon-Trends everywhere?

Apart from the traded futures markets and thus the asset classes, another major parameter is the horizon over which trends are detected. Relying on the past month or the past years' prices results in big difference in position. As explained in the methodology, our trend signal is the simple average of five momentums (each with a specific timeframe) and we showed the TREND can be linearly decomposed into *horizon*-Trend factors, noted TREND1M, TREND3M, TREND6M, TREND1Y and TREND2Y. First, we want to test whether Systematic Diversified and Macro styles are exposed to all types of trends or specific ones. Second, we want to check for the strategies that did not exhibit any Trend exposure on the macro level as well as the asset class if there is some exposure on specific trends. We will rely on the t-statistics per factor to conclude.

Table 11 tells us six months (TREND6M) and two-years trends (TREND2Y) are not significant for both the Systematic Diversified and the Macro styles. Three-months and one-year trends seem to be the horizon most present in these strategies. Assuming the portfolio managers are doing a good job, thus positioning themselves on the most lucrative horizon, this confirms the finding of MOP (2012) [27] who show the autocorrelation of risk-adjusted returns is the highest around 260 days. Across the non-directional strategies, we can find some statistically significant betas (with t-statistic just above 2). Surprisingly, Equity Hedge and Relative Value indexes exhibit a negative loading on the 6 months-Trends. T-statistics are higher than 2 but not enough for a 1% significancy, which point toward a statistical artifact rather than a true short exposure. However, there are no strong economically meaningful exposures in the space apart from Systematic Diversified and Macro styles.

[Insert here Table 11]

5 Cross-sectional analysis

In this section, we conduct parametric and nonparametric tests to examine the relationship between TREND returns and hedge funds returns. First, we form portfolios of hedge funds based on their rolling beta to our factor and we analyze the difference in return between the opposite portfolios being the low beta portfolio and the high beta one. Secondly, we follow the standard Fama-MacBeth approach and regress the overall beta of the funds against their overall return to get an estimation of the "premium" associated to this risk factor, after controlling for fund level characteristics such as fees.

[Insert here Table 13]

Before analyzing the relationship between trend exposure and returns, Table 13 displays distribution statistics of hedge funds characteristics. The sample covers all funds from 2000 to end of 2017. Despite the presence of the GFC in the period, the average mean monthly return is 0.34%, which is equivalent to an average of 4.16% per year. However, median age of the funds is 8 years, meaning that at least half of the funds were not alive in 2008. Another interesting fact is the large difference between mean and median AUM, pointing toward a right-skewed distribution, with few very large funds. In terms of fees, hedge fund investing is getting cheaper, with a mean management fee of 1.46% and a mean incentive fee of 16.98%. Still, around 25% of the funds still charge the standard 2/20 structure. Note that the fees reported in the EuroHedge database are relative to a share of a fund and not to the whole asset management company, and often for the most expensive share, so the actual AUM-weighted fee might be lower.

5.1 Portfolios of hedge funds

We start by exploring whether the differences in funds' TREND exposure can explain the cross-sectional differences in their performances. On a 36-months rolling basis, we estimate the following linear regression:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}\text{TREND}_t + \epsilon_{i,t} \tag{9}$$

where $r_{i,t}$ denotes the volatility-adjusted returns of the fund i over the 36-months window, TREND_t the returns of our factor over the same period. Here, both series of returns have the same volatility, in order not to detect an increase in the fund volatility as an increase in the Trend exposure and to be able to compare funds between them.

The objective is to detect if this assertion (or the opposite) is true: the bigger the Trend exposure of the fund, the bigger the return. A nonparametric way to test it is to form portfolios of funds with different betas. The obtained portfolios will exhibit a beta to TREND close to its components' betas. At each date t, we split the available pool of funds into four groups, corresponding to the four quartiles of betas, and we compute the average return of each group, thus forming a portfolio. Quartile 1 (4) portfolio contains funds with the lowest (highest) TREND exposure.

[Insert here Table 14]

Table 14 reports average TREND beta, annual return and 9-factor alphas of TREND beta sorted quantiles portfolios. The portfolio composed of funds with low Trend beta, noted 1 (LOW), performs better than its high beta counterpart, with an annual return of 11.44% against 7.72%. However, risk-adjusted returns are the other way around: the high TREND beta portfolio delivers a significant alpha of 56 basis points per month, versus a non-significant 15 basis points for the low TREND beta portfolio.

This indicates a strong positive link between TREND exposure and the risk-adjusted fund performance. However, the quartile portfolios are equal-weight baskets of funds which might have very different characteristics such as other risk exposures or even fund characteristics, resulting in two quartiles that do not differ only by the TREND exposure degree of freedom. There are two solutions to address this problem: the first is is to create portfolios based on a bivariate or even multivariate sorting method, but the number of funds in each category dramatically drops thus reducing the tests' significancy; the second is to conduct a multivariate cross-sectional regression at the fund level. The latter solution is the one we pick and is described in the following section.

5.2 Parametric test

In this section, we apply the Fama-MacBeth (1973) approach to estimate the reward associated to the TREND risk factor. The first step consists in a time-series estimation of the overall beta of each fund on the factor:

$$r_{i,t} = \alpha_i + \beta_i^{TREND}\text{TREND}_t + \epsilon_{i,t} \tag{10}$$

where $r_{i,t}$ denotes the returns of fund i, TREND_t the returns of the TREND factor.

The second-step is cross-sectional and consists in regressing the annual performance of each fund against its beta, as well as fund characteristics. Specifically, we estimate the following OLS model:

$$R_{fund} = \alpha + \lambda_{\beta^{TREND}}\beta^{TREND} + \lambda_{MngtFee} * MngtFee + \lambda_{IncFee} * IncFee + \lambda_{Age} * Age + \epsilon \tag{11}$$

where R_{fund} denotes the series of annual returns across funds, β^{TREND} is the beta estimated in the first step, $MngtFee$ and $IncFee$ describe the fee structure, and Age is the number of years since inception as of 31/12/2017. Equation 11 is the full specification, where the premium $\lambda_{\beta^{TREND}}$ is risk-adjusted in the sense other risk factors known to drive difference in hedge funds performance are put as covariables. All things equal, $\lambda_{\beta^{TREND}}$ is the sensitivity of the overall annual performance of the fund to the value of its β^{TREND}. So, a positive and significant coefficient will act as evidence for a trend following reward.

[Insert here Table 15]

Table 15 shows a negative coefficient on the TREND beta significant at a 5% level. At a fixed level of fund characteristics, a higher beta is related to a lower annual return. In the nonparametric test, returns are controlled for the exposure to other known risk factors. To better understand the difference in outcome between these two methods, a solution would be to enchance our nonparametric test with a multivariate Trend beta.

From this, we cannot conclude whether exposure to the Trend risk factor improves the risk-adjusted performance of the fund.

5.3 CTA profiling

This section focuses on the Managed Futures space. In addition to the AUM, track record and currency constraints, only funds labelled as Managed Futures were selected, constituting a sample of 236 funds.

Table 16 shows the distribution metrics of the funds' characteristics, for all relevant hedge funds for the first table and for Managed Futures for the second one. Systematic Diversified Index is the HFR index that has the largest exposure to TREND, so it is expected individual funds exhibit the same behavior. As expected, β^{TREND} is higher on average for Managed Futures than for all hedge funds, 0.32 versus 0. The Welch test for the mean difference gives a t-statistic of 12.61. At a similar level of volatility, hedge funds earn more than Managed Futures. Despite not being adjusted by firm characteristics, this is consistent with the negative premium observed in the parametric test. As for the rest of the fund characteristics, no significant difference can be observed.

[Insert here Table 16]

From the previous analysis, all things equal, hedge funds with a higher sensitivity to TREND exhibit lower returns. We wan to test if this cross-section variation is also present in the Managed Futures space. In other words, do CTAs with higher TREND exposure exhibit lower risk-adjusted returns? The Fama-MacBeth regression results can be found in Table 17.

[Insert here Table 17]

In both specifications, the sensitivity of the annual return to the TREND beta is negative and statistically significant. We can conclude the previous result holds when restricting to CTA funds. The CTA space can be divided into three groups: the pure trend followers with a median size, the larger "multistrategies" funds that diversify trend following with other systematic strategies, and the small specific funds. If the CTA funds with a low TREND beta are small in comparison to large high TREND beta funds, the difference in performance could be related to a capacity issue. Size was added to the model but did not change economically the results. [5] Another interpretation is that pure trend following funds with a low TREND beta exposure have a more complex trading system, with smarter signals, a better vision of risk. A large portion of their performance comes from alpha. These "alpha" funds are thus doing better than the "beta" funds (funds with a high TREND exposure). In addition, funds in the sample do not have the same track record, resulting in annual return of each depending on the period since inception. All the CTA funds that exist for at least two years but less than five years experience a difficult period for trend followers, as shown by the SG indexes performances. The consequence is an increase in the intensity of the relation between high TREND beta and low performance. A way to mitigate this effect would be to analyze the funds on a common period, with the adverse effect of reducing the sample size and eventually t-statistics.

6 Robustness checks

[Insert here Tables 18 and 19]

In order to check the contribution of our factor, we ran the HFR indexes regressions with TREND replaced by its equity-only version, TRENDSTK. This factor trades 12 futures indices. For all specifications, as we can see on Table 18, results are far worse than with the full version 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. As Table 19 shows, 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 model. That confirms a big part of our contribution lies in the diversified feature of our factor.

[Insert here Table 20]

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.

7 Conclusion

We introduce a transparent cross-asset factor, based on the time series momentum methodology [27, 8] that shows good performances during the 2008 crisis, thus making it a potential candidate for explaining the differences in performance within the hedge funds industry during this period.

This article investigates the presence of a trends 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 have a beta close to 0.70. All other things equal, a TREND exposure is associated with a lower return, both in the whole hedge funds space and for Managed Futures only. However, non-parametric tests point show the nine-factor alpha is higher for the high TREND beta portfolio than for the low TREND beta. Focusing on Managed Futures funds, low beta funds higher performances might be due to their expertise, resulting in a large alpha contribution to the overall return.

An interesting and natural extension of our analysis would be to study the stability through time of the TREND betas to test for change in the strategy allocation, and if there is a typical profile for this kind of behaviour, especially related to the size of the fund and a potential capacity issue.

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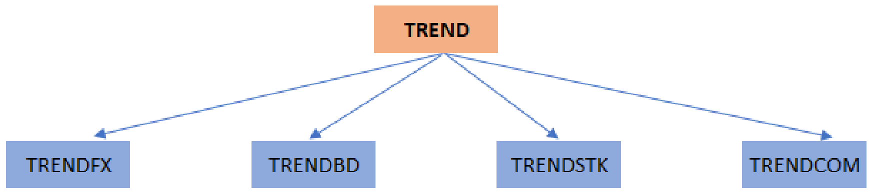

Figure 1. Diagram of the asset class decomposition of the TREND factor.

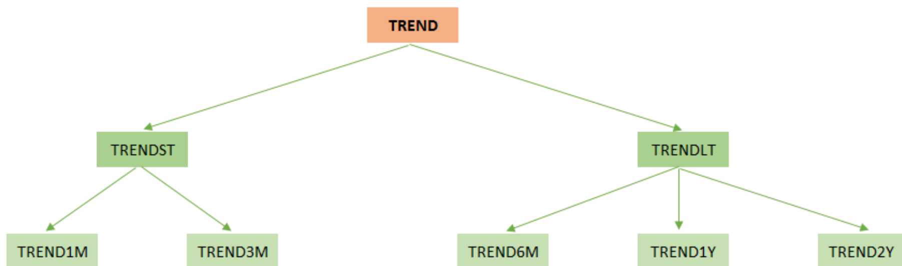

Figure 2. Diagram of the signal decomposition of the TREND factor.

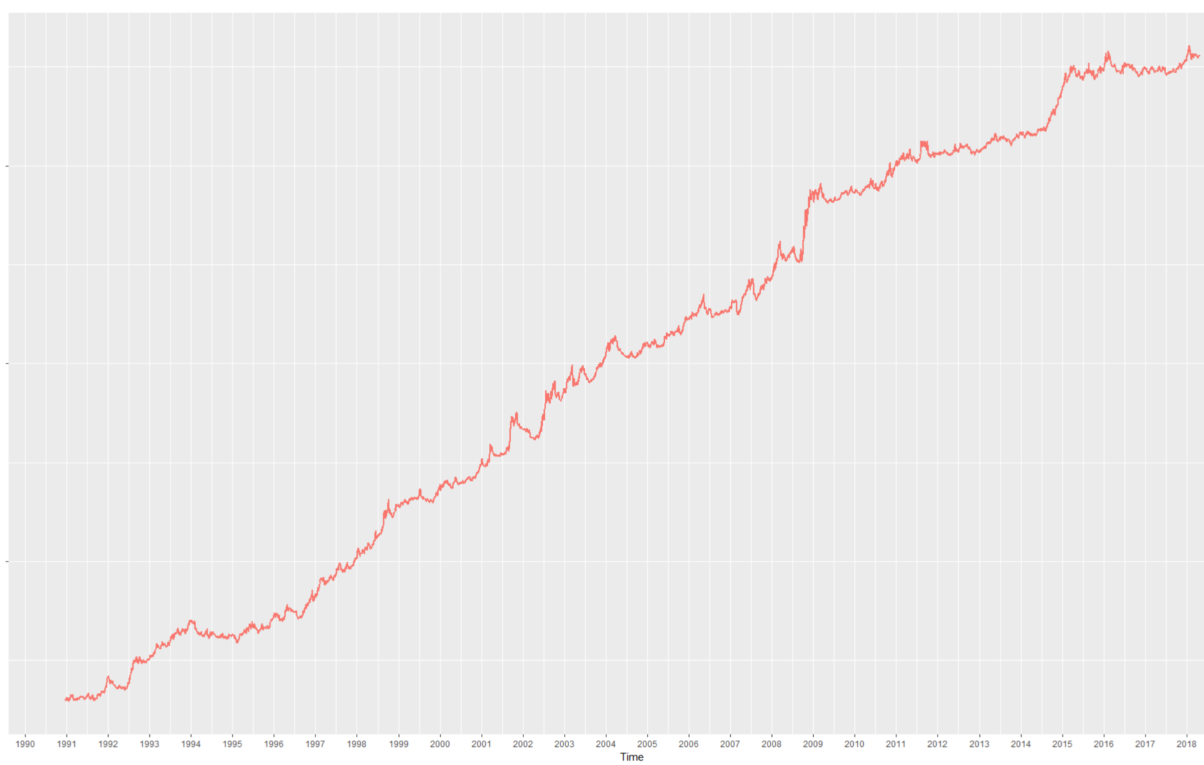

Figure 3. Track record of our TREND factor. *Note: Log prices are displayed.*

	Ann. Return	Volatility	VaR (95%)	MDD	S	K	ρ	First Trading Date
R.CBOT.Emini_DJIndex	6.13	16.35	1.49	-53.65	-0.06	15.06	-0.02	2002-04-05
R.CME.Emini_Midcap	7.70	20.12	1.84	-57.27	-0.23	13.36	-0.01	2002-01-29
R.CME.Emini_Nasdaq	3.43	26.97	2.52	-86.50	-0.02	9.83	-0.05	1999-06-22
R.CME.Emini_SP500	4.22	18.26	1.71	-63.47	-0.24	11.59	-0.02	1997-09-10
R.MX.SPCanada	4.10	18.15	1.69	-55.95	-0.61	12.67	-0.04	1999-09-08
R.Eurex.Eurostoxx50	1.40	22.79	2.27	-68.16	-0.15	7.19	0.02	1998-06-23
R.Eurex.DAX	4.79	21.80	2.13	-75.30	-0.30	8.71	0.03	1990-11-26
R.Eurex.SMI	3.28	17.82	1.69	-57.06	-0.34	10.57	0.06	1998-10-14
R.ICE.Emini_Russel	7.43	23.44	2.19	-58.38	-0.09	10.67	-0.01	2007-08-20
R.NELLondon.Footsie	2.50	17.05	1.68	-57.17	-0.17	7.37	0.02	1990-01-03
R.NELParis.CAC40	3.08	21.20	2.09	-67.20	-0.09	7.15	0.02	1990-01-03
R.NELAmst.AEX	4.83	20.20	1.97	-73.27	-0.24	8.76	0.03	1990-01-03
R.CBOT.US10YTnote	3.46	5.84	0.59	-14.06	-0.14	6.01	0.02	1990-01-03
R.CBOT.US2YTnote	1.35	1.58	0.16	-4.46	0.06	7.76	0.02	1990-06-26
R.CBOT.US5YTnote	2.57	17.80	0.40	-46.07	0.01	2340.24	-0.48	1990-01-03
R.CBOT.USTBond	4.06	9.33	0.95	-19.28	-0.11	4.94	0.02	1990-01-03
R.MX.CGB	3.32	5.96	0.60	-15.86	-0.23	5.65	0.03	1990-01-03
R.Eurex.Bobl	2.69	3.06	0.31	-8.29	-0.24	5.22	0.01	1991-10-07
R.Eurex.BundDTB	3.97	5.12	0.52	-11.58	-0.21	4.92	0.02	1990-11-26
R.Eurex.Schatz	0.82	1.16	0.12	-4.63	-0.31	7.49	0.05	1997-03-10
R.CME.EuroDollar	0.52	0.64	0.06	-2.47	0.49	21.58	0.08	1990-01-03
R.NELLondon.Euribor	0.23	0.37	0.03	-2.28	0.88	20.33	0.16	1999-01-11
R.NELLondon.Gilt	3.00	6.67	0.66	-17.44	0.01	6.73	0.01	1990-01-03
R.NELLondon.ShortSterling	0.31	1.01	0.07	-4.20	14.16	629.03	0.02	1990-01-03
R.CME.AUD_USD	2.11	11.34	1.10	-41.39	-0.32	10.41	-0.01	1990-01-03
R.CME.CAD_USD	0.23	7.80	0.77	-34.79	0.05	9.01	0.01	1990-01-03
R.CME.CHF_USD	0.67	11.36	1.12	-51.01	0.94	27.62	0.01	1990-01-03
R.CME.EUR_USD	-0.06	9.69	0.99	-35.54	0.17	5.39	0.02	1998-11-16
R.CME.GBP_USD	0.84	9.51	0.92	-40.61	-0.30	9.84	0.04	1990-01-03
R.CME.JPY_USD	-0.97	10.71	1.05	-62.81	0.57	9.63	0.00	1990-01-03
R.CME.MEP_USD	3.46	11.61	1.04	-39.90	-1.28	21.24	-0.02	1995-04-26
R.CBOT.Corn	-6.92	24.84	2.48	-90.09	0.05	7.85	-0.02	1990-01-03
R.CBOT.SoybeanMeal	7.94	24.72	2.49	-49.07	0.03	6.02	-0.01	1990-01-03
R.CBOT.SoybeanOil	-2.91	22.00	2.25	-76.00	0.06	5.45	0.03	1990-01-03
R.CBOT.Soybeans	2.56	22.17	2.18	-51.62	-0.20	6.65	-0.02	1990-01-03
R.CBOT.Wheat	-10.54	27.42	2.73	-97.47	0.16	6.13	-0.04	1990-01-03
R.CME.LiveCattle	3.89	14.17	1.49	-43.16	-0.07	4.91	0.07	1990-01-03
R.ICE.Cocoa	-3.84	28.34	2.88	-91.04	0.13	6.09	0.01	1990-01-03
R.ICE.Coffee	-8.16	34.60	3.41	-96.22	0.24	10.22	0.02	1990-01-03
R.ICE.Cotton	-2.70	25.44	2.54	-93.31	0.03	6.10	-0.00	1990-01-03
R.ICE.Sugar11	-1.22	30.38	3.09	-73.76	-0.19	5.56	-0.01	1990-01-03
R.ComEx.Copper	4.65	24.56	2.44	-67.60	-0.19	6.97	-0.01	1990-01-03
R.ComEx.Gold	1.37	15.64	1.50	-62.76	-0.28	10.48	0.01	1990-01-03
R.ComEx.Silver	0.63	27.43	2.68	-73.66	-0.34	9.71	0.01	1990-01-03
R.Nymex.Palladium	6.38	31.22	2.97	-87.43	-0.35	9.68	0.04	1990-01-03
R.Nymex.Platinum	2.35	20.33	1.99	-67.23	-0.47	7.93	0.05	1990-01-03
R.Nymex.CrudeOil	-0.08	34.25	3.34	-93.34	-0.86	19.56	0.01	1990-01-03
R.Nymex.HeatingOil	1.80	32.59	3.24	-84.56	-0.90	23.29	0.02	1990-01-03
R.Nymex.NaturalGas	-22.48	46.45	4.68	-99.86	0.07	6.02	-0.01	1990-04-04
R.Nymex.RBOBGasoline	-4.02	33.23	3.34	-76.35	-0.11	5.50	0.02	2005-10-04

Table 1. Summary statistics of our continuous futures. *Note: Ann. return refers to the annualized return in %, annualized 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. Statistics were calculated on the period starting on the first trading date until 2017-12-31 for each market.*

	Before GFC	After GFC
Systematic Diversified	0.98	0.18
Equity Market Neutral	0.54	0.24
Equity Quant. Directional	0.92	0.51
Equity Short Selling	0.38	-0.99
Fund of funds	0.46	0.30
Convertible Arbitrage	0.52	0.77
Fixed Income Multistrat.	0.50	0.57
Event-Driven	0.84	0.57
Equity Hedge	0.89	0.54
Global Macro	0.82	0.17
Relative Value	0.65	0.61

Table 2. Average monthly return (expressed in %) of the HFR indexes on the periods running from December 1993 to March 2009 (Before GFC) and from April 2009 to July 2017 (After GFC).

	Ann. Return (in %)	Ann. Volatility (in %)	Sharpe Ratio ($r_f = 0\%$)	VaR (95%, in %)	Maximum Drawdown (in %)	Calmar Ratio
Equity Market Neutral	2.86	2.46	1.17	1.10	-5.82	0.49
Equity Quant. Directional	4.06	6.68	0.61	2.92	-12.75	0.32
Equity Short Selling	-8.74	9.86	-0.89	4.68	-49.31	-0.18
Fund of funds	2.45	3.78	0.65	1.80	-6.98	0.35
Systematic Diversified	2.23	7.36	0.30	3.32	-11.27	0.20
Convertible Arbitrage	4.27	4.46	0.96	2.33	-8.96	0.48
Fund of funds	4.77	3.25	1.47	1.64	-4.57	1.04
Event-Driven	4.08	5.44	0.75	2.61	-10.37	0.39
Equity Hedge	3.62	7.60	0.48	3.74	-12.88	0.28
Global Macro	1.43	4.46	0.32	2.14	-7.85	0.18
Relative Value	5.11	3.31	1.55	1.66	-5.62	0.91

Table 3. Main statistics of the HFR indexes (net of fees). *Note: Calmar ratio is the ratio of the annual return to the maximum drawdown.*

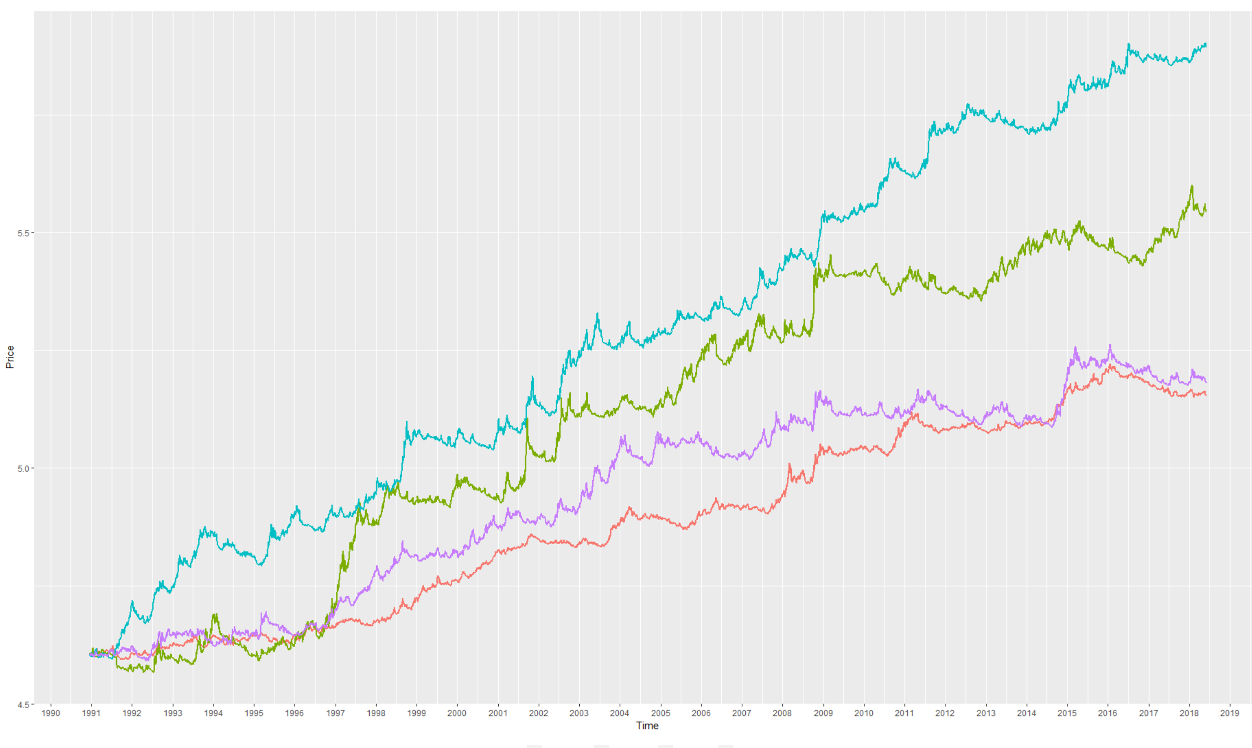

Figure 4. Track record of our *sector*-TREND factors. *Note: Log prices are displayed.*

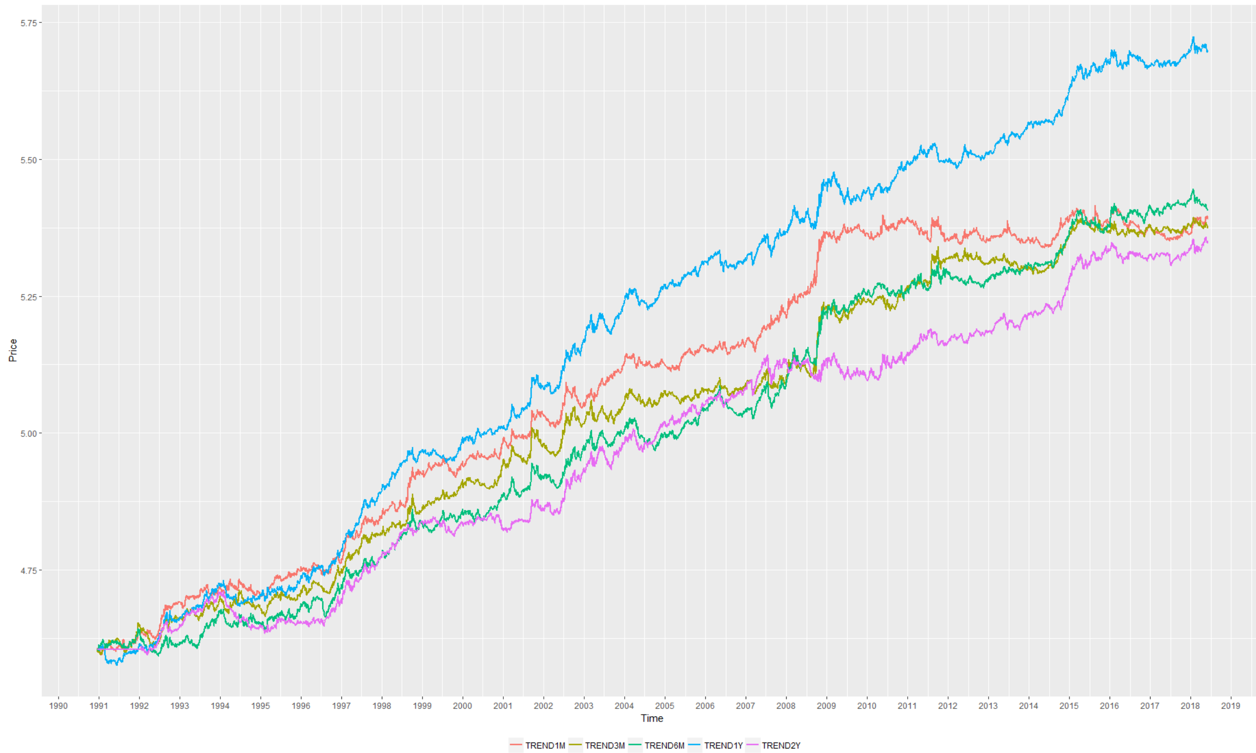

Figure 5. Track record of our *horizon*-TREND factors. *Note: Log prices are displayed.*

FH Period												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Mean (in %)	0.85	0.83	0.10	0.85	0.35	0.15	0.46	0.55	0.87	0.91	0.35	0.88
Std. Dev (in %)	2.72	3.31	2.29	2.99	3.08	2.63	2.58	2.74	2.87	3.04	2.53	2.69
Q25 (in %)	-0.81	-1.40	-1.23	-1.27	-1.61	-1.54	-1.32	-1.19	-0.97	-0.92	-1.46	-0.66
Median (in %)	0.53	0.97	-0.42	0.33	-0.08	0.11	0.62	0.70	0.39	0.81	0.03	0.78
Q3 (in %)	2.73	2.24	1.25	2.20	1.66	2.02	1.96	2.50	2.98	2.80	2.03	2.44
Skewness	0.27	0.47	0.41	1.05	0.94	0.10	0.15	-0.15	0.03	-0.03	0.39	0.18
Kurtosis	2.80	3.32	2.78	3.91	4.14	2.81	3.09	2.89	2.86	2.77	2.96	2.99
Whole Period												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Mean (in %)	0.98	0.66	0.49	0.82	0.44	0.65	0.66	0.71	0.95	0.67	0.74	0.88
Std. Dev (in %)	2.91	3.23	2.79	3.08	2.79	2.69	2.84	2.88	2.83	2.82	2.81	2.82
Q25 (in %)	-0.86	-1.39	-1.16	-1.24	-1.44	-1.19	-1.31	-1.21	-0.91	-1.04	-1.10	-0.98
Median (in %)	0.66	0.32	-0.01	0.33	0.12	0.37	0.44	0.63	0.75	0.56	0.37	0.79
Q3 (in %)	2.65	2.21	1.57	2.13	1.89	2.13	2.11	2.52	2.81	2.39	2.16	2.53
Skewness	0.79	1.05	1.02	0.87	0.98	0.91	1.13	0.36	0.21	0.02	1.47	0.25
Kurtosis	4.95	7.63	5.11	4.05	4.88	5.73	7.32	4.37	3.25	3.17	8.59	3.30
Before GFC												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Mean (in %)	1.15	0.75	0.65	0.89	0.56	0.94	0.76	0.79	1.10	0.72	0.96	1.00
Std. Dev (in %)	3.03	3.29	3.04	3.14	2.77	2.74	3.01	2.98	2.85	2.75	2.96	2.90
Q25 (in %)	-0.72	-1.22	-0.98	-1.16	-1.34	-1.00	-1.30	-1.17	-0.79	-0.83	-0.94	-0.97
Median (in %)	0.77	0.33	0.02	0.38	0.27	0.51	0.44	0.58	1.21	0.54	0.42	0.88
Q3 (in %)	2.74	2.33	1.65	2.28	2.02	2.51	2.28	2.58	2.81	2.44	2.49	2.64
Skewness	0.88	1.18	1.01	0.73	0.96	1.13	1.32	0.50	0.24	0.03	1.63	0.24
Kurtosis	2.80	3.32	2.78	3.91	4.14	2.81	3.09	2.89	2.86	2.77	2.96	2.99
After GFC												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Mean (in %)	0.60	0.46	0.15	0.66	0.18	0.02	0.43	0.51	0.60	0.55	0.26	0.63
Std. Dev (in %)	2.60	3.08	2.11	2.97	2.82	2.48	2.43	2.64	2.78	2.98	2.38	2.61
Q25 (in %)	-1.03	-1.55	-1.20	-1.30	-1.61	-1.72	-1.31	-1.22	-1.12	-1.30	-1.35	-1.07
Median (in %)	0.45	0.29	-0.05	0.14	-0.15	0.07	0.50	0.71	0.28	0.72	0.02	0.65
Q3 (in %)	1.90	2.03	1.31	1.99	1.21	1.44	2.01	2.36	2.45	2.23	1.72	2.11
Skewness	0.33	0.64	0.36	1.20	1.04	0.21	0.14	-0.14	0.12	-0.00	0.48	0.22
Kurtosis	2.93	3.73	3.00	4.62	4.81	2.99	3.16	2.83	3.05	2.81	3.21	3.07

Table 4. Summary statistics of all TREND factors' monthly returns, on the periods running from January 2010 to March 2016 (FH period), from December 1993 to July 2017 (Whole period), from December 1993 to March 2009 (Before GFC) and from April 2009 to July 2017 (After GFC).

	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Ann. Return (in %)	11.62	7.65	6.01	9.78	4.97	7.94	7.63	8.08	11.23	8.15	8.81	10.43
Ann. Volatility (in %)	9.98	11.08	9.71	10.54	9.65	9.31	9.74	9.90	9.79	9.74	9.68	9.71
Sharpe Ratio ($r_f = 0\%$)	1.16	0.69	0.62	0.93	0.52	0.85	0.78	0.82	1.15	0.84	0.91	1.07
VaR (95%, in %)	1.16	0.69	0.62	0.93	0.52	0.85	0.78	0.82	1.15	0.84	0.91	1.07
Maximum Drawdown (in %)	-10.33	-21.47	-13.81	-13.24	-16.47	-13.71	-10.87	-14.78	-11.65	-19.51	-11.41	-13.01
Calmar Ratio	1.12	0.36	0.44	0.74	0.30	0.58	0.70	0.55	0.96	0.42	0.77	0.80

Table 5. Main statistics of our monthly TREND factors (gross of fees) over the global period. *Note: Calmar ratio is the ratio of the annual return to the maximum drawdown.*

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M
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	0.41	0.51	0.18	0.15	0.21	-0.13	-0.1	-0.17	0.08	1							
TRENDCOM	0.15	0.31	0.29	0.04	0.09	-0.07	0.05	0.15	-0.08	0.71	1						
TRENDSTK	-0.14	-0.08	-0.17	-0.11	0.16	0.44	0.02	0.18	-0.2	0.41	0.02	1					
TRENDBD	0.67	0.46	0.13	0.32	0.08	-0.51	-0.28	-0.65	0.42	0.55	0.11	-0.17	1				
TRENDFX	0.22	0.59	0.21	0.1	0.18	-0.17	0.03	0.03	0	0.73	0.61	0.09	0.27	1			
TREND1M	0.5	0.57	0.29	0.3	0.43	-0.26	-0.17	-0.29	0.2	0.64	0.36	0.18	0.5	0.47	1		
TREND3M	0.38	0.45	0.26	0.16	0.3	-0.25	-0.11	-0.19	0.09	0.78	0.55	0.33	0.39	0.61	0.47	1	
TREND6M	0.31	0.39	0.1	0.02	0.12	-0.15	-0.13	-0.17	0.07	0.84	0.5	0.45	0.42	0.64	0.41	0.7	1
TREND1Y	0.26	0.41	0.09	0.05	0.05	0.08	0.05	-0.03	0.01	0.8	0.57	0.33	0.4	0.65	0.35	0.52	0.58
TREND2Y	0.09	0.22	-0.1	0.08	-0.06	0.02	-0.02	0	0	0.61	0.34	0.22	0.39	0.57	0.18	0.22	0.44
TRENDST	0.51	0.6	0.32	0.27	0.42	-0.3	-0.17	-0.28	0.17	0.82	0.53	0.3	0.52	0.63	0.86	0.86	0.65
TRENDLT	0.26	0.42	0.04	0.06	0.05	-0.02	-0.04	-0.08	0.03	0.91	0.57	0.41	0.49	0.76	0.38	0.58	0.82

Table 6. Pearson Correlation matrix of Fung-Hsieh and TREND factors, on the FH sub-period running from January 2010 to March 2016.

	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Equity Market Neutral	-0.09	0.00	0.29	-0.43	-0.00	-0.30	-0.28	-0.16	0.19	0.21	-0.34	0.10
Equity Quant. Directional	-0.06	-0.01	0.39	-0.44	-0.04	-0.26	-0.22	-0.10	0.16	0.17	-0.28	0.09
Equity Short Selling	0.15	0.05	-0.40	0.57	0.08	0.24	0.18	0.17	-0.05	0.03	0.24	0.06
Fund of funds	0.19	0.15	0.59	-0.37	0.14	-0.06	0.03	0.10	0.33	0.27	-0.02	0.29
Systematic Diversified	0.85	0.56	0.40	0.47	0.60	0.50	0.70	0.70	0.78	0.45	0.70	0.78
Convertible Arbitrage	-0.11	0.01	0.33	-0.44	-0.15	-0.21	-0.20	-0.18	0.03	0.05	-0.23	-0.04
Fixed Income Multistrat.	-0.03	-0.01	0.43	-0.37	-0.10	-0.14	-0.08	-0.08	0.09	0.05	-0.13	0.03
Event-Driven	-0.15	-0.09	0.44	-0.54	-0.14	-0.26	-0.24	-0.19	0.03	0.05	-0.29	-0.04
Equity Hedge	-0.15	-0.07	0.41	-0.53	-0.15	-0.28	-0.25	-0.21	0.04	0.06	-0.31	-0.04
Global Macro	0.75	0.53	0.48	0.28	0.52	0.39	0.57	0.59	0.72	0.47	0.56	0.73
Relative Value	-0.17	-0.15	0.35	-0.41	-0.21	-0.27	-0.24	-0.22	-0.02	0.06	-0.29	-0.07

Table 7. Pearson Correlation of HFR indexes and our TREND factors, on the FH sub-period running from January 2010 to March 2016.

	Systematic Diversified		Global Macro	
	(With TREND)	(Without TREND)	(With TREND)	(Without TREND)
Alpha	**-0.60%**	0.09%	**-0.40%**	0.02%
	(-3.60)	(0.30)	**(-3.71)**	(0.09)
Equity	**0.16**	**0.24**	**0.15**	**0.20**
	(4.30)	**(3.43)**	**(6.08)**	**(4.59)**
Size	-0.08	-0.16e	-0.02	-0.07
	(-1.38)	(-1.56)	(-0.44)	(-1.05)
Bond	-0.02	-0.04	-0.01	-0.02
	(-1.31)	(-1.14)	(-0.68)	(-0.83)
Credit	0.01	-0.05	0.00	-0.03
	(0.36)	(-0.88)	(0.11)	(-1.00)
PTFSBD	0.01	0.03	-0.00	0.01
	(0.59)	(1.94)	(-0.44)	(1.35)
PTFSFX	0.01	**0.05**	0.01	**0.03**
	(1.54)	**(3.84)**	(1.14)	**(3.57)**
PTFSCOM	0.01	0.01	0.00	0.00
	(1.26)	(0.86)	(0.33)	(0.38)
PTFSIR	0.00	0.01	0.00	0.01
	(0.44)	(0.33)	(0.80)	(0.56)
PTFSSTK	**-0.02**	-0.02	**-0.01**	-0.01
	(-2.97)	(-1.14)	**(-2.76)**	(-1.18)
TREND	**0.80**		**0.48**	
	(12.30)		**(11.43)**	
R^2	0.82	0.38	0.79	0.37

Table 8. Regressions of Systematic Diversified and Global Macro indexes on the Fung-Hsieh factors, combined with our TREND factor for both specifications (with and without TREND). T-statistic is displayed below the coefficients. *Note: Significant variables are in bold.*

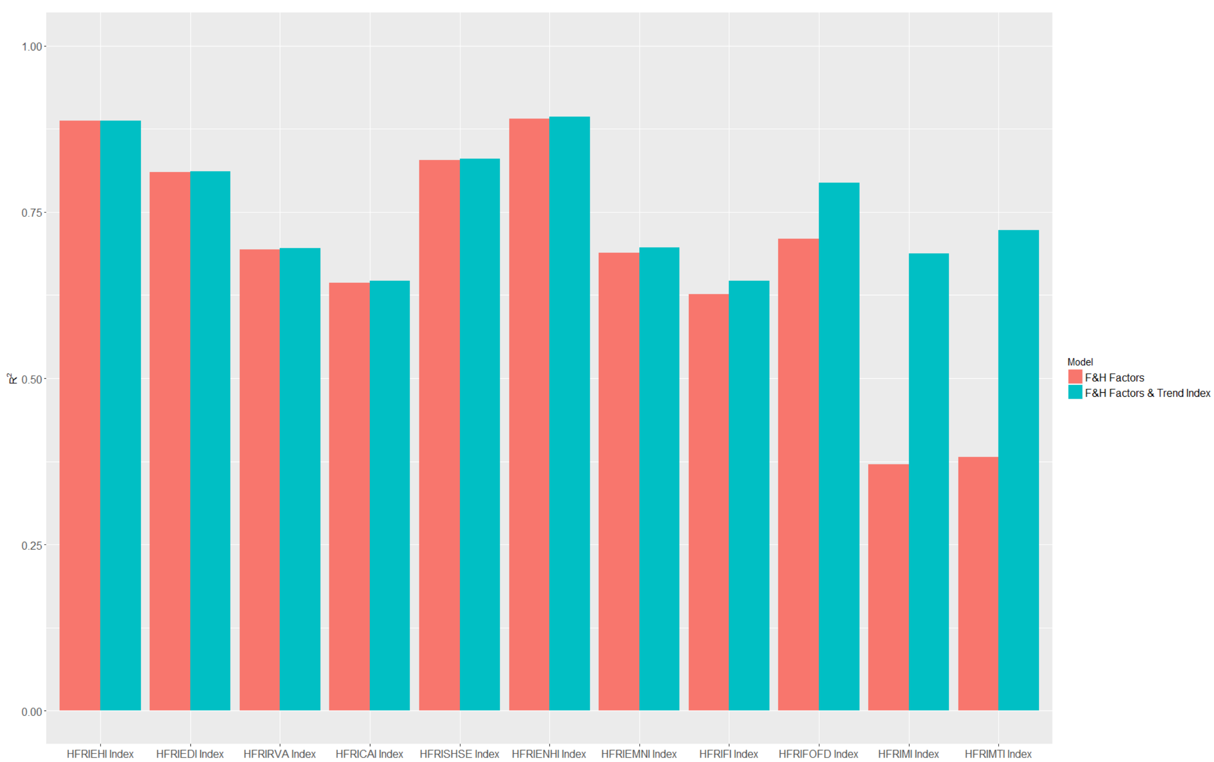

Figure 6. R^2 of two factor models (9- and 10-factor models) on selected HFR indexes.

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	TREND	R^2
Equity Market Neutral	0.00	-0.01	0.00	-0.01	-0.00	-0.00	0.12	0.00	0.02	0.00	0.02	0.69
	(1.16)	(-1.52)	(1.12)	(-2.63)	(-0.37)	(-0.25)	(6.89)	(0.06)	(1.88)	(0.11)	(0.86)	
Equity Quant. Dir.	-0.00	-0.02	0.01	-0.01	0.00	-0.02	0.41	0.07	0.01	0.02	**0.10**	0.90
	(-1.94)	(-2.65)	(1.84)	(-1.29)	(0.66)	(-3.13)	(15.72)	(1.84)	(0.91)	(1.12)	**(2.18)**	
Equity Short Selling	-0.00	0.02	-0.00	-0.01	-0.01	-0.00	-0.51	-0.27	-0.01	0.05	-0.03	0.83
	(-1.10)	(2.00)	(-0.21)	(-0.51)	(-0.61)	(-0.04)	(-10.25)	(-3.74)	(-0.46)	(1.34)	(-0.31)	
Fund of funds	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.19	0.04	0.01	-0.04	**0.17**	0.79
	(-1.59)	(-0.91)	(0.61)	(-0.63)	(-0.48)	(-0.75)	(8.85)	(1.17)	(1.14)	(-2.35)	**(4.88)**	
Systematic Diversified	-0.01	0.00	0.01	0.01	0.00	-0.02	0.17	-0.08	-0.02	0.01	**0.80**	0.82
	(-3.64)	(0.51)	(1.55)	(1.21)	(0.42)	(-2.85)	(4.27)	(-1.36)	(-1.27)	(0.38)	**(12.30)**	
Convertible Arbitrage	0.00	-0.00	0.00	-0.01	-0.01	-0.01	0.21	0.04	-0.01	-0.05	0.02	0.64
	(0.19)	(-0.20)	(0.18)	(-1.45)	(-0.72)	(-0.71)	(6.49)	(0.78)	(-0.45)	(-2.08)	(0.39)	
Fixed Income Multistrat.	0.00	-0.01	0.00	-0.00	0.00	-0.00	0.13	0.03	-0.02	-0.07	0.05	0.63
	(2.05)	(-1.73)	(0.91)	(-0.85)	(0.36)	(-0.93)	(5.28)	(0.91)	(-1.63)	(-3.85)	(1.16)	
Event-Driven	-0.00	-0.00	0.00	-0.01	-0.01	-0.00	0.27	0.08	0.00	-0.08	0.00	0.81
	(-0.05)	(-0.69)	(0.39)	(-1.85)	(-0.89)	(-0.17)	(9.14)	(1.94)	(0.07)	(-3.58)	(0.06)	
Equity Hedge	-0.00	-0.01	0.01	-0.01	-0.00	-0.00	0.44	0.15	0.00	-0.04	-0.01	0.89
	(-1.42)	(-1.15)	(1.18)	(-2.19)	(-0.27)	(-0.54)	(14.18)	(3.30)	(0.31)	(-1.50)	(-0.10)	
Global Macro	-0.00	-0.00	0.01	0.00	0.00	-0.01	0.15	-0.02	-0.01	0.00	**0.48**	0.79
	(-3.71)	(-0.44)	(1.14)	(0.33)	(0.80)	(-2.76)	(6.08)	(-0.44)	(-0.68)	(0.11)	**(11.43)**	
Relative Value	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.14	0.02	-0.02	-0.07	-0.00	0.69
	(2.22)	(-1.20)	(0.20)	(-1.16)	(0.01)	(-2.01)	(6.05)	(0.71)	(-1.67)	(-3.79)	(-0.11)	

Table 9. Regressions of the HFR indexes on the Fung-Hsieh factors, combined with TREND. T-statistic is displayed below the coefficients. *Note: Significant Trend exposures are in bold.*

	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	R^2
Equity Market Neutral	-0.01	-0.07	0.08	0.09	0.72
	(-0.17)	(-1.57)	(1.23)	(1.54)	
Equity Quant. Directional	0.01	0.05	0.1	0.14	0.90
	(0.09)	(0.63)	(0.93)	(1.45)	
Equity Short Selling	0.18	-0.19	0.25	-0.21	0.84
	(0.79)	(-1.33)	(1.24)	(-1.13)	
Fund of funds	0.09	**0.26**	0.05	0.12	0.81
	(0.9)	**(4.47)**	(0.57)	(1.6)	
Systematic Diversified	**0.89**	**0.66**	**0.59**	**0.37**	0.82
	(4.94)	**(6.01)**	**(3.74)**	**(2.61)**	
Convertible Arbitrage	0.24	0.02	-0.04	-0.13	0.66
	(1.61)	(0.27)	(-0.32)	(-1.1)	
Fixed Income Multistrat.	0.09	**0.17**	0.02	-0.11	0.67
	(0.85)	**(2.52)**	(0.24)	(-1.29)	
Event-Driven	-0.09	0.14	-0.05	-0.01	0.82
	(-0.69)	(1.76)	(-0.43)	(-0.06)	
Equity Hedge	0.03	0.09	-0.03	-0.09	0.89
	(0.2)	(1.05)	(-0.22)	(-0.78)	
Global Macro	**0.57**	**0.39**	**0.37**	**0.19**	0.80
	(4.87)	**(5.48)**	**(3.66)**	**(2.04)**	
Relative Value	-0.07	0.09	0.07	-0.07	0.71
	(-0.65)	(1.38)	(0.82)	(-0.87)	

Table 10. Regressions of the HFR indexes on the Fung-Hsieh factors, combined with the four sector TREND factors. T-statistic is displayed below the coefficients. *Note: Only sector TREND factors are displayed but the model used is the full one, with Fung-Hsieh nine factors.*

	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	R^2
Equity Market Neutral	-0.05	-0.07	-0.1	**0.16**	0.11	0.76
	(-0.76)	(-0.91)	(-1.37)	**(2.4)**	(1.93)	
Equity Quant. Directional	0.01	0.06	-0.08	0.06	**0.25**	0.91
	(0.1)	(0.45)	(-0.6)	(0.52)	**(2.63)**	
Equity Short Selling	-0.26	-0.37	0.19	-0.02	0.12	0.84
	(-1.14)	(-1.47)	(0.77)	(-0.1)	(0.66)	
Fund of funds	0.16	0.18	-0.03	0.11	**0.18**	0.80
	(1.63)	(1.66)	(-0.28)	(1.23)	**(2.27)**	
Systematic Diversified	**0.37**	**0.86**	0.26	**0.78**	0.13	0.85
	(2.29)	**(4.71)**	(1.48)	**(5.02)**	(0.98)	
Convertible Arbitrage	0.18	0.21	-0.27	-0.05	0.11	0.67
	(1.22)	(1.26)	(-1.69)	(-0.34)	(0.94)	
Fixed Income Multistrat.	0.13	0.19	-0.12	0.01	0.02	0.65
	(1.23)	(1.57)	(-1.02)	(0.06)	(0.2)	
Event-Driven	0.14	0.14	-0.22	-0.05	0.13	0.82
	(1.1)	(0.96)	(-1.53)	(-0.36)	(1.24)	
Equity Hedge	0.08	0.27	**-0.34**	-0.13	**0.24**	0.90
	(0.55)	(1.74)	**(-2.27)**	(-0.99)	**(2.07)**	
Global Macro	**0.29**	**0.51**	0.11	**0.40**	0.17	0.81
	(2.61)	**(4.01)**	(0.91)	**(3.67)**	(1.81)	
Relative Value	0.11	0.17	**-0.23**	-0.07	0.13	0.73
	(1.15)	(1.54)	**(-2.16)**	(-0.71)	(1.56)	

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

	TRENDST	TRENDLT	R^2
Equity Market Neutral	**-0.21**	**0.21**	0.73
	(-2.21)	**(2.81)**	
Equity Quant. Directional	-0.07	**0.31**	0.90
	(-0.42)	**(2.6)**	
Equity Short Selling	**-0.61**	0.26	0.84
	(-2.07)	(1.13)	
Fund of funds	0.25	**0.31**	0.80
	(1.97)	**(3.17)**	
Systematic Diversified	**1.31**	**1.23**	0.82
	(5.62)	**(6.83)**	
Convertible Arbitrage	0.23	-0.12	0.65
	(1.18)	(-0.79)	
Fixed Income Multistrat.	0.27	-0.06	0.65
	(1.91)	(-0.52)	
Event-Driven	0.14	-0.06	0.81
	(0.79)	(-0.41)	
Equity Hedge	0.11	-0.08	0.89
	(0.58)	(-0.53)	
Global Macro	**0.79**	**0.72**	0.79
	(5.2)	**(6.17)**	
Relative Value	0.14	-0.09	0.70
	(1.02)	(-0.83)	

Table 12. Regressions of the HFR indexes on the Fung-Hsieh factors, combined with the two horizon Trends. T-statistic is displayed below the coefficients. *Note: Only horizon Trend factors are displayed but the model used is the full one, with Fung-Hsieh nine factors.*

Fund Characteristic	Mean	Std. Dev.	P25	Median	P75
Return (% per month)	0.34	0.34	0.11	0.27	0.49
Mgt. Fee (in %)	1.46	1.13	1.00	1.50	2.00
Incentive Fee (in %)	16.98	7.04	15.00	20.00	20.00
Age (years)	8.14	4.67	4.33	8.00	11.84
AUM (US$M)	1 454.66	4 335.61	30.00	179.93	792.00

Table 13. Summary statistics of the EuroHedge database (N=1685 funds).

	QUANTILE PORTFOLIOS		
	1 (LOW)	4 (HIGH)	4 - 1
Ann. Return (in %)	11.44	7.72	-3.72
	(5.52)	(3.10)	
9-factor Alpha (in %)	0.15	0.56	0.41
	(0.88)	(2.19)	
Avg. β_{TREND}	-0.29	0.44	

Table 14. Quantile portfolios statistics (based on univariate β_{TREND} sorts). T-statistic is displayed below the coefficients. Results concern the period starting in January 2010 ending in March 2016. *Note: Funds have been scaled to have the same volatility as TREND, on each window.*

	1	2
β_{TREND}	-3.25%	-3.25%
	(-2.55)	(-2.51)
Mngt. Fee		0.42
		(1.08)
Incentive Fee		0.03
		(0.63)
Age		-0.00
		(-0.58)
Alpha	9.07%	8.40%
	(28.12)	(8.10)
R^2	0.7%	0.9%

Table 15. Fama-MacBeth regressions. *Note: Specification 1 contains only the TREND beta as a regressor, whereas the specification 2 is the full one. Funds have been scaled to have the same volatility as TREND. The model was applied on a subset of 889 hedge funds which met the following criteria: at least 20$M and 2 years of track record.*

Hedge Funds					
	β_{TREND}	Annual Return	Management Fee	Incentive Fee	Age (in years)
Mean	0.00	8.70%	1.45%	16.51%	8.90
Q1	-0.18	5.48%	1.00%	15.00%	5.33
Median	-0.05	8.12%	1.50%	20.00%	8.59
Q3	0.11	11.49%	2.00%	20.00%	12.01
Managed Futures					
	β_{TREND}	Annual Return	Management Fee	Incentive Fee	Age (in years)
Mean	0.32	6.94%	1.42%	18.94%	8.45
Q1	0.03	1.88%	1.00%	20.00%	4.50
Median	0.37	5.28%	1.83%	20.00%	7.92
Q3	0.64	9.06%	2.00%	20.00%	12.59

Table 16. Statistics of the Hedge Funds sample (N=889) and the Managed Futures subsample (N=236). *Note: Funds have been scaled to have the same volatility as TREND. The subset contains 889 hedge funds which met the following criteria: at least 20$M and 2 years of track record. The subsample contains 236 hedge funds which are in the Managed Futures category.*

	1	2
β_{TREND}	-3.84%	-3.67%
	(-2.46)	(-2.40)
Mngt. Fee		0.74
		(1.06)
Incentive Fee		-0.02
		(-0.23)
Age		0.00
		(1.74)
Alpha	7.39%	4.99%
	(9.67)	(2.84)
R^2	6.0%	11.3%

Table 17. Fama-MacBeth regressions for Managed Futures funds only. *Note: Specification 1 contains only the TREND beta as a regressor, whereas the specification 2 is the full one. Funds have been scaled to have the same volatility as the TREND factor.The model was applied on a subset of 236 hedge funds which met the following criteria: in the Managed Futures category, and at least 20$M and 2 years of track record.*

	(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)**
TRENDSTK	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 18. Regressions of Global Macro (GM) and CTA indexes on the Fung-Hsieh factors, combined with our TRENDSTK factor. T-statistic is displayed below the coefficients.

	(Commodities) *(COM)*		*(Currencies)* *(FX)*		*(Equities)* *(STK)*		*(Bonds)* *(BD)*	
	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)
TRENDXXX	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 19. Regression (full specification) of GM and CTA indexes with Fung and Hsieh nine factors and TRENDXXX, where XXX denotes the asset class specified at the top of the table (COM for commodities, FX for currencies, STK for stocks and BD for bonds and interest rates). 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 20. Regressions of GM and CTA HFR indexes with a Trend factor built on a selection of futures. T-statistic is displayed below the coefficients.

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 Instru
HFRI RV: Multi-Strategy Index (HFRIFI Index)	Multi-Strategy	Relative Value Strategies on Fixed Income, derivatives, Equity, Real Esta
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 21. Description of the HFRI database.

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	TREND
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	0.43	0.52	0.23	0.32	0.25	-0.13	0	-0.3	0.34	1

Table 22. Pearson Correlation of F&H factors and TREND on a selection of 6 futures (S&P500, US10Y T-note, EUR/USD, Corn, Gold and Crude Oil), on the FH sub-period running from January 2010 to March 2016.

	TREND	HFRIMTI	HFRIEMNI	HFRIENHI	HFRISHSE	HFRIFOFD	HFRICAI	HFRIFI	HFRIEDI	HFRIEHI	HFRIMI	HFRIRVA
TREND	1.00	0.45	0.14	-0.05	0.07	0.13	-0.11	-0.08	-0.11	-0.02	0.49	-0.16
HFRIMTI	0.45	1.00	0.23	0.54	-0.41	0.46	0.05	0.14	0.34	0.46	0.65	0.14
HFRIEMNI	0.14	0.23	1.00	0.37	-0.18	0.48	0.36	0.41	0.48	0.52	0.34	0.46
HFRIENHI	-0.05	0.54	0.37	1.00	-0.86	0.77	0.46	0.59	0.83	0.91	0.53	0.61
HFRISHSE	0.07	-0.41	-0.18	-0.86	1.00	-0.59	-0.35	-0.45	-0.64	-0.78	-0.35	-0.44
HFRIFOFD	0.13	0.46	0.48	0.77	-0.59	1.00	0.58	0.74	0.81	0.84	0.69	0.72
HFRICAI	-0.11	0.05	0.36	0.46	-0.35	0.58	1.00	0.83	0.69	0.63	0.23	0.87
HFRIFI	-0.08	0.14	0.41	0.59	-0.45	0.74	0.83	1.00	0.79	0.71	0.39	0.86
HFRIEDI	-0.11	0.34	0.48	0.83	-0.64	0.81	0.69	0.79	1.00	0.88	0.49	0.83
HFRIEHI	-0.02	0.46	0.52	0.91	-0.78	0.84	0.63	0.71	0.88	1.00	0.53	0.74
HFRIMI	0.49	0.65	0.34	0.53	-0.35	0.69	0.23	0.39	0.49	0.53	1.00	0.32
HFRIRVA	-0.16	0.14	0.46	0.61	-0.44	0.72	0.87	0.86	0.83	0.74	0.32	1.00

Table 23. Pearson Correlation matrix of HFR indexes and TREND, on the period running from December 2010 to March 2016.

Notes

[1]Backwardation and contago refer to the two possible shapes of any futures curve, the first relates to when the futures price is below the expected spot price and the opposite for the latter.

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

[3]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.

[4]Performances of our factor are gross of fees (management, performance and expense fees) as well as gross of transaction costs.

[5]Results of the model with the size variable are available upon request.