Article:

Stafylas, D, Anderson, K and Uddin, M orcid.org/0000-0003-1035-0365 (2018) Hedge fund performance attribution under various market conditions. International Review of Financial Analysis, 56. pp. 221-237. ISSN 1057-5219

https://doi.org/10.1016/j.irfa.2018.01.006

Hedge Fund Performance Attribution Under Various Market Conditions

Dimitrios Stafylas[1]

Keith Anderson[2]*

Moshfique Uddin[3]

Abstract

We investigate US hedge funds' performance. Our proposed model contains exogenous and endogenous break points, based on business cycles and on a regime switching process conditional on different states of the market. During difficult market conditions most hedge fund strategies do not provide significant alphas. At such times hedge funds reduce both the number of their exposures to different asset classes and their portfolio allocations, while some strategies even reverse their exposures. Directional strategies share more common exposures under all market conditions compared to non-directional strategies. Factors related to commodity asset classes are more common during these difficult conditions whereas factors related to equity asset classes are most common during good market conditions. Falling stock markets are harsher than recessions for hedge funds.

Keywords: hedge funds, performance, statistical factors, multi-factor models, risk exposures, alpha and beta returns

* Corresponding author

1 Introduction

The last financial crisis raised doubts about the hedge fund (HF) industry which has long been considered as being able to produce positive returns irrespective of the market conditions (Hentati-Kaffel and de Paretti, 2015). However this cannot be completely answered with stronger, more

[1] Aston Business School, Aston University, Birmingham, B4 7ET, England.
[2] The York Management School, University of York, Freboys Lane, Heslington, York YO10 5GD, England. Tel. +44 1904 325001. Email keith.anderson@york.ac.uk
[3] Leeds University Business School, Maurice Keyworth Building, University of Leeds, Moorland Road, Leeds LS6 1AN, England.

comprehensive evidence as the existing knowledge cannot sufficiently explain HF performance under various market conditions including any financial crisis. In this paper we investigate the impact of multiple business cycles and different market conditions on the performance of different HF strategies (alpha and risk exposure), focusing on the North America region. We use the terms multiple business cycles based on the National Bureau of Economic Research (NBER) definition and market conditions based on the Wilshire 5000 market index. We make the distinction between business cycles and different market conditions because we want to shed light on the difference between them in HF strategies, assisting investors in their decision-making process. We examine HF performance in a more comprehensive way and not just isolating one or two economic periods or financial crisis events. By using a parsimonious empirical specification described later, we focus on HFs that invest primarily in the North America region due to our use of three full U.S. business cycles. This region represents more than $1.9 trillion of HF assets under management corresponding to almost 72% of worldwide total (Preqin Global Hedge Fund Report, 2016).

Although there are studies that examine funds' variability over time (see section 2), there is a need to examine HF strategy performance in a more comprehensive way. More specifically, the direct impact of different business cycles and market conditions on HFs needs to be examined further. The current knowledge is fragmented (e.g. focusing on only one crisis or economic event). Also within current models there is no direct link between fund performance and market conditions, as some studies (e.g. Bollen and Whaley, 2009; Jawadi and Khanniche, 2012) focus on the internal change of funds' exposures, and the macro variables used by other authors (e.g. Avramov et al., 2013, Bali et al., 2014, and Racicot and Theoret, 2016) do not necessarily represent the different states of the economy. According to NBER, the recession has as an attribute a significant decline in the economic activity lasting more than few months usually visible in the real GDP, industrial production, employment, real income, and wholesale-retail sales. Down market regimes have as an attribute substantial return downturns and market volatility (see section 4.2)[4]. Moreover, the

[4] In other words, a recession refers to a decline in economic activity and is related mostly to real assets. On the other hand, a down market refers to periods where there is a significant downturn in returns with high market volatility, and is related mostly to financial assets. We implicitly assume that down regimes which are related mostly to financial assets have a more direct and severe impact on HFs' performance (in alphas and exposures) than recessions. Our results in section 4.3 confirm this. The binary classification of business cycles or regimes focus on these two most important elements. In this study, we examine the different implications of these two phenomena on HFs' performance (see also section 4.3). This paper does not study the business cycle itself, nor does it examine different states of business cycles as this is beyond its scope. We use similar terminology as NBER.

single models used to describe all HF strategies or conditions are over-simplistic and do not efficiently capture the exposures and excess returns delivered to investors.

Our model uses a stepwise regression and then applies it to business cycles (NBER expansions/recessions) and to the market via a regime switching model with up/down regimes. This is implemented for each of the 11 HF strategies that we model (see section 3.2). Our proposed modeling approach differs from the studies cited here, as it uses a parsimonious model that is flexible enough to accurately identify for each strategy changes in asset and portfolio allocations, within each of the underlying market conditions. Our study covers an important gap and since there is a need to focus on one region as different regions of the world have different business cycles, we choose the most important economically: North America and HFs that invest primarily in this region. HFs that invest only in the emerging markets do not have a direct exposure to these economic conditions. Another important gap is the lack of an investigation into HF performance within different business cycles and market conditions together as these two different states do not necessarily coincide and they have different implications for HFs, causing confusion to investors. Thus, we are the first to compare HFs under these two states that present different attributes (as shown later). Furthermore, instead of using one general commodity factor, we use specific ones (agriculture/food, energy, industrial and precious metals) for more accurate results. We use for the first time a commodity factor related to the agricultural/food industry that caters specifically for HFs that invest in this "traditional" sector.

Our findings contribute to the literature, in terms of the dynamic nature of HFs (e.g. Bali, Brown and Caglayan, 2011, and Giannikis and Vrontos, 2011), common risk factors among strategies (e.g. Billio, Getmansky and Pelizzon, 2012), changes in asset classes and portfolio allocations (e.g. Patton and Ramadorai, 2013) and high significance of specific factors (e.g. Meligkotsidou and Vrontos, 2014). The contribution of our paper further lies in the fact that we provide the first examination of the performance of different HF strategies within multiple U.S. business cycles and up/down market conditions. We use a transparent, easy to follow approach, to get a more comprehensive explanation of HF performance. In addition, unlike previous studies, we do not use only one general commodity factor but many specific ones. This is important because, as suggested by Bhardwaj and Dunsby (2012), commodities cannot all be considered to behave in the same way in the market. In addition, we use a commodity factor related to the agriculture/food industry, as we do not expect that it fluctuates a lot during business cycles; also it is a factor that has not been given attention in the HF academic literature. Moreover, we use a customized parsimonious model that tackles the “dimensionality” reduction issue in HFs and can accurately capture changes in asset and portfolio allocations for each strategy within different conditions. This helps investors to know what to expect from different strategies, especially during multiple stressful financial conditions. Furthermore, we perform a systematic database merging and cleaning approach that can be used as a benchmark for future studies since this is not a trivial process that can be followed easily. Also, our study helps fund administrators to apply more flexible fee policies considering changing market conditions.

In this study we have several interesting results. First, during bad times most HF strategies do not provide significant alphas and fund managers are concerned with minimizing their risk. At such times HF strategies have fewer exposures in terms of different asset classes and portfolio allocations and some strategies even reverse their exposures. During ‘good’ times fund managers focus more on delivering high returns, increase their systematic risk and exploit the upward market movement. Second, more directional strategies have, on average, more common exposures within different market conditions compared to less directional strategies that by nature have more systematic risk. Third, factors related to commodity asset classes (e.g. agriculture, energy and industrial metals factors) are more common (in addition to the market factor) during ‘bad’ times, whereas factors related to equity asset classes (e.g. market, momentum, small minus big and high minus low factors) are most common during ‘good’ times. Fourth, market volatility appears to affect HF performance more than business cycle volatility does. We use a battery of robustness tests and our findings are still valid.

The outline of the paper is as follows. The next section briefly reviews the relevant literature. Section 3 presents our empirical specification and describes the data used in our analysis. Section 4 empirically estimates our model and discusses the implications of the results along with a battery of robustness checks. Section 5 concludes the paper.

2 Literature Review

This section presents the relevant literature associated with HF performance. We consider mostly studies that follow the down-up and up-down approaches, also including studies that consider methodological issues and structural breaks, as explained later in this section.

Early studies (such as Sharpe, 1992) explained HFs in a linear framework. However there was soon a development toward non-linear models that explained the non-linear payoffs of HF returns following the down-up approach. This approach begins with the underlying assets to find the sources of HF returns and involves HF replication portfolios by trading in the corresponding securities. These trading constructed factors are specified as asset-based style (ABS) factors (Fund and Hsieh, 2002). We distinguish studies that explained HFs through option portfolios and trend followers (Fung and Hsieh 2001, 2002, 2004) and option-based buy and hold strategies (Agarwal and Naik, 2000, 2004) or studies that showed that the so-called market neutral strategies are not so neutral for investors (Duarte, Longstaff, and Yu, 2007). Although important, these studies do not significantly help investors to choose and evaluate HFs for three reasons. First, these exposures are not static and change over time (as we show later). Second, the factors are not easy for investors to replicate (e.g. lookback straddles[5]). Third, some strategies (e.g. global macro or multi-strategy) are not well defined, and thus are difficult to replicate.

The up-down approach begins with identifying the sources of HF returns and relates pre-specified risk factors for HF performance attribution, and consists of two streams. The first uses additional refined factors that better explain HF returns. The second stream, which can be regarded as an extension of the first, deals with methodological issues and funds' structural breaks. Although both streams use more advanced econometric techniques (e.g. regime-switching models) and confirmed previous studies that HFs have nonlinear returns and exposures, there remain significant gaps in many of the non-linear models mentioned above which we address in this paper. In particular, these non-linear models are not enough sufficient or cannot completely describe the changing exposures across different business cycles and market conditions (many of them just use specific macro variables or isolate a specific crisis/event). Moreover a single model is not sufficient to describe all HF strategies or conditions because it is over-simplistic. The single general commodity factor used to date is very broad, and (as we show later) HF managers following many strategies switch from equities into commodities during hard times.

In the first stream of the up-down approach, we distinguish studies from Bali, Brown and Caglayan (2011, 2014) and Avramov, Barras, and Kosowski (2013). Bali et al. (2011) found that there is a positive correlation between HF exposure to default risk premium and HF returns,

[5] A lookback straddle is a combination of a lookback call plus a lookback put. Both options are traded in Over-The-Counter markets. These respectively grant the holder the right but not the obligation to buy (sell) an asset at the lowest (highest) price identified during the lifetime of the option.

meaning that risk premia on risky assets are negatively correlated with present economic activity. Moreover, HFs with lower exposure to inflation derive higher returns in the future. Extending their previous work in 2011 Bali et al. (2014) found that macroeconomic risk factors such as default spread, term spread, short-term interest rates changes, aggregate dividend yield, equity market index, inflation rate, unemployment rate, and the growth rate of real gross domestic product per capital, are more powerful determinant on HF returns compared to other factors such as market, momentum, high minus low, especially for directional strategies. Similarly, Avramov et al. (2013), although focusing more on forecasting, showed that macro variables such as default spread, dividend yield, VIX index, and net flows in the HF industry can assist in fund return predictability. Ibbotson, Chen, and Zhu (2011) examined HF alphas, exposures and cost in a common framework. Their results showed that the average fund could add value both in bull and bear markets and their exposures were, in general, reduced during bear markets. Patton and Ramadorai (2013) discovered patterns where the exposure variation was higher early in the month and then got progressively lower until the reporting date.

Concerning the second stream of the up-down approach, which identifies structural breaks in HFs through the use of advanced econometric methods, an important study is that of Bollen and Whaley (2009). They showed that risk factors change over time and funds that switch their exposures over time outperform their peers. Their model examined just one change-point of HF exposures, in a probabilistic manner. Another interesting study is from Billio, Getmansky and Pelizzon (2012), who found that HFs have non-linear exposures beyond the market factor, such as liquidity, volatility, credit, term spreads and commodities. Moreover, during the down regimes, market, credit spread and the spread between small and large cap stock returns are the most common HF factors. Giannikis and Vrontos (2011), in accordance with the above studies, showed that different strategies present non-linear relationships to different risk factors. O'Doherty, Savin, and Tiwari (2015) confirmed that a selection of specific factors (e.g. equity, global and fixed income factors) is able to model HFs return with a lower error. Racicot and Theoret (2016) showed that macroeconomic uncertainty represented by the conditional variances of six macro and financial variables (growth on industrial production, interest rate, inflation, market return, growth of consumer credit, and the term spread) reduces HFs' market beta and increases the dispersion of HFs' returns and alphas. Finally, Agarwal, Arisoy and Naik (2017) found that the uncertainty about equity market volatility is able to explain HF performance both cross-sectionally and over time.

The above studies explain a large part of the HF return generating process, showing that HFs have nonlinear returns in terms of market returns, and that their exposures vary over time. Unsurprisingly, different strategies usually have different exposures. However, there are a few exposures that are valid for nearly all HFs (e.g. equity market, volatility and liquidity). The theoretical motivation of this study is to examine HF performance in a more comprehensive way, as described in the previous section.

3 Methodology

3.1 Empirical Specification

Linear factor models such as the CAPM (Sharpe, 1964) and its extensions as represented by the APT model (Ross, 1976) are the foundation of most of the theoretical and empirical asset pricing literature. Within the linear multi factor model the rates of returns of funds are dependent via a linear relationship on several variables, that is, factors:

$$R_i = \alpha_i + \beta_{i,1}F_1 + \beta_{i,2}F_2 + \cdots + \beta_{i,k}F_k + \varepsilon_i \tag{1}$$

or equivalently:

$$R_i = \alpha_i + \sum_{j=1}^{k} \beta_{i,j}F_j + \varepsilon_i \tag{2}$$

Where R_i denotes the return on the ith fund (or strategy), K>0 is the number of factors, $F_1, \dots, F_K$ are the values of the factors, $\beta_{i,1}, \dots., \beta_{i,K}$ are the relevant sensitivities and ε_i is a zero mean random variable.

However, the theory constrains the factors to be linearly related to the fund (or security) returns. It cannot price funds where the payoffs are non-linearly related to risk factors, as in the case of returns that characterized by the implementation of dynamic strategies. For this reason and in the spirit of other authors such as Fung and Hsieh (1997) and Agarwal and Naik (2004) we examine HFs so as to capture dynamic strategies but in a different way. We propose a parsimonious empirical specification using the stepwise regression technique that contains structural breaks or break points so as to capture HFs' non-linearity[6]. Moreover, we move one step further towards

[6] This custom model is not a typical non-linear model (e.g. non-linear in parameters). It is rather a piecewise model using a stepwise regression, explained later in this section. However the definition of a linear model is not an easy

other authors (mentioned in this section) by implementing the stepwise regression technique at a regime/cycle level for more accurate results. Our empirical specification is agile due to its flexibility to determine, for each group observations, the "best" set of HF factors.

The exogenous break points depend on the expansion and recession periods of multiple business cycles[7]. Our model takes the form:

$$R_{iS} = \alpha_{iS} + \beta_{i,1}F_1(S) + \beta_{i,2}F_2(S) + \cdots + \beta_{i,k}F_k(S) + \varepsilon_i(S) \quad (3)$$

Where $S = \begin{cases} G \\ R \end{cases}$ is the state variable, (4)

G is the growth variable that takes the vector values G_m, m = *1,..., m,* when we are in one of the m periods, R is the recession variable that takes the vector values G_n, n = *1,...n*, when we are in one of the n periods, R_{iS} and α_{iS} are the return and the constant for HF i in the state S, respectively, F_k is a systematic factor, $k = 1, \dots, K$, and $\beta_{j,k}$ is the sensitivity of the j^{th} HF to factor k.

Our model is able to adjust taking into consideration only the variables (dependent and non-dependent) that belong to a particular stage of the economy. Employing a combination of statistical methods and empirical judgement we use the most appropriate factors for a given strategy under a specific state of the economy.

Within each state of the economy we apply a step-wise regression technique to limit the final list of factors for each strategy. This eliminates variables with less significant relationship to ratings from the beginning and certainly it is much better than manually selected factors, just based on other authors' suggestions, only. This technique has been used by many authors such as Dor, Dynkin and Gould (2006), Brown and Gaylor (2009), and Jawadi and Khanniche (2012), Aebi, Sabato, and Schmid (2012).

task because the term linear can be interpreted in different ways (e.g. in terms of parameters, independent variables, or structural changes).

[7] These business cycles are officially denoted by the National Bureau of Economic Research (NBER) and the Economic Cycle Research Institute (ECRI). The expansion periods are: 01/1990-07/1990, 04/1991-03/2001, 12/2001-12/2007 and 07/2009-03/2014, and the recession periods are: 08/1990-03/1991, 04/2001-11/2001, and 01/2008-06/2009. We note that the prediction of business cycles or different market conditions is out of the scope of this paper. Our HF data are from 01/1990 to 03/2014, without biases (as explained in section 3.2). In our robustness tests at the end of section 4.3, we excluded pre-1994 data for verification purposes.

In this technique the variables are added or removed from the model depending on the significance of the F-value. 5% significance is used for both inclusion and exclusion. The single best variable is chosen initially. That is, variable i is added to the p-term equation if

$$F_i = max_i\left(\frac{RSS_p - RSS_{p+1}}{\left(\hat{\sigma}_{p+i}\right)^2}\right) > F_{in} \tag{5}$$

The subscript (p+i) refers to quantities calculated when variable i is adjoined to the current p-term equation, one at a time. The specification of the quantity F_{in} results in a rule for terminating the computations. Where RSS_{p+i} denotes the residual sum of squares when a variable i is added to the current p-term equation. Our study considers a large number of monthly observations (from 01/1990-03/2014), hence, the stepwise regression allows us to examine the importance of a large set of variables. It is important to mention that the independent variables should be uncorrelated (as we have already examined) otherwise the results would be spurious.

The proposed model has also break points that are specified by a stochastic process using a Markov regime-switching model (Hamilton, 1989). Meligkotsidou and Vrontos (2014) and Billio, Getmansky and Pelizzon (2012) measured the structural breaks of HF returns and volatility. However, in our model we measure the exposures of HF returns taking into consideration the different states of the market index, as the market is the most important factor. We use the Wilshire 5000TRI including dividends, represented by two different states: up regime and down regime, covering a 24 year period[8].

Under the Markov switching approach the possible outcomes lie in m states of the world, denoted s_i, i=1,2,…,m, corresponding to m regimes. In our analysis, we will assume two regimes, m=1 or m=2. Hence if s_1=1 the process is in regime 1 at time t, and if s_t=2, the process is in regime 2 at time t. The movements of the state variable between regimes are uncontrollable and governed by the Markov process. That Markov property can be expressed as:

$$P[\alpha < y_t \leq b\ |y_1, y_2, \ldots, y_{t-1}] = P[\alpha < y_t \leq b|y_{t-1}] \tag{6}$$

[8] The time period under examination is divided to up regimes (01/1990-06/1990, 11/1990-10/2000, 10/2002-05/2008, 03/2009-03/2014) and down regimes (07/1990-10/1990, 11/2000-09/2002, 06/2008-02/2009).

The above equation states that the probability distribution of the state of any time t depends only on the state at time t-1, only.

The most basic form of Hamilton's (1989) model comprises an unobserved state variable, denoted z_t, that is theorized to evaluate according to a first order Markov process:

$$prob[z_t = 1|z_{t-1} = 1] = p_{11} \tag{7}$$

$$prob[z_t = 2|z_{t-1} = 1] = 1 - p_{11} \tag{8}$$

$$prob[z_t = 2|z_{t-1} = 2] = p_{22} \tag{9}$$

$$prob[z_t = 1|z_{t-1} = 2] = 1 - p_{22} \tag{10}$$

Where p_{11} and p_{22} stand for the probability of being in regime one, given that the system was in regime one during the previous period, and the probability of being in regime two, given that the system was in regime two during the previous period, respectively. Hence, $1 - p_{11}$ defines the probability that y_i will change from state one in period t-1 to stage two in period t, and $1 - p_{22}$ defines the probability of a shift from state two to state one between times t-1 and t. Under this specification, z_t evolves as an AR(1) process:

$$z_t = (1 - p_{11}) + \rho z_{t-1} + \eta_t \tag{11}$$

where $\rho = p_{11} + p_{22} - 1$

Roughly speaking, z_t can be viewed as a generalization of the dummy variables for one-off shifts in the above series. According to the Markov switching approach, there can be multiple shifts from one state to the other. In this framework, the observed return series can be written as:

$$y_t = \mu_1 + \mu_2 z_t + (\sigma^2{}_1 + \varphi z_t)½u_t \tag{12}$$

Where $u_t \sim N(0,1)$. The expected values and variances of the series are μ_1 and $\sigma^2{}_1$, respectively in state one, and $(\mu_1 + \mu_2)$ and $\sigma^2{}_1 + \varphi$ respectively in state two. The variance in state two is also defined as $\sigma^2{}_2 = \sigma^2{}_1 + \varphi$. The unknown parameters of the model $\mu_1, \mu_2, \sigma^2{}_1, \sigma^2{}_2, p_{11}, p_{22}$ are computed using maximum likelihood. Further details of this model can be found in Engel and Hamilton (1990).

In the case where there are 2 states, the transition probabilities are best expressed in a matrix as:

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \text{ and in case with m states the matrix is } P = \begin{bmatrix} p_{00} & p_{01} & \cdots & p_{0m} \\ p_{10} & p_{11} & \cdots & p_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m0} & p_{m1} & \cdots & p_{mm} \end{bmatrix} \quad (13)$$

Where $p_{i,j}$ is the probability of moving from regime i to regime j. Since, at any given time, the variable must be in one of the m states, it must be true that:

$$\sum_{j=1}^{m} P_{i,j} = 1 \; \forall i \quad (14)$$

A vector of current state probabilities is then defined as

$$\pi_t = [\pi_1 \; \pi_2 \; \dots \; \pi_m] \quad (15)$$

Where π_t is the probability that the variable y is currently in state i. Given π_t and P, the probability that the variable y will be in a given regime next period can be forecast using:

$$\pi_{t+1} = \pi_t P \quad (16)$$

Within each regime of the market index we apply a step-wise regression technique to limit the final list of factors for each strategy. Employing a combination of statistical method and empirical judgement we are able to use a parsimonious model using the most appropriate factors for a given strategy under a specific market regime. Unlike many authors, we did not rely on a single model just adding one or more factors on existing models. The reason is that we take an approach selecting the most appropriate candidate factors for HFs, following other authors (e.g. Jawadi and Khanniche, 2012). Furthermore, many authors use a single model for all HF strategies, mentioning nothing about the statistical properties of these factors (e.g. correlation between two or more factors). We take this issue into consideration. Due to the multifaceted nature of the HF industry it is unwise to use exactly the same model when trying to explain HF strategies. Different HF strategies have different behaviour (in terms of alpha and exposures) and investment characteristics.

3.2 Data

We use three HF databases (one with live/dead funds, one with live funds and one with dead funds) from two database vendors. These are EurekaHedge and BarclayHedge covering the period from January 1990 (similar to Denvir and Hutson 2006, Harris and Mazibas, 2010 and Giannikis and Vrontos 2011) to March 2014. We include at least three business cycles to enable our analysis to be as comprehensive as possible. The majority of the databases for commercial use came into existence in the early/mid 1990s, with a few exceptions such as the EurekaHedge and BarclayHedge databases that came earlier. Our dataset contains pre-1994 dead funds, hence we do not have this type of survivorship bias. However, in our robustness checks we exclude the years prior to 1994 so as to verify our results.

After the merging and cleaning process (such as removing records containing consecutive returns of zero, N/A and null) we select funds that invest primarily in the North America region. After the selection process, the total number of funds (live and dead) is 7,541. We minimize the survivorship and instant history biases by including in our sample dead/ceased reporting funds and eliminating the first 12 monthly returns of each HF. In order to deal with outliers we use a winsorizing technique: each month we rank HFs returns, excluding null values. We assign extreme outliers below the 0.5% percentile returns values equal to that represented by the 0.5% percentile, and similarly for the 99.5% percentile. The returns are net of fees. Our final dataset consists of 6,373 funds. Similar to other authors (such as Ramadorai, 2012) we treat multiple share classes of funds as separate funds. This is to eliminate selection bias due to variations in liquidity restrictions, returns, and fee structures that describe different share classes of the same fund, despite the fact that they belong to the same strategy. Due to space limitations details of all the above procedures are available as appendices on request. Many authors do not give full details of their merging and cleaning processes, but we believe that our algorithms for merging and elimination of duplicates can be regarded as benchmarks in the literature.

We adopt the strategies that fund managers report in these databases[9]. We implement a mapping between database strategies that has been used by other authors (e.g. Joenvaara, Kosowski and Tolonen, 2012) using these two databases. We ended up with eleven HF strategies: Short Bias (SB), Long Only (LO), Sector (SE), Long Short (LS), Event Driven (ED), Multi Strategy (MS), Others (OT), Global Macro (GM), Relative Value (RV), Market Neutral (MN) and CTAs (CT)[10].

Our fourteen candidate factors are selected according to specific criteria (availability, what other authors used based on their significance, the collinearity between them and correlation with strategies). They are related to different asset classes: equity factors, real estate factors, commodity factors, credit factors, currency factors and option factors. In section 4.3, we discuss how these factors explain HF returns. We take into consideration:

- Wilshire 5000 Total Return Monthly Index (MAI)
- MSCI World Excl. US U$ - Tot Return Index (GEMI)
- S&P GSCI Energy - Total Return Index (COEN)
- S&P GSCI Precious Metal - Total Return Index (COPM)
- S&P GSCI Industrial Metals - Total Return Index (COIM)
- S&P GSCI Agriculture Total Return Index (COAG)
- Differences in Promised Yields - Term Spread Premium (TERM) which is the spread between 10-year U.S. government bonds and 3-month U.S. treasury rate
- Differences in Promised Yields - Default Premium (DEF) which is the spread between Moody's corporate AAA and BAA bond yields
- DJ US Select Real Estate Sec - Tot Return Index (RLE)
- US Trade-Weighted Value of US Dollar Against Major Currencies (EXCH)
- CBOE SPX Volatility VIX (DVIX) - Price Index
- Small Minus Big (SMB)
- High Minus Low (HML)

[9] Unfortunately, there is no universal classification scheme for HFs' strategies. Although fund managers may change their investment style over time, they are legally obliged to proceed according to the offering memorandum (used for private placements, contrary to the prospectus that is for publicly-traded issues) that describes the fund, its strategy, how it trades and operates, as well as the details of the organization.

[10] The Others strategy contains HFs reported as 'PIPES' (private investment in public equity), 'No category', 'Closed-End Funds' or 'Other'. CTA means Commodity Trading Advisors funds. This strategy makes extensive use of derivatives and commodity trading or uses systematic trading.

- Momentum (MOM)

The first eleven factors were sourced from Datastream whereas the last three were derived from Fama and French's online data library (Ibottson Associates). We do not consider lookback straddles that according to the literature (e.g. Fung and Hsieh, 2001) are highly appropriate to the CT strategy. Unfortunately, there was no data available for the early examined period (early 1990s). However these are covered in the sub-section that details with the robustness tests.

Equity factors have been used widely in measuring the general market exposure of HFs. We use the most comprehensive index, the Wilshire 5000 index, as do Dor, Dynkin and Gould (2006) and Amenc and Goltz (2008). Fung and Hsieh (2004), Billio, Getmansky and Pelizzon (2009, 2012) and Patton and Ramadorai (2013) used the S&P 500, but that is mainly a large cap index. Commodity related factors have been also used by many authors such as Capocci and Hubner (2004), Agarwal and Naik (2000) to explain HFs' behavior. Others such as Giannikis and Vrontos (2011) and Jawadi and Khanniche (2012) have also used commodity factors represented by the GSCI commodity index. In our case we do not use the composite GSCI total commodity index, or gold-only indices as Billio, Getmansky and Pelizzon (2009, 2012) used. Instead, we use sub-indices related to energy, metals and agriculture for more precise results.

Credit factors have been also examined by many authors using the term and credit spread as proxies. For instance Billio, Getmansky and Pelizzon (2009 and 2012) used the 10-year T-Bond rate minus 6-month LIBOR, and the difference between BAA and AAA indices provided by Moody's. Credit spread has also been examined by Ibbotson, Chen and Zhu (2011) using Moody's index. Giannikis and Vrontos (2011) used the Barclay high yield index as a credit spread factor. Bali, Brown and Caglayan (2011) also used these credit factors when analyzing HFs' risk exposures. Similar to Capocci (2009), we consider exchange rates by using the currency factor which is the Federal Reserve Bank Trade Weighted Dollar Index.

Following Billio, Getmansky and Pelizzon (2009 and 2012), we use as an option factor the VIX CBOE volatility index. This index is widely used as a measure of market risk. It represents market expectations of near term (30 days) volatility of the S&P 500 stock index. The VIX index is currently investable through various ETFs products.

It is known that fund managers reduce their leverage during crises, however in this dataset we do not have sufficient information about it as there are funds that simply mention yes/no on the leverage field and there are many others that do not give this information. Moreover, we do not have leverage information for different time periods so as to compare and analyse HF responses under different conditions. In addition, we do not have information about fund holdings to compute the net leverage, which is the difference between long and short exposure per share divided by the NAV (Net Asset Value), or the gross value of assets controlled (long plus shorts) and divide by the total capital (Gross Market Value/Capital). Prior work on HF leverage (e.g. Duarte, Longstaff, and Yu, 2007) only estimates leverage, or relies on static leverage ratios or static yes/no leverage as reported in the databases (e.g. Agarwal and Naik, 2000). Nevertheless, not allowing for leverage can be considered as one of the limitations of this paper. Another limitation is that we may have omitted other potential factors that we are not aware of, though this is an issue that applies to other authors too.

4 Empirical Analysis

In this section we set out some basic statistics on our data (4.1), give details of the regime switches we arrived at (4.2), then report the main results from our empirical analysis (4.3).

4.1 Basic Statistics

Following Bali, Brown and Caglayan (2011), we first present our results using the simple classification technique of dividing HF strategies into directional, semi-directional and non-directional. We classify them according to their correlation with the market index Wilshire 5000TRI, including dividends. This index is more representative of the whole market than the S&P 500 since it captures most quoted firms within the U.S. economy. Table 1 presents the correlation of each strategy with the Wilshire 5000 index. The most directional strategies are at the top of the table whereas the most non-directional strategies lie at bottom of the table. As expected, SB (Short Bias) has a large negative correlation to the market index of -0.924. The market neutral strategy MN has a very low correlation of 0.059. CT (CTAs) also has a very low correlation to market index of 0.048, which is not significantly different from zero.

Table 1 provides basic statistics on the raw net-of-fees returns of the eleven HF strategies. Each strategy is a representative-average time series of their relevant (equally weighted) HFs. Some strategies (e.g. Sector, Long Short, Others, CTA) provide high monthly mean returns (more than

1.1%) and are more aggressive than non-directional strategies (e.g. Event Driven, Market Neutral). On the other hand, some strategies (e.g. Short Bias) provide low monthly mean returns (0.1%). On average, directional strategies have more volatile returns than all the non-directional strategies except the CTA strategy. Full statistical information (with raw and excess returns) along with histograms is available upon request[11].

Table 1. Summary Statistics and Market Correlation

This table presents the summary statistics of monthly raw returns for each HF strategy. It also presents for each strategy the correlation with the Wilshire 5000TRI including dividends over the entire period under examination (01/1990-03/2014). We rank by the correlation with the market index, from extreme directional strategies (Short Bias) to completely non-directional strategies (CTAs). Each strategy is a representative-average time series of all the relevant HFs. *** denotes a correlation significantly different from zero at the 1% level (using a two tailed test). Directional strategies have correlations with the market index of greater than 0.5, and semi-directional strategies have correlation between 0.22 and 0.5.

Directional Strategies	Mean	Standard Deviation	Correlation Coefficient	Std. Error
Short Bias	0.050%	5.197	-0.924***	0.042
Long Only	0.999%	3.437	0.707***	0.023
Sector	1.151%	3.259	0.637***	0.026
Long Short	1.125%	2.663	0.550***	0.019
Semi-Directional Strategies				
Event Driven	0.937%	1.839	0.338***	0.019
Multi Strategy	1.062%	1.713	0.271***	0.021
Others	1.349%	1.091	0.232***	0.018
Global Macro	0.934%	2.017	0.223***	0.026
Non-Directional Strategies				
Relative Value	0.821%	1.238	0.211***	0.015
Market Neutral	0.525%	0.874	0.059***	0.013
CTAs	1.184%	3.415	0.048***	0.048

4.2 Regime Switching Model

From January 1990 to March 2014 there are three official business cycles. Hence the period under examination is divided into expansion periods (01/1990-07/1990, 04/1991-03/2001, 12/2001-

[11] A note on the parametric techniques used (e.g. t-values): the HF data are not normal (but stationary as we found no trend in their mean and volatility); this is an issue that is shared by many other authors as well. However the large number of observations do not affect the significance of the tests and the use of the 'winsorizing' technique for the extreme outliers mitigates this issue. Serial correlation is also a common problem when dealing with time-series data, hence, with HFs too. The estimation regression coefficients (see section 4.3) are still unbiased and consistent but may be inefficient. This means that the standard errors of the estimate of the regression parameters may be underestimated. Taking that into consideration we used several robustness tests including the HAC/Newey-West estimator for verification purposes, and our results were still valid. Lastly, although the set of risk factors that we choose from is relatively large, even within the sub-periods examined we have sufficient degrees of freedom in our model.

12/2007 and 07/2009-03/2014) and recession periods (08/1990-03/1991, 04/2001-11/2001, and 01/2008-06/2009). Regarding the market regimes, we perform a unit root test with breaks and the Augmented Dickey-Fuller t-statistic resulted in value -16.4 with p-value less than 0.01, leading us to reject the null hypothesis of a unit root. We implement the Markov Switching process in order to identify the regimes (up and down) based on the mean and volatility of the Wilshire 5000TRI. We examine two regimes so as to compare the two different stages with business cycles.

Table 2 shows the results of the Markov Switching process. In Panel A, both up and down regime coefficients are highly significant. Panel B shows the probabilities of the transitions between the regimes. For example, if, at time t, we are in regime one (down) then the probability at time t+1, of staying in the same regime is 38.02%, whereas the probability moving to regime two (up) is 61.98%. Panel C shows that an up regime could be expected to last 19 months whereas a down regime lasted on average only two months. Panel D presents the time-varying transition regime coefficients and Panel E present the time varying transition probabilities. We tested for inverse roots of AR polynomials and no root lies outside the unit circle (have a modulus less than 1).

Table 2. Different Market Conditions

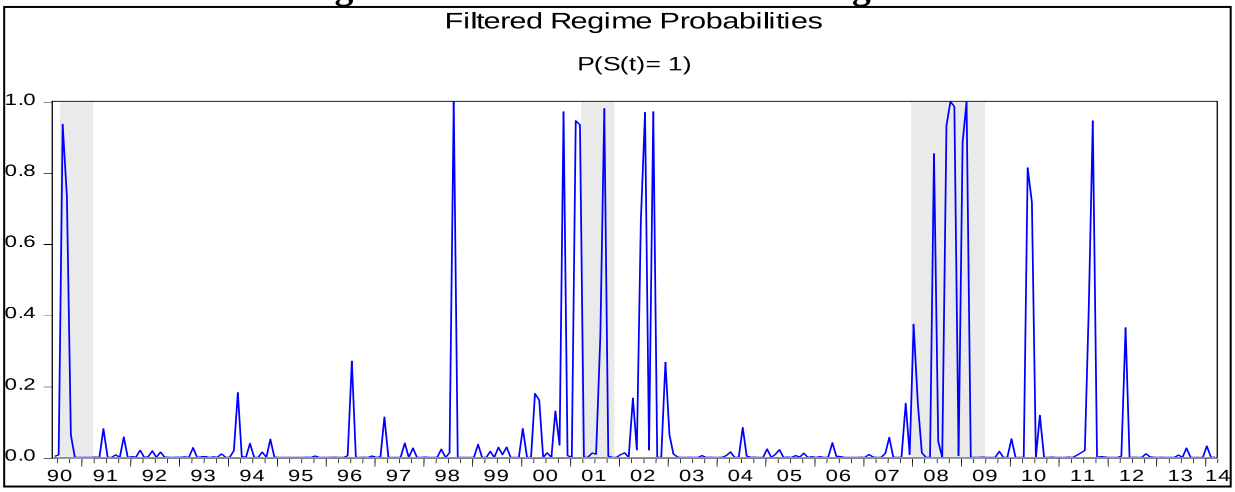
This table shows the two regimes calculated for the market index (Wilshire 5000TRI including dividends) using the Markov Switching model. The probability shows that the coefficients are statistically significant.

Panel A: Regime coefficients			
	Coefficient	Std. Error	Prob
Down regime	-8.6530	1.2982	0.0000
Coef. Confidence interval 95%	Low: -11.2086	High: -6.0972	
Coef. Confidence interval 99%	Low: -12.0202	High: -5.2857	
	Coefficient	Std. Error	Prob
Up regime	1.5804	0.2166	0.0000
Coef. Confidence interval 95%	Low: 1.1539	High: 2.0069	
Coef. Confidence interval 99%	Low: 1.0185	High: 2.1423	
Panel B: Transition probabilities			
	Down	Up	
Down regime	0.3802	0.6198	
Up regime	0.0532	0.9468	
Panel C: Regime duration			
Constant expected durations:	Down	Up	
	1.6135	18.7934	
Panel D: Regime Coefficients, Time-Varying Transitions			
	Coefficient	Std. Error	Prob
Down	-9.7269	1.2989	0.0000
Coef. Confidence interval 95%	Low:-12.284	High:-7.169	
Coef. Confidence interval 99%	Low:-13.096	High:-6.358	
	Coefficient	Std. Error	Prob
Up	1.2911	0.2162	0.0000
Coef. Confidence interval 95%	Low:0.865	High:1.717	

Coef. Confidence interval 99%	Low:0.730	High:1.852
Panel E: Time-Varying Transition Probabilities		
	Down	Up
Down regime	0.0035	0.9965
Up regime	0.0747	0.9252

Figure 1 presents the business cycles and the down regime probabilities. The down regime is not simply the result of splitting of the data sample into periods of positive or negative returns, but captures periods when the market volatility was high and there were substantial return downturns, not necessarily just a single shock. The combination of substantial return downturns and market volatility can be regarded as a down regime's attribute. In all these different regimes we may have positive or negative returns. Our period is divided into four up regimes (01/1990-06/1990, 11/1990-10/2000, 10/2002-05/2008 and 03/2009-03/2014) and three down regimes (07/1990-10/1990, 11/2000-09/2002 and 06/2008-02/2009). Down regime periods cover higher oil prices in summer 1990 due to the Persian Gulf crisis, the Japanese down market in March 2001, 9/11 and the financial crisis 2008-2009. There are other negative shocks outside our identified down regimes, however the Wilshire 5000TRI was not then characterized by high volatility and substantial return downturns.

Figure 1: Recessions and Down Regimes



This figure shows the probabilities of being in the down regime. The vertical axis shows the probabilities between 0 and 1 and the horizontal axis is the time period under examination. The shadow areas represent the business cycle recession periods.

4.3 Multi-Factor Model

This sub-section presents the results for our empirical specification. First, we discuss some key findings concerning the general performance of HFs during each of the underlying periods under examination. We then describe HF performance for each strategy (briefly since there 11 of them), followed by a detailed exposure analysis at the strategy group level. This is followed by a more general discussion of our results, and finally details of the robustness checks we carried out.

Expansion Periods

Table 3 presents our findings for expansion periods. All HF strategies deliver strongly significant alpha[12] to investors and increase their exposures so as to benefit from the overall market movement. The most common factor across all strategies is the MAI factor, as expected. The second most common factor is the MOM factor and the third is the SMB factor. The MOM factor is the essential factor when the market is in an expansion state as fund managers keep up their investments' momentum. The SMB factor is also an important element as when there is expansion, small cap companies tend to outperform large cap companies, being more sensitive to market conditions. The DEF factor is negative for five strategies as the uncertainty and therefore the spread between promised yields are lower during expansion periods. As a consequence, strategies that have strongly negative DEF deliver high alpha. In total there are fifty exposures to the various asset classes. Overall, within the expansion period, HF managers try to benefit from the upward market movement and have relatively high asset class and portfolio exposures for higher HF returns. Fund managers pay more attention to returns than the systematic risk derived from investing in equity asset classes.

[12] The alpha is the intercept of the equation. It is also called Jensen's alpha (1968). Taking the perspective of investors, it is HF investors' realized return. We denote alpha as the (mean) excess return per month in percentage terms. HF risk-free returns are raw returns minus the risk free return which is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates).

Table 3. Multi-Factor Model During Expansion Periods

This table shows the results in terms of alphas and exposures using stepwise regression within our empirical specification for expansion periods. HFs returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. ** denotes significance at P < 0.05 and *** denotes significance at P < 0.01. The t-statistics are in parentheses. An empty cell means there is no significant exposure to this factor.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
Alpha	0.5741***	0.2903***	1.5764***	1.4655***	0.4965***	1.4297***	1.4816***	0.3725***	0.2545***	0.5242***	0.8174***
	(3.3184)	(3.4816)	(3.8089)	(5.4502)	(8.5422)	(4.5960)	(6.1593)	(3.2733)	(3.1474)	(2.9978)	(3.7917)
Market Index-MAI	-0.8544***	0.6725***	0.5930***	0.5279***	0.3045***	0.2198***	0.1552***	0.3057***	0.14826***	0.0684***	
	(-13.3174)	(31.7104)	(22.6857)	(29.9863)	(20.4472)	(10.7826)	(6.5516)	(8.3602)	(12.5996)	(6.2038)	
Momentum-MOM	-0.1836***	0.0417**	0.1020***	0.0899***		0.0429**	0.0397***			0.0760***	0.1153**
	(-4.5980)	(2.1941)	(4.1671)	(5.6980)		(2.3595)	(2.8038)			(7.3612)	(2.2867)
Small minus Big-SMB	-0.2556***	0.2502***	0.1562***	0.2006***	0.1638***	0.0910***			0.0703***		
	(-4.9304)	(9.7241)	(4.9638)	(9.1875)	(9.0695)	(3.6407)			(4.8214)		
Global Market Index (excl. U.S.)-GEMI	-0.1941***						0.0725***				
	(-3.3394)						(3.5418)				
Comm. Industry Metals-COIM	0.1126***										
	(3.3252)										
High minus Low-HML		0.2077***		0.0666***	0.1774***	0.0580**			0.0676***		
		(7.2650)		(2.8075)	(8.8007)	(2.1147)			(4.2406)		
Comm. Energy-COEN		0.0226**	0.0436***	0.0316***							
		(2.2440)	(3.3348)	(3.7329)							
Comm. Precious Metals-COPM			0.0735***	0.0319**		0.0427**		0.0888***			
			(3.2081)	(2.1592)		(2.5119)		(3.7381)			
Default Spread-DEF			-1.3262***	-0.9403***		-0.8946***	-0.8748***			-0.3826**	
			(-2.9148)	(-30885)		(-2.6214)	(-3.3064)			(-1.9932)	
Term Spread-TERM				-0.1649***					0.1235***		
				(-2.9027)					(3.3405)		
Real Estate Index-RLE							-0.0371**				
							(-2.3581)				
Change in VIX-DVIX								0.0214***			
								(2.6184)			
Exchange Rate-EXCH											-0.4015***
											(-2.9292)
Adj. R-squared:	0.6971	0.8250	0.7201	0.8253	0.6699	0.3757	0.4287	0.2873	0.4507	0.2576	0.0417
F-statistic:	118.8076	242.3137	110.7509	152.1313	174.1677	26.6785	39.4161	35.3934	53.5171	30.6072	6.575
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016

Recession Periods

Table 4 shows that the majority of HF strategies do not deliver significant alpha during recessions as fund managers are trying to minimize their exposures. Also, there are significant differences in alphas between growth and recession periods for 8 of 11 strategies, and for 7 of 11 strategies with regard to the market exposures (see exposure analysis subsection below). All HF strategies have less exposure compared to the expansion period. Moreover, there are differences in exposures in terms of asset allocation and portfolio allocation. It is clear that HF managers adjust their portfolios by minimizing their exposures during recessions in terms of asset and portfolio allocations. Again, MAI is the most common factor across all HF strategies. However, the average exposure is 0.147 compared to 0.214 to the expansion period. Furthermore, only seven strategies have exposure to MAI compared to twelve within the expansion period. The second and third more common exposures are COAG (agriculture total return index) and COEN (energy total return index) respectively. We interpret this as fund managers moving towards more counter-cyclical industries using agricultural/food or energy commodities. Indeed, agricultural/food commodities are obvious essentials for people. Food consumption cannot easily be disturbed by “bad” economic conditions, thus its demand can be considered as inelastic. Energy can be also regarded as an essential service or good, with an inelastic demand. In general, cycles in economic activity are not the main drivers of the evolution of commodity prices (Cashin, McDermott, Scott, 2002). Thus, fund managers have an incentive to increase their exposures to these factors during bad economic times. Overall, there are 28 exposures to assets classes compared to 50 during expansion periods.

Table 4. Multi-Factor Model During Recessions

This table shows the results in terms of alphas and exposures using stepwise regression within our empirical specification, during recession periods. HFs returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05 and *** denotes significance at P < 0.01. The t-statistics are in parentheses. An empty cell means there is no significant exposure to this factor.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
Alpha	-0.4633	-0.4417	0.5627**	0.3497	0.0696	0.3990	2.0808***	-1.1783	0.3688	0.1356	0.8365
	(-0.9518)	(-1.2102)	(2.0864)	(1.4670)	(0.2082)	(1.3481)	(3.6397)	(-1.5418)	(1.2350)	(0.7977)	(2.0359)
Z-value, alpha abs difference growth vs recession	2.0084**	1.9551**	2.0520**	3.1050***	1.2592*	2.4008***	0.9661	2.0070**	0.3696	1.5933**	0.0412
Market Index-MAI	-1.0123***	0.6094***	0.5409***	0.4663***	0.2892***				0.2839***		-0.1474**
	(-13.8966)	(9.4005)	(12.4293)	(12.1225)	(5.2282)				(6.3773)		(-2.3962)
Comm. Energy-COEN	0.1302***						0.0246**	0.0735***			0.1045***
	(3.9577)						(2.1341)	(4.3722)			(3.7649)
Small minus Big-SMB		0.4291***					0.1491***				
		(3.5949)					(2.9841)				
Comm. Agriculture-COAG		0.1118**	0.1445***	0.0781**				0.1399***		0.0600***	
		(2.2248)	(3.8158)	(2.3317)				(4.1236)		(2.6532)	
High minus Low-HML			-0.3843***	-0.2013***							
			(-5.0381)	(-2.9864)							
Comm. Industry Metals-COIM					0.1158**	0.1096***		-0.0858**			
					(2.7056)	(3.1212)		(-2.6899)			
Change in VIX-DVIX						-0.0613***					
						(-5.0613)					
Global Market Index (exc. U.S.)-GEMI							0.1349***				
							(6.7292)				
Term Spread-TERM							-0.6613**	0.9206**			
							(-2.6003)	(2.6859)			
Momentum-MOM										0.0559***	
										(2.8421)	
Adj. R-squared:	0.8561	0.8727	0.8830	0.8608	0.6323	0.5677	0.7258	0.5326	0.5459	0.2324	0.3261
F-statistic:	99.1289	76.4402	84.0448	69.0318	29.3702	22.6712	22.8366	10.4024	40.6694	5.9962	8.9853
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0063	0.0008

Up Regime

Table 5 shows the performance of HF strategies when the Wilshire 5000 is rising. Almost all strategies deliver strongly significant alphas to investors. Similar to the expansion period, almost all HF strategies are trying to increase their exposures so as to gain higher returns. Fund managers take advantage of the upward market movement and invest in more risky assets such as small cap equities in order to have higher returns. They pay more attention to returns than to systematic risk during these conditions. On average, less directional strategies deliver lower alpha as they benefit less from the upward market movement. However, they have fewer exposures compared to the other strategies, as by nature these are less risky strategies. In total, there are fifty one asset class exposures across all strategies. As for expansion periods, the most common exposures across all strategies are MAI followed by MOM then SMB.

Table 5. Multi-Factor Model During a Rising Market

This table shows the results in terms of alphas and exposures using stepwise regression within our empirical specification, for the up regime. HFs returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. ** denotes significance at P < 0.05 and *** denotes significance at P < 0.01. The t-statistics are in parentheses. An empty cell means there is no significant exposure to this factor.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
Alpha	0.4899***	0.2880***	0.4838***	0.6267***	0.4967***	0.6387***	1.2702***	0.2970**	-0.2192	0.1528***	0.8312***
	(2.6382)	(3.3733)	(4.4458)	(4.6581)	(7.9609)	(7.5211)	(6.7701)	(2.4371)	(-1.3816)	(3.0690)	(3.8515)
Market Index-MAI	-0.9337***	0.6690***	0.5878***	0.5737***	0.2523***	0.2256***	0.1482***	0.2846***	0.1505***	0.0751***	
	(-13.7157)	(30.2888)	(20.9548)	(23.0726)	(10.9270)	(10.3531)	(5.9860)	(7.3072)	(12.0191)	(5.9065)	
Small minus Big-SMB	-0.2704***	0.2581***	0.1428***	0.1990***	0.1639***	0.0949***			0.0696***		
	(-4.8304)	(9.4069)	(4.3638)	(8.2788)	(8.3147)	(3.4741)			(4.3992)		
Momentum-MOM	-0.1431***	0.0517***	0.1048***	0.0923***		0.0565***		0.0503**	0.0237**	0.0751***	
	(-3.6275)	(2.8137)	(4.5153)	(5.8522)		(3.1235)		(2.0351)	(2.1054)	(7.2279)	
Comm. Industry Metals-COIM	0.1067***										
	(3.1326)										
Global Market Index (exc. U.S.)-GEMI	-0.1477**				0.0561***		0.0806***				
	(-2.5269)				(2.8826)		(4.0705)				
High minus Low-HML		0.2348***		0.0856***	0.1838***	0.0853***			0.0760***	0.0347**	
		(7.3084)		(3.0792)	(7.9487)	(2.6828)			(4.2019)	(2.0222)	
Comm. Energy-COEN		0.0338***	0.0468***	0.0420***	0.0187**			0.0341**			
		(3.3503)	(3.5352)	(4.8566)	(2.5082)			(2.3862)			
Comm. Precious Metals-COPM			0.0757***			0.0434**		0.0931***			0.1373***
			(3.3752)			(2.5700)		(3.8755)			(2.9884)
Term Spread-TERM				-0.1829***					0.1114***		
				(-3.0336)					(2.7577)		
Change in VIX-DVIX				0.0111**				0.0176**			
				(2.1083)				(2.0842)			
Default Spread-DEF							-0.5920***		0.5683***		
							(-2.9541)		(3.4555)		
Real Estate Index-RLE							-0.0318**				
							(-2.1332)				
Adj. R-squared:	0.6787	0.8182	0.6942	0.8082	0.6633	0.3499	0.3829	0.2761	0.4795	0.2260	0.0302
F-statistic:	108.3144	229.6584	116.2964	153.948	101.056	28.3362	40.3992	20.3706	40.0062	25.7152	8.9304
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0031

Down Regime

Table 6 presents results for when the Wilshire 5000 is falling. Similar to the recession period, most HF strategies do not produce significant alpha for investors as fund managers are more concerned about risk. Also, there are significant differences in alphas between up and down regimes for 4 of 11 strategies, and for 8 of 11 strategies with regard to the market exposures (see exposure analysis subsection below). As with business cycles, during the down regimes there are fewer exposures compared to the up regimes. On average, there are 29 asset class exposures across all HF strategies compared to 51 for the up regime. This is because fund managers during difficult market conditions, are trying to minimize their exposures and consequently their losses. The most common exposure across all HF strategies is MAI. This is consistent with all the other regimes and business cycle conditions. There is almost the same number of exposures across all strategies for both stressful market conditions (28 exposures for the recession periods and 29 exposures for the down regimes). However, in the down regimes there is a lower average number of factors within groups compared to the recession periods (see Table 9). This means that during down regimes, fund managers are trying even harder to minimize their exposures than they do during recessions so as to protect themselves. Down regimes that are related mostly to financial assets have a larger impact on HFs compared to recessions that refer to a decline in economic activity and are related mostly to real assets. Similar to recessions, during bad market conditions fund managers have an incentive to invest in counter-cyclical industries and more specifically in agriculture/food and energy commodities. We interpret this as commodities constituting essential goods or services for people and the economy, and their driving forces having more to do with global demand and supply shocks or supply risks (Gleich, Achzet, Mayer, and Rathgeber, 2013)[13].

[13] The exposures mentioned in our analysis remain statistically significant under the robustness tests reported at the end of section 4. In table 4 and 6 we present the z-scores in differences for alphas per strategy for growth vs recession and up vs down regimes. For the differences in the market exposures, see table 8. Market exposure is the most important factor. In addition, HF strategies often have different asset allocations, hence, it is not valid to compare different factor exposures.

Table 6. Multi-Factor Model During a Falling Market

This table shows the results in terms of alphas and exposures using stepwise regression within our empirical specification, when the Wilshire 5000 is falling. HFs returns are raw returns minus the risk free return. The Risk free (RF) return is the one-month Treasury bill rate from the Fama and French online data-library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * denotes significance at P < 0.1, ** denotes significance at P < 0.05 and *** denotes significance at P < 0.01. The t-statistics are in parentheses. An empty cell means there is no significant exposure to this factor.

Dependent variable	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTAs
Alpha	0.3522	-0.3603	0.4854	-0.0660	0.1776	0.5781**	0.7432***	0.8767***	0.0502	0.1579	0.8324
	(0.7968)	(-0.8730)	(1.4854)	(-0.2702)	(0.5356)	(2.3134)	(3.6741)	(4.3127)	(0.1900)	(1.3120)	(1.7790)
Z-value, alpha abs difference up vs down regime	0.2870	1.5384*	0.0045	2.4853***	0.9444	0.2293	1.9102**	2.4452***	0.8744	0.0396	0.0024
Market Index-MAI	-0.8491***	0.5509***	0.5016***	0.3117***	0.2028***		0.1858***	0.0810**			-0.1562**
	(-13.0650)	(8.1254)	(9.8764)	(6.1120)	(3.7053)		(6.0885)	(2.7081)			(-2.2707)
Comm. Energy-COEN	0.1091***							0.0401***			0.0676**
	(4.1149)							(3.2188)			(2.4078)
Small minus Big-SMB		0.4113***		0.1976***					0.1987***		
		(4.2053)		(3.4591)					(2.9516)		
Comm. Agriculture-COAG		0.1131**	0.1224***							0.0445**	
		(2.0826)	(2.7412)							(2.5907)	
High minus Low-HML			-0.2175***					-0.1650***		-0.0702***	
			(-3.8436)					(-4.5526)		(-2.8440)	
Change in VIX-DVIX				-0.0253**		-0.0313***			-0.0314***		
				(-2.1933)		(-2.7992)			(-2.9077)		
Comm. Industry Metals-COIM					0.1547***	0.1175***			0.1236***		
					(3.4023)	(3.2737)			(3.4409)		
Global Market Index (excl. U.S.)-GEMI						0.0919**					
						(2.1294)					
Exchange Rate-EXCH							-0.2678***				
							(-3.3022)				
Momentum-MOM										0.0780***	
										(4.7392)	
Adj. R-squared:	0.8385	0.8281	0.8218	0.8429	0.5600	0.6302	0.6266	0.4938	0.5639	0.4396	0.1962
F-statistic:	91.8462	57.2018	54.7957	63.6048	23.275	20.8836	30.3635	12.3816	16.0859	10.1524	5.2707
Prob (F-stat):	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0103

Analysis by Strategy

This sub-section presents an overview and a brief analysis of the most important results for each of the 11 HF strategies. See Table 7.

The Short Bias strategy does not deliver significant alpha during “bad” market conditions. This strategy was very successful in the early 1990s with high returns[14]. It delivers high returns from specific unexpected negative events. During ‘good’ times it provides frequent small losses accompanied with less frequent large gains that provide significant alpha. There are many negative exposures compared to all the other strategies. The Long Only strategy does not deliver significant alpha during stressful conditions and behaves similarly to other “conventional” investments. The Sector strategy delivers significant alpha during “good” times and recessions. It seems that HF managers are able to identify the most profitable companies/sectors, or at least those that are less affected by recessions. Particularly interesting (explained later in the sub-section on opposite/reverse exposures) are the statistically significant negative exposures for DEF and HML. The Long Short strategy also has negative exposures to DEF and HML and delivers higher alphas and fewer exposures compared to Long Only due to short selling. Nevertheless, it is unable to provide significant alpha during ‘bad’ times.

The Event Driven strategy does not provide significant alphas during ‘bad’ times. By nature, it has relatively few exposures. The Multi Strategy, due to the fact that is a mixture of other strategies, is able to provide significant alpha even in down regimes, whereas during expansion periods it delivers one of the highest alphas. It also has negative exposure to the DEF factor during expansion periods, as other strategies (e.g. Sector and Long Short). Similarly, the Others strategy has negative exposure to the DEF factor during “good” times (see opposite/reverse exposures section). This strategy has a GEMI exposure, meaning that a part of its portfolio is invested in global markets for higher returns. The Others strategy has styles/tools (PIPES, Close-Ended strategies) or allocations (start-ups) that allow them to invest in promising shares or utilizing illiquidity premia providing high alphas. The Global Macro strategy delivers higher alpha in down

[14] We went through the Short Bias time series and found that during the early 1990s the returns were much higher compared to other time periods. During the first nine months of 1990 the average monthly raw return was 5.94% (only May’s return was negative). Practitioners made high returns from specific events such as the Russian default in 1998, the technology bubble crash in 2000, the Lehman Brothers bankruptcy in 2008 and the Eurozone debt crisis in 2010.

compared to up regimes. This may have to do with the fact that it is able to invest temporarily in other regions beyond North America when there are stressful market conditions.

The Relative Value along with the Market Neutral strategy exploits market pricing anomalies between similar assets and minimizes its risk exposure. The Relative Value strategy delivers significant low alpha during expansions. Similarly, the Market Neutral strategy has one of the lowest alphas during “good” times. Contrary to other strategies, it has a positive MOM exposure during down regimes and this might explain why it is unable to deliver significant alpha. It is not also a trivial task to keep a market neutral portfolio balanced for all market conditions. The CTA strategy has an extensive use the trend-trading and derivatives thus it has one of the fewest exposures. Its exposures are related to lookback straddles. During ‘bad’ times it does not deliver significant alpha.

Alpha Analysis

We briefly discuss some points for the alphas for all strategies. Within business cycles all strategies except CTA provide average alpha for expansion periods of 0.847 while for the up regime this is 0.558. This is because during expansions some strategies (e.g. Sector, Others) provide extra alpha compared to the up regime. One explanation that we give is that the Sector strategy specializes in certain sectors and can invest in cyclical industries (e.g. the IT industry) during expansions. During recessions this strategy can invest in counter-cyclical or defensive industries (e.g. the food industry). For recessions the average alpha is 1.322 compared to 0.733 for the down regime; the difference has to do with the excess high alpha produced by some strategies (e.g. the ‘Others’ strategy) during recessions. Similar logic to the Sector strategy applies to the Other strategy that can invest in promising start-ups or private investment in public equity during recessions. CTA during expansion and up periods provides 0.817 and 0.831 respectively. During recessions and down regimes CTAs’ alphas are not significant, meaning that this strategy performs well only in good times (one of the highest alphas across all strategies). Overall, concerning ‘bad’ times, down regimes seem to be harsher for HF strategies in terms of excess returns. Fund managers are more concerned with minimizing their risk in down regimes than in recessions, even at the cost of lower returns.

Table 7. Exposures per Strategy

This table is a summary of Tables 3, 4, 5, and 6. It shows the exposures of our multi-factor model for all HF strategies across all market conditions. The up-left side contains more directional strategies whereas the down-right side contains more non-directional strategies. The exposures (in each strategy and according to each market condition) are presented according to their importance (the intensity in absolute terms) from left (more intense) to the right (less intense). In order to facilitate the reader we mention again the acronyms of the factors: COAG: Commodity Agriculture/Food, COEN: Commodity Energy, COIM: Commodity Industrial Metals, COPM: Commodity Precious Metals, DEF: Default Spread, TERM: Term Spread, DVIX: Change in VIX, EXCH: Exchange Rate, HML: High minus Low, GEMI: Global Market Index excluding U.S. MAI: Market Index, MOM: Momentum, RLE: Real Estate Index, SMB: Small minus Big.

1. Short Bias	Significant alpha	Significant Exposures	2. Long Only	Significant alpha	Significant Exposures	3. Sector	Significant alpha	Significant Exposures
Expansion	0.574	-MAI, -SMB, -GEMI, -MOM, -COIM	Expansion	0.290	MAI, SMB, HML, MOM, COEN	Expansion	1.576	-DEF, MAI, SMB, MOM, COPM, COEN
Recession	-	-MAI, COEN	Recession	-	MAI, SMB, COAG	Recession	0.563	MAI, -HML, COAG
Up	0.490	-MAI, -SMB, -GEMI, -MOM, COIM	Up	0.288	MAI, SMB, HML, MOM, COEN	Up	0.484	MAI, SMB, MOM, COPM, COEN
Down	-	-MAI, COEN	Down	-	MAI, SMB, COAG	Down	-	MAI, -HML, COAG
4. Long Short	Significant alpha	Significant Exposures	5. Event Driven	Significant alpha	Significant Exposures	6. Multi-Strategy	Significant alpha	Significant Exposures
Expansion	1.466	-DEF, MAI, SMB, -TERM, MOM, HML, COPM, COEN	Expansion	0.497	MAI, HML, SMB	Expansion	1.430	-DEF, MAI, SMB, HML, MOM, COPM
Recession	-	MAI, - HML, GOAG	Recession	-	MAI, COIM	Recession	-	MAI, COIM, -DVIX
Up	0.627	MAI, SMB, -TERM, MOM, HML, HML, COEN, DVIX	Up	0.497	MAI, HML, SMB, COEN	Up	0.639	MAI, SMB, HML, MOM, COPM
Down	-	MAI, SMB, -DVIX	Down	-	MAI, COIM	Down	0.578	COIM, GEMI, -DVIX
7. Others	Significant alpha	Significant Exposures	8. Global Macro	Significant alpha	Significant Exposures	9. Relative Value	Significant alpha	Significant Exposures
Expansion	1.482	-DEF, MAI, GEMI, MOM, -RLE	Expansion	0.373	MAI, COPM, DVIX	Expansion	0.255	MAI, TERM, SMB, HML
Recession	2.081	-TERM, SMB, GEMI, COEN	Recession	-	TERM, COAG, -COIM, COEN	Recession	-	MAI
Up	1.270	-DEF, MAI, GEMI, -RLE	Up	0.297	MAI, COPM, MOM, DVIX, COEN	Up	-	DEF, MAI, TERM, HML, SMB, MOM
Down	0.743	-EXCH, MAI	Down	0.877	-HML, MAI, COEN	Down	-	SMB, COIM, DVIX
10. Market Neutral	Significant alpha	Significant Exposures	11. CTA	Significant alpha	Significant Exposures			
Expansion	0.524	-DEF, MOM, MAI	Expansion	0.817	-EXCH, MOM			
Recession	-	GOAG, MOM	Recession	-	-MAI, COEN			
Up	0.153	MAI, MOM, HML	Up	0.831	COPM			
Down	-	MOM, -HML, COAG	Down	-	-MAI, COEN			

Exposure Analysis

Table 8, panel A presents the MAI exposure changes for all HF strategies, comparing expansion to recession periods and up regimes to down regimes. Almost all HF strategies have low or negative exposures during stressful market conditions as fund managers try to minimize their risk. A few of them do not even have significant market exposure. These results suggest that fund managers are able to hedge market exposures at such times. Comparing expansion to recession periods, most HF strategies decrease their exposures to MAI during recessions. The Short Bias strategy in the expansion period already has negative exposure, however during recession periods its exposure becomes more negative so as to benefit from expected downward market movement. Relative value has one of the lower exposures during the expansion growth period but it is almost double that during recession periods. Although this is unusual, this strategy during the recessions has the lowest exposure to the MAI factor across all HF strategies. Furthermore, during the expansions this strategy has three more factor exposures (SMB, HML and TERM) and these may interact positively overall (e.g. this portfolio with these asset class exposures is better in terms of risk incurred and alpha produced to the investor).

Regarding the up-down regimes, all the strategies decrease or eliminate their exposures to the market factor during falling markets. The largest decrease is by the Global Macro strategy, equal to 72%, whereas the smallest decrease is by the SB strategy at 9%. This is because during stressful market conditions, Global Macro strategies are able to switch to other regions (relying on the top-down approach) for a relatively short period of time as their main focus is in North America. Hence they demonstrate a large decrease in their MAI exposure. On the contrary, the Short Bias strategy already has a negative correlation with MAI, thus there is no need for a large change in their position. Moreover, during down regimes the SB strategy has only two exposures, compared to the five within the up regimes as it tries to reduce its exposures (to protect themselves from "bad" conditions).

Table 8, Panel B reports other statistically significant important factors (excluding MAI) across all strategies. During expansion periods fund managers invest more in equity factors such as MOM, SMB and HML. Hence momentum sub-strategies, investing in small firms compared to large or investing in value versus growth stocks are efficient in delivering high excess returns to investors. During recessions, the three most important factors are COAG, COEN, and COIM. Fund managers change their asset allocations and are trying to invest in commodity factors (food/agriculture, energy, and industrial metals) that relate to more defensive or counter-cyclical industries. This is in agreement with Cashin, McDermott, Scott (2002) who found that economic cycles are not the fundamental drivers of the evolution of commodity prices and Gleich, Achzet, Mayer, and Rathgeber (2013) who found that commodity prices depend on other fundamental factors such as economic scarcity and supply risk. However, the Others strategy is able to deliver significant excess returns as it has significant exposures to the GEMI factor meaning that is investing in global markets. The same applies to the Sector strategy that invests in certain (counter-cyclical) industries, providing significant alpha.

During the up regime, similar to expansion periods, the most common exposures are to MOM, SMB, and HML. Fund managers invest in equity factors and implement momentum sub-strategies investing more heavily in smaller firms, and value stocks. Like the expansion periods, directional and semi-directional strategies mainly have these exposures. During down regimes, fund managers invest primarily in commodity factors. Although, SMB is still a main exposure for HF strategies, nevertheless, this exposure is lower compared to the up regime. Similarly to the recession period, in the down regime fund managers take exposures to the factors COAG and COIM, as they are related to more defensive counter-cyclical industries[15]. This aligns with the results of the studies of Cashin, McDermott, Scott (2002) and Gleich, Achzet, Mayer, and Rathgeber (2013), mentioned above.

---

[15] We calculated that, on average, during recession and down regimes HF managers lower their exposures to the equity class factors by 17% and 22% respectively. For commodities, during recession and down regimes, HF managers increase their exposures to the commodity asset classes by 50% and 57% respectively.

Table 8. Exposures to the market and most common factors

Panel A shows the exposures to the MAI market index for all HF strategies during expansion and recession periods as well as the up and down regimes. Since the expansion periods and up regimes times are the longest we use them as the base to measure the percentage change of the exposure. * denotes significance at P < 0.1, ** denotes significance at P < 0.05 and *** denotes significance at P < 0.01. "-" denotes that the HF strategy does not have significant market exposure; this mostly happens during 'bad' times. Panel B shows the most frequent exposures for all strategies across business cycles and during different market conditions. The x symbol represents the existence of a statistically significant exposure. During down regimes we have more common exposures (e.g. COAG), however we present the three most intense.

Panel A

Strategy	Expan-sion	Recession	% Difference (Base = Expansion)	Z-score, abs diff	Up	Down	% Difference (Base = Up)	Z-score, abs diff
Short Bias	-0.854	-1.012	18%	1.627**	-0.934	-0.849	-9%	0.899
Long Only	0.672	0.609	-9%	0.943	0.669	0.551	-18%	1.657**
Sector	0.593	0.541	-9%	1.283*	0.588	0.502	-15%	1.485**
Long Short	0.528	0.466	-12%	1.457**	0.574	0.312	-46%	4.617***
Event Driven	0.304	0.289	-5%	0.267	0.252	0.203	-20%	0.834
Multi-Strategy	0.219	-	-	-	0.226	-	-	-
Others	0.155	-	-	-	0.148	0.186	25%	0.958
Global Macro	0.306	-	-	-	0.285	0.081	-72%	4.144***
Relative Value	0.148	0.284	91%	2.946***	0.151	-	-	
Market Neutral	0.068	-	-	-	0.075	-	-	
CTAs	-	-0.147	-	-	-	-0.156	-	

Panel B

Expansion Period	Short Bias	Long Only	Sector	Long Short	Event Driven	Multi Strategy	Others	Global Macro	Relative Value	Market Neutral	CTA
MOM	x	x	x	x		x	x			x	x
SMB	x	x	x	x	x	x			x		
HML		x		x	x	x			x		
Recession Period											
COAG		x	x	x				x		x	
COEN	x						x	x			x
COIM	x						x	x			
Up Regime											
MOM	x	x	x	x		x		x	x	x	
SMB	x	x	x	x	x	x			x		
HML		x		x	x	x			x	x	
Down Regime											
SMB		x		x					x		
COIM					x	x			x		
COEN	x							x			x

Opposite/Reverse Exposures

So far we have shown that HF strategies, conditional on market conditions, reduce both the number of their exposures to different asset classes and their portfolio allocations. However, there are some exposures for a few HF strategies that are systematically negative (positive) during stressful market conditions and positive (negative) during good times. For example, during expansion and recession periods fund managers (e.g. Sector, Long Short, Others) take positions with statistically significant negative exposures toward DEF (default premium) and HML (High minus Low), respectively. We computed that the DEF spread is lower during expansion periods (average equal to 0.88) than during recessions (average equal to 1.60) due to market uncertainty. Hence, fund managers during expansion periods take negative exposure against DEF for higher returns. The HML spread is higher during expansion periods (average equal to 0.51) compared to recessions (average equal to -0.39), as value stocks are in better (worse) position than growth stocks during expansion periods (recessions). Thus, fund managers during recessions take negative exposures against the HML. Overall, there is evidence that fund managers take statistically significant negative positions to some factors conditional on changing market conditions.

There are also fund managers who reverse their exposure from negative to positive and vice versa in the same asset class, depending on market conditions. For example, Long Short and Market Neutral strategies have statistically significant positive HML exposure during "good" times and statistically significant negative HML exposure during "bad" times. By doing this they provide high excess returns when there is upward market movement and protect themselves from risk during "bad" times. Ultimately, fund managers, beyond taking negative positions in some asset classes as mentioned previously, move further by taking statistically significant negative or positive positions on the same asset class conditional on changing market conditions.

Exposure by Group

We now examine the most common exposures for the three groups of strategies: directional, semi-directional and non-directional[16]. For directional the most common exposures (excluding MAI)

[16] Recall that we consider directional strategies to be Short Bias, Long Only, Sector and Long Short, semi-directional strategies to be Event Driven, Multi Strategy, Others and Global Macro and non-directional strategies to be Relative Value, Market Neutral and CTAs. There is a grading from extreme directional strategies such as Short Bias to extreme non-directional strategies such as CTAs.

during “good” times are SMB and MOM as fund managers exploit the momentum and the size effect. During stressful market conditions fund managers are trying to minimize their risk. Hence, for recession periods the exposures are COAG and then HML (with negative exposures) while for the down regime these are SMB and COAG. Semi-directional strategies have fewer common exposures between them as they have less systematic risk than directional strategies. The most important for expansion periods (in terms of intensity) are DEF (negative exposures) and SMB. For recession periods the most common are COIM and TERM. For the up regime they are the HML and SMB (in terms of intensity) whereas for the down regime it is the COIM factor. Regarding the non-directional strategies these by nature have very low systematic risk and are less sensitive to business cycles and market conditions. For expansion periods the most common is the MOM factor whereas for the up regime there is an additional factor, the HML. For recession periods and down regimes, except for the MAI, there is no common factor as each strategy may exploit different factors.

Table 9 shows that directional strategies have less dispersed (more common) factors concerning their asset class exposures within different business cycles and market conditions (on average, 2.2 asset class exposures per group). Next are the semi-directional strategies (on average 1.8 asset class exposures per group) and then the non-directional strategies (1.3), i.e. the last group has the least common exposures within its HF strategies. This dispersion increases gradually when moving from directional to non-directional strategies.

Table 9. Exposures per Group (excluding MAI)

This table shows the number of exposures and the most common factor within different business cycles and market conditions across three groups: directional, semi-directional and non-directional strategies (depending on their correlation with the MAI market index).

	Expansion	Recession	Up	Down
Panel A	Directional Strategies			
Average number of factors within group	2.4	2.2	2.2	1.8
Total number of factors	10	5	10	6
Most common factors	SMB, MOM	COAG, HML	SMB, MOM	SMB,GOAG
Panel B	Semi Directional Strategies			
Average number of factors within group	1.9	1.5	1.9	1.4
Total number of factors	8	8	10	7
Most common factors	DEF, SMB	COIM, TERM	HML, SMB	COIM
Panel C	Non-Directional Strategies			
Average number of factors within group	1.3	1.3	1.4	1
Total number of factors	7	4	7	8
Most common factors	MOM	-	MOM, HML	-

Discussion

Our results confirm our initial assumption that HFs have exposures to different factors and are time-varying, conditional on different cycles and regimes. Moreover, our results do not confirm our assumption that HFs are superior investment vehicles, i.e. they do not deliver excess returns to investors in all business cycles and market conditions. In general, our findings agree with other authors (e.g. Bali, Brown and Caglayan, 2011, Jawadi and Khanniche, 2012 and Giannikis and Vrontos, 2011) that HF strategies are dynamic in terms of exposures and returns. More specifically, our model agrees with the literature that returns and factor exposures change over time, as we found major switches of HF returns (as modelled by Jawadi, Khannich, 2012) occurred in stressful market conditions. In addition, we partly agree with Bollen and Whaley (2009) since we found that only one of their two samples, containing spikes of exposures' switching to appear during our stressful market conditions. However, it is important to mention that they focus (contrary to this study) on the internal change of funds' exposures examining funds during the period 1994 to 2005, allowing for a single shift in the parameters (asset weightings) of the funds. We have shown that different strategies (especially between directional and non-directional) have different exposures. In addition, there are some common risk factors such as the market, credit, the term spread and commodities that are shared between many HF strategies (as mentioned by

Billio, Getmansky and Pelizzon, 2012) and there are some other factors such as default spread and VIX that are economically important (Avramov et.al. 2013). Our findings agree with Meligkotsidou and Vrontos (2014) that the market index and the spread of small cap minus large cap were the most significant factors in HF returns. Fourth, there are changes in portfolio allocations that are more intense than changes in exposures to asset classes, as Patton and Ramadorai (2013) found. We partly agree with Ibbotson, Chen and Zhu (2011) as only a few strategies add significant value to investors during bear market conditions because fund managers are concerned about risk. Nonetheless, they examined alpha and exposures only during the 2008 financial crisis. Finally, as Agarwal and Naik (2004) found, we find that many HF strategies exhibited significant exposures to Fama and French's (1993) three-factor model and Carhart's (1997) momentum factor.

Robustness Checks

We first examined HF strategies' alphas and exposures using the basic market (one factor) model within business cycles and different market conditions. The statistical significance of the factor loadings on the Wilshire 5000TRI, conditional on the different regimes, is almost the same as that obtained in the simple market model with only the Wilshire 5000 TRI risk factor. This indicates that the analysis performed above is robust to the inclusion of other factors that may affect hedge index returns. Moreover, the average adjusted R^2 for all strategies (excluding CTA) within all periods/regimes is 0.61 for our multi-factor model. The average highest is 0.84 for the Long Only strategy and the lowest is 0.29 for the Market Neutral strategy; It is 0.15 for CTA. This is compared to 0.48 for the simple market model.

We tested our model by using Carhart's (1997) four-factor model and all the regressors in the model had the same sign and most were statistically significant. This process took place for all periods/regimes under consideration. Moreover, our model adjusted R^2 was higher than Carhart's model which was 0.53. An essential robustness test is that we performed the analysis again by excluding the first 48 months (1/1990-12/1993) and implementing our model again. Within all cycles/regimes, all the regressors had the same sign and mostly statistically significant, making our findings more robust. Another robustness test we implemented was to model only the first 48 months (1/1990-12/1993). Our results were qualitatively similar. We confirmed that during "good" times HF strategies invest mainly in equity asset classes (MAI, MOM, SMB, and HML). An additional robustness check was to examine our model for the post-1994 period (1/1994-

3/2014) using lookback straddles on bonds, currencies, commodities, short term interest rates and stock indices. As well as the lookback straddles, we found that COAG, COEN, and COIM were significant for this HF strategy. We examined several sample periods so as to assure that our results are not driven by data-mining and do not change. We proceeded to another statistical test of our model for all HF strategies using the HAC/Newey-West estimator for any unknown residual autocorrelation and heteroscedasticity and our results were still valid. Finally, we used a holdback period to test the underlying model out-of-sample. Half of the data were used (in-sample data) to test our model whereas the other half were reserved (out-of-sample data), for different business cycles and market conditions. Our results still held [17].

5 Conclusion

In this paper we have modelled 11 different HF strategies using exogenous break points, based on multiple business cycles. Also, we used a Markov Switching model to identify in our model the endogenous break points conditional on the different states of the market index incorporating the stepwise regression technique.

Our conclusions contribute significantly to the HF literature. First, stressful market conditions have a negative impact on HF performance in terms of alphas as the majority of HF strategies do not provide significant excess returns. In addition, fund managers are concerned more about risk at times when it is difficult to find opportunities and deliver high returns. HF strategies have much less exposure during stressful market conditions in terms of different assets classes and portfolio allocations (e.g. equity classes) as fund managers are concerned more about risks even at the cost of low excess returns. There are some strategies such as Long Short that even see statistically significant reversals of their exposures to some factors, to protect themselves from risk. Second, directional strategies have, on average, more common exposures between themselves, within all business cycles / different market conditions, compared to less directional strategies as by nature they have more systematic risk than non-directional strategies. Third, factors related to commodities such as COAG, COEN and COIM are the most common exposures during stressful market conditions (in addition to the MAI factor) as they are regarded counter-cyclical industries

[17] The results in the robustness part of section 4 concerning (1) the one factor model, (2) Carhart's model, (3) those concerning the pre-1994 period that was omitted, (4) those that include the first four years e.g. 1/1990-12/1993 (we implemented our model for "good" only times as in recessions and down regimes there were only 8 and 4 monthly observations, respectively), (5) those of the CTA strategy concerning the post-1994 period, e.g. 1/1994-3/2014, using lookback straddles (Fung and Hsieh, 2001), (6) the HAC/Newey-West estimator test, and (7) the out-of-sample tests are available on request. We do not include them for space reasons.

or essential goods/services. On the contrary, some factors such as MAI, MOM, SMB and HML are the most common factors for the "good" time periods because fund managers benefit from the upward market movement, paying attention more to high returns compared to the systematic risk. Fourth, market volatility appears to affect HF performance more than business cycles volatility as down regimes are difficult to predict or to instantly realize once they happen.

Our results are important because they enable us to better understand HFs' performance and we reveal aspects that have not been examined before. Although HFs are complex investment vehicles and difficult to model, there are nevertheless some consistent patterns in their performance. These patterns are related to fund managers' response in terms of the excess returns and their exposures to factors within business cycles and different market conditions. The long period of our database enables us to examine HF performance in a more comprehensive way, not isolating a relatively short period of time containing just one bubble or financial crisis. Instead of using one general commodity factor we used specific ones for more precise results including for the first time (to our knowledge) the commodity factor COAG (agricultural/food industry). This is one of the prime exposure factors during recession and down regimes for many strategies. The economic significance of our results is important. More specifically, overall, HF strategies are affected by 'bad' times, in other words they are not able to consistently produce excess returns for investors. Furthermore, as market volatility is related mostly to financial assets, down regimes have a more direct and severe impact on HFs' performance (in alphas and exposures). On the other hand, business cycles are related mostly to real assets and have less impact on HF performance. Therefore, investors should worry more when there is market volatility.

Investors can benefit from our findings as they are able to know what to expect from different strategies, having a clear distinction between business cycles and bull/bear market conditions. This is essential as these two different states do not necessarily coincide and they have different implications for HFs. Our results should help investors in their strategic asset allocation process, for instance, selecting specific strategies during "bad" times that do not suffer a lot; however, they should predict in a probabilistic way these market conditions (this is out of scope of this study) and then use our findings. Fund administrators could use our findings for more flexible fee policies that can better capture HF managers' performance.

6 References

Aebi, V., Sabato, G., and Schmid, M. (2012). Risk management, corporate governance, and bank performance in the financial crisis, Journal of Banking and Finance, 36(12), pp.3213-3226.

Agarwal, V., Arisoy, E. and Naik, N. (2017). Volatility of aggregate volatility and hedge fund returns, Journal of Financial Economics, in press. https://doi.org/10.1016/j.jfineco.2017.06.015.

Agarwal, V. and Naik N. (2000). Performance Evaluation of Hedge Funds with Option-based and Buy-and-Hold Strategies, Working Paper, [Online]. Available at http://www2.gsu.edu/~fncvaa/benchmark.pdf, [Accessed 06 July 2015].

Agarwal, V. and Naik, N. (2004). Risks and Portfolio Decisions Involving Hedge Funds. The Review of Financial Studies, 17(1), pp.63-98.

Amenc, N. and Goltz, F. (2008). Revisiting the Limits of Hedge Fund Indices: A Comparative Approach, The Journal of Alternative Investments, 10(4), pp.50-63.

Avramov, D., Barras, L., and Kosowski, R. (2013). Hedge fund return predictability under the magnifying glass, Journal of Financial and Quantitative Analysis, 48(4), pp.1057-1083.

Bali, T., Brown, S. and Caglayan, M. (2011). Do Hedge Funds' Exposures to Risk Factors Predict their Future Returns? Journal of Financial Economics, 101(1), pp.36-68.

Bali, T., Brown, S., and Caglayan, M. (2014). Macroeconomic risk and hedge fund returns, Journal of Financial Economics, 114(1), pp.1-19.

Bhardwaj, G., and Dunsby, A. (2012). How Many Commodity Sectors are There, and How doThey Behave?, Working Paper, [Online]. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1973753 [Accessed 28 July 2015].

Billio, M., Getmansky, M. and Pelizzon, L. (2009). Crises and Hedge Fund Risk, Working Paper, [Online]. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1130742 1-54 [Accessed 06 July 2015].

Billio, M., Getmansky, M. and Pelizzon, L. (2012). Dynamic Risk Exposures in Hedge Funds, Computational Statistics and Data Analysis, 56(11), pp.3517-3532.

Bollen, N. and Whaley, R. (2009). Hedge fund risk dynamics: Implications for performance appraisal, The Journal of Finance, 66(2), pp.985-1035.

Brown, L. and Caylor, M. (2009). Corporate governance and firm operating performance, Review of Quantitative Finance and Accounting, 32(2), pp.129-144.

Capocci, D. (2009). The Persistence in Hedge Fund Performance: Extended Analysis, International Journal of Finance and Economics, 14(3), pp.233-255.

Capocci, D. and Hubner, G. (2004). Analysis of Hedge Fund Performance, Journal of Empirical Finance, 11(1), pp.55-89.

Carhart, M. (1997). On Persistence in Mutual Fund Performance, Journal of Finance, 52(1), pp.57-82.

Cashin, P., McDermott, Scott, A. (2002). Booms and slumps in world commodity prices, Journal of Development Economics, 69(1), pp.277-296.

Denvir, E. and Hutson, E. (2006). The performance and diversification benefits of funds of hedge funds, Journal of International Financial Markets, Institutions and Money, 16(1), pp.4-22.

Dor, A.B., Dynkin, L. and Gould, T. (2006). Style Analysis and Classification of Hedge Funds, The Journal of Alternative Investments, 9(2), pp.10-29.

Duarte, J, Longstaff, F., and Yu, F. (2007). Risk and return in fixed-income arbitrage: Nickels in front of steamroller?, Review of Financial Studies, 20(1), pp.770-811.

Engel, C. and Hamilton, J. (1990). Long swings in the dollar: Are they in the data and do markets know it?, The American Economic Review, 80(4), pp.689-713.

Fama, E. and French, K. (1993). Common Risk Factors in the Returns of Stocks and Bonds, Journal of Financial Economics, 33(1), pp.3-56.

Fung, W. and Hsieh, D. (1997). Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds, The Review of Financial Studies, 10(2), pp.275-302.

Fung, W. and Hsieh, D. (2001). The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, The Review of Financial Studies, 14(2), pp.313-341.

Fung , W. and Hsieh, D. (2002). Asset-Based Style Factors for Hedge Funds, Financial Analysts Journal, 58(5), pp.16-27.

Fung, W. and Hsieh, D. (2004). Hedge Fund Benchmarks: A Risk-Based Approach, Financial Analysts Journal, 60(5), pp.65-80.

Giannikis, D., Vrontos, I. (2011). A Bayesian Approach to Detect Nonlinear Risk Exposures in Hedge Fund Strategies, Journal of Banking and Finance, 35(6), pp.1399-1414.

Gleich, B, Achzet, B, Mayer, H. and Rathgeber, A. (2013). An empirical approach to determine specific weights of driving factors of the price of commodities – A contribution to the measurement of the economic scarcity of minerals and metals, Resources Policy, 38(3), pp.350-362.

Hamilton, J.D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, Econometrica, 57(2), pp.357-384.

Harris, R.D.F., and Mazibas, M. (2010). Dynamic hedge fund portfolio construction, International Review of Financial Analysis, 19(1), pp.351–357.

Hentati-Kaffel, R. and Peretti, P. (2015). Generalized Runs to Detect Randomness in Hedge Funds Returns, Journal of banking and Finance, 50(1), pp.608-615.

Ibbotson, R., Chen, P. and Zhu, K. (2011). The ABC of Hedge Funds: Alphas, Betas and Costs, Financial Analysts Journal, 67(1), pp.15-25.

Jawadi, F. and Khanniche, S. (2012). Modeling Hedge Fund Exposure to Risk Factors, Economic Modelling, 29 (4), pp.1003-1018.

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945-1964, The Journal of Finance, 23(2), pp.389-416.

Joenvaara, J., Kosowski, R., and Tolonen, P. (2012). Revisiting “Stylized Facts” About Hedge Funds, Working Paper, Centre for Hedge Fund Research, Risk Management Laboratory, Imperial College Business School. [Online]. Available at https://workspace.imperial.ac.uk/business-school/Public/RiskLab/wp10.pdf [Accessed 01 July 2015].

Meligkotsidou, L. and Vrontos, I. (2014). Detecting Structural Breaks in Multivariate Financial Time Series: Evidence from Hedge Fund Investment Strategies, Journal of Statistical Computation and Simulation, 84(5), pp.1115-1135.

O’Doherty, M., Savin, N.E., and Tiwari, A. (2015). Evaluating hedge funds with pooled benchmarks, Management Science, (Articles in Advance), pp.1-21.

Patton, A. and Ramadorai, T. (2013). On the High-Frequency Dynamics of Hedge Fund Risk Exposures, The Journal of Finance, (68)2, pp.597-635.

Preqin Corporation (2016). Global Hedge Fund Report. [Online]. Available at https://www.preqin.com/docs/samples/2016-Preqin-Global-Hedge-Fund-Report-Sample-Pages.pdf [Accessed 24/01/2017].

Racicot, F.E. and Theoret, R. (2016). Macroeconomic shocks, forward-looking dynamics, and the behaviour of hedge funds, Journal of Banking and Finance, 62(1), pp.41-61.

Ramadorai, T. (2012). The Secondary Market for Hedge Funds and the Closed Hedge Fund Premium, The Journal of Finance, 67(2), pp.479-512.

Ross, S. (1976). The Arbitrage Theory of Capital Asset Pricing, Journal of Economic Perspectives, 13(3), pp.341-360.

Sharpe, W. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk, Journal of Finance, 19(3), pp.425-442.

Sharpe, W. (1992). Asset Allocation: Management Style and Performance Measurement, The Journal of Portfolio Management, 18(2), pp.7-19.