Journal Pre-proof

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PII: S0275-5319(19)30563-X

DOI: https://doi.org/10.1016/j.ribaf.2019.101130

Reference: RIBAF 101130

To appear in: *Research in International Business and Finance*

Received Date: 17 May 2019

Revised Date: 11 September 2019

Accepted Date: 16 November 2019

Determinants of hedge fund performance during 'good' and 'bad' economic periods

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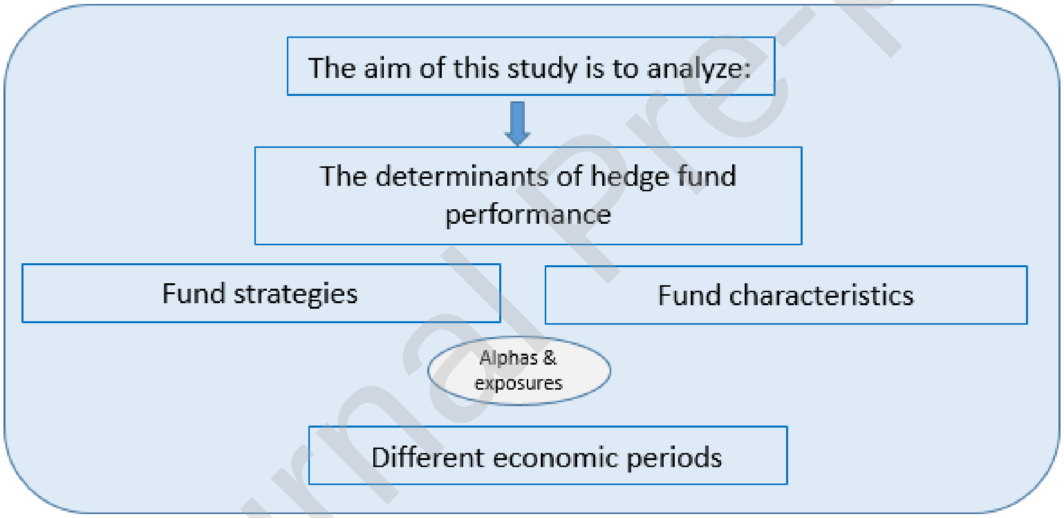
Graphical Abstract



Highlights

- Hedge funds deliver alpha only in "good" times, irrespective of their fundamentals.
- During "bad" times, hedge funds minimise their systematic risk.
- Small, young, and lock-up funds, outperform their peers in terms of alpha.
- During "bad" times, some hedge funds deliver even negative alpha.

Abstract

We analyse the drivers of hedge fund performance, focusing simultaneously on fund size, age, lockup period, fund strategies, business cycles and different market conditions, dealing with the omitted variable bias. We use exogenous break points and a switching Markov model to endogenously determine different market conditions. We find that HFs deliver positive alpha only during "good" times, irrespective of their fundamentals. During "bad" times, they minimise their systematic risk. Small and young funds, and those with redemption restrictions deliver higher alpha compared to their peers during "good" times. Finally, specific strategies deliver significantly negative alpha during "bad" times.

Keywords: Hedge funds; Hedge funds characteristics; Hedge fund performance

JEL Classification Numbers: C58; G11; G20; G23

1 Introduction

Hedge funds (HFs) are investment vehicles, which raise capital from institutional investors and wealthy individuals. In the fourth quarter of 2018, the assets under management (AUM) in HFs were almost US$3 trillion (Barclay Hedge, 2019).[1] HF performance is measured with reference to a benchmark, and the difference in return between a portfolio and its benchmark is the active return of the portfolio. Performance attribution analyses this active return.

There is a considerable number of studies in the literature that investigate the relationship between fund returns and fund-specific characteristics, such as size, age, lockup periods and fees (e.g. Frumkin and Vandegrift, 2009; Bae and Yi, 2012) and the relationship between fund returns and specific investment styles (e.g.; O'Doherty et al., 2016; Racicot and Theoret, 2016). There is also agreement in the literature that fund exposures change over time. Despite the importance of these studies the exact association between HF performance, HF strategies, HF characteristics and different market conditions has not yet been fully examined. In addition, there is an absence of a systematic examination of the commodity asset classes. Investors have not a clear understanding of how the above associations work together when forming their asset and portfolio allocation in their decision process.

The previous limitations in the literature serve as the main motivation of this study, which seeks to offer an understanding of the drivers of hedge fund performance. Our study assists investors in having a better knowledge of the determinants of HF risk and performance, to know what to expect from HFs with different characteristics, considering business cycles and market conditions. Moreover, the investors can have a guide and construct a portfolio of selected funds according to their needs and fund managers' fees. In this study, we also deal with the omitted variable bias of the preceding studies (see below in this section) referred to specific commodity factors. These commodity factors are related to energy, industrial metals, and agriculture/food index.

Our main objective is to shed further light on the drivers of HF performance in terms of alpha and risk exposure, focusing on fund-specific characteristics, namely size, age and lockup period, fund strategies, business cycles and different market conditions. There are four hypotheses that are derived from the literature, as described in the next section. Business cycles are officially

[1] https://www.barclayhedge.com/solutions/assets-under-management/hedge-fund-assets-under-management/

announced by the National Bureau of Economic Research (NBER) and the Economic Cycle Research Institute (ECRI) and have as an attribute a significant change in economic activity that lasts more than a few months. In the Summary Statistics section, we present, the specific time periods of these cycles. We follow a dual classification of business cycles as there is a focus on the two most important elements (growth and recessions) of business cycles. This exercise does not study business cycles or their different states, as this is beyond its scope. To our knowledge, the peak (trough) represents the highest (lowest) part of the expansion (recession) phase and, therefore, represents a very short period that cannot be sufficiently used for statistical analysis. A peak and a trough are usually identified after they have ended.

We contribute to the literature in a number of different ways. Although there are studies (see Bollen and Whaley, 2009; and Patton and Ramadorai, 2013) that analyse HF performance, styles and state variations, and downside risk, we are the first — to the best of our knowledge — to study the relationship between fund performance, fund strategies and fund characteristics considering both multiple business cycles and different market conditions simultaneously. In addition, we make a distinction between business cycles and market conditions, as these events are not the same, having different implications for HF performance and resulting in sub-optimal investors' decisions. We study North American HFs and identify three full business cycles since 1990. Furthermore, we do not isolate just one recession or one stressful event, since they have different implications for HF performance, as we describe later in our findings. Moreover, we characterise different economic states, classifying and ranking them from the most to the least desirable overlapping states (see empirical results section), showing that the relation between fund characteristics and fund performance is not static. The current study assists investors and fund of funds managers to better understand fund performance and have a guide in their investment decisions. They can consider the different exposures of different funds with different characteristics and can construct portfolios, which are balanced according to their needs. The controversial view that HFs produce positive alpha constantly is challenged, as investors may pay high fees that they should not normally pay.

We propose a piecewise and parsimonious empirical specification with predefined and non-defined structural breaks. This specification is flexible enough to capture HF behaviour within different regimes/periods, helping investors with their asset and portfolio allocations (see methodology and data section). In other words, helping them to make educated decisions on their investments based on market conditions, fund characteristics, and their strategies, and avoiding paying high fees for poor or even negative alpha presented in our findings. We also use a systematic database merging and cleaning process. HFs that invest primarily in North America are examined, as North America accounts for 72% of the worldwide HF industry (Preqin Corporation 2014), and we can identify three full BCs there since 1990. Funds that invest in equity or fixed-income emerging markets that do not have direct exposure to North America is beyond the scope of this paper, although it could prove a future direction for study. Finally, since different commodities behave differently within the market (see Bhardwaj and Dunsby, 2014), we use several factors, namely agriculture/food, energy, industrial and precious metals, instead of a general commodity factor.

We have a number of interesting findings. First HFs, on average, deliver significant alphas to investors only during "good" times, irrespective of their characteristics.[2] Second, during "good" times, small and young funds – and those with redemption restrictions – outperform their peers. However, during "bad" times, small funds suffer more than large funds; young funds continue to outperform old ones; and funds that do not impose restrictions (and survive) outperform funds with lockups. It seems that fund managers who feel the pressure of not having the "safety" of redemption restrictions are more innovative and do better than their peers. Third, during stressful conditions, funds, on average, try to minimize their systematic risk, irrespective of the fundamental characteristics. Fourth, the Long Only strategy funds with no redemption restrictions, and the Multi Strategy for young funds, deliver significant negative alphas in 'bad' times. We provide a battery of robustness checks and our results are still valid (see empirical results section).[3]

2 Related literature and hypotheses development

HF literature is quite broad and studies the relationships between HF performance, HF fundamental characteristics and HF strategies, though not all simultaneously.

[2] We define the excess returns during "good"("bad") times as the average excess returns during bull (bear) regimes and the excess returns during growth (recessions) periods.

[3] Many previous studies exclude data before 1994 because the majority of the databases for commercial use only came into existence from the early/mid 1990s, with a few exceptions such as the Eureka Hedge and Barclay Hedge DBs that also include pre-1994 dead funds. However, as an extra robustness test, we have excluded prior 1994 data and our results are similar.

Although there are contradictory results due to different time periods, databases and methodologies, most studies conclude that the relationship between HF size and performance is negative (see Schneeweis et al., 2002; Harri and Brorsen, 2004; Meredith, 2007; Joenväärä et al., 2012). Commercial studies (e.g. Pertrac Corporation, 2012) also show that there is a negative relationship between size and performance. However, Gregoriou and Rouah (2002) find no evidence of a relationship, whereas Koh et al. (2003) study Asian HFs and find a positive relationship and economies of scale. Gregoriou and Rouah use the AUM at the inception date of each fund and not the average, as is most commonly used in the literature.

The age of the HF is measured in months since it was launched, or since the date, it was entered in vendor databases. Howell (2001), Meredith (2007) and Frumkin and Vandegrift, (2009) find that young funds outperform old ones, and commercial studies (e.g. Pertrac Corporation, 2012) reach the same conclusion. An exception is Schneeweis et al. (2002) who find a strong positive relationship between age and performance. However, Schneeweis et al. (2002), contrary to other studies, take into account funds, which started in the same month.

Many studies (e.g. Ling, 1999, Ackerman et al., 1999; Budiono and Martens, 2010; Edwards and Caglayan, 2001; Joenväärä et al., 2012) find a positive relationship between performance fees and fund performance. Exceptions are Schneeweis et al. (2002) and Koh et al. (2003), who find no significant relationship, although the latter studies Asian HFs. It is natural to expect that higher performance fees correspond to managers with higher skills.

Ling, (1999), Aragon, (2007) and Joenväärä et al. (2012) show that funds that impose redemption restrictions outperform funds that do not, as they are able to exploit liquidity premia for higher returns. Later studies (see Hong, 2014; and the references therein) show that although funds may have lower returns after decreasing share restrictions, investors reward fund managers by increasing flows. Getmansky at al. (2015) show the complexity of the relationship between fund flow and restrictions. More specifically, they show that the flow-performance relationship is convex for funds without share restrictions and concave for funds with share restrictions. Kaushik and Pennathur (2013) do not find a link between prior fund flows and fund returns, although they focus on real estate mutual funds.

In this study, we challenge the above findings regarding size, age, and lockups. We believe that the above results do not always hold, as they are dynamic and change over time, according to different market conditions.[4] So, our first hypothesis has as follows:

H1: At the fundamental level, small and young funds, and funds with redemption restrictions, deliver higher alpha with respect to their peers, during all market conditions.

Liquidity has a prominent role in HFs and can affect even their survivability (Di Tommaso and Piluso, 2018). Schaub and Schmid (2013) find that in the pre-crisis period, more illiquid funds produce a share illiquidity premium; and in the crisis period, an illiquidity discount. While share restrictions allow funds to manage illiquid assets effectively in the pre-crisis period, they are insufficient to ensure effective management of illiquid portfolios during the crisis. Siegmann and Stefanova (2017) find that equity-focused HFs show a significant shift from negative to positive relation between market beta and liquidity after the major market microstructure changes in 2000.

Teo (2011) finds that the return impact of fund flows is stronger when funds embrace liquidity risk, when market liquidity is low and when funding liquidity is tight. Hwang, et al. (2017) argue that systemic risk is positively related to cross-sectional variations in HF returns.

Finally, a prominent issue in the HF literature is the stylised fact that HFs have dynamic correlations with markets (Stoforos et al., 2017), fund exposures change over time and different strategies demonstrate different exposures in a non-linear framework (see Bollen and Whaley, 2009; Billio et al., 2012; Meligkotsidou and Vrontos, 2014; O'Doherty et al., 2016). We proceed one step further and test the hypothesis of the alpha delivered to investors and the changing exposures in relation to fundamental characteristics and market conditions. Therefore, our hypothesis for alpha has as follows:

H2: HFs deliver positive alpha irrespective of their fundamental characteristics during all market conditions.

The above hypothesis examines whether HFs always deliver positive alpha to investors considering their fundamentals as well. Our hypothesis for market exposures has as follows:

H3: During stressful conditions, funds decrease their market exposures irrespective of the fundamental characteristics.

[4] When dealing with this and the other hypotheses, in our proposed empirical specification we also, use several commodity-specific variables.

We challenge also the conventional wisdom that HFs always deliver a positive alpha, which implies that investors should always pay high fees. This is because we observe that HF performance is dependent not only on HF characteristics, but also on HF strategies and different market conditions. There might be cases (e.g. Long Only and Global Macro) where HFs could deliver negative alpha to investors. Similar to our previous hypothesis, we test the following:

H4: Within specific market conditions, HFs with specific fundamental characteristics and following specific strategies deliver negative alpha to investors.

The above hypothesis moves further from H2 by examining also the possibility that HFs — considering also their fundamentals and their strategies — deliver negative alpha. In other words, we not only challenge the conventional wisdom that HFs deliver a positive alpha, but also consider the possibility of a negative alpha under certain conditions.

3 Methodology and data

3.1 Empirical Specification

Following Fung and Hsieh (1997) and Agarwal and Naik (2004), we examine HFs to capture their dynamic strategies. We suggest that it is not wise to use the same model as Fung and Hsieh when we explain HF strategies because of the complex nature of the HF industry and because different HF groups have different characteristics. To capture the non-linear risk exposures in HF strategies we propose a parsimonious empirical specification with predefined and non-defined structural breaks.

The proposed empirical specification refers to business cycles and different market conditions. This model is flexible as it uses the stepwise regression technique (see Dor et al., 2006; and Jawadi and Khanniche, 2012) within each regime/cycle, considering fundamental fund characteristics alone and fundamental fund characteristics and strategies simultaneously.[5]

The first specification contains predefined structural breaks conditional on the growth and recession periods. These are defined based on the National Bureau of Economic Research (NBER).

[5] Under the stepwise regression technique, the variables are added or removed from the model based on the significance of the F-value at 5% level of significance. First, the single best value is chosen and then is paired with the other independent variables, one at a time. Next, a second variable is chosen and so on, until no further variables are included or excluded from the estimation process. Stepwise regression allows to examine the importance of a large set of variables, even if there is a relatively small number of observations.

A recession is denoted as a significant decline in economic activity that spreads through the economy, lasting from few months to many years that has a visible effect on production, employment, real income, and other major economic indicators. [6]

$$r_{j,S} = \alpha_{j,S} + \beta_{j,1}F_{1,S} + \beta_{j,2}F_{2,S} + \cdots + \beta_{j,k}F_{k,S} + \varepsilon_{j,S} \quad (1)$$

where $r_{j,S}$ and $\alpha_{j,S}$ are the return and a constant for HF j in state S respectively, $F_{k,S}$ is a systematic factor, $k = 1, \dots, K$, $\beta_{j,k}$ is the sensitivity of the j HF to factor k. $S = \{G_1, G_2 \dots G_M, R_1, R_2 \dots R_L\}$ is a state variable that takes the values of the vector G_m, $m = 1, \dots, M$, when we are in one of the M growth periods and the values of the vector R_l, $l = 1, \dots, L$, when we are in one of the L recessions, where the vectors $G_m = [G_{m,1}, G_{m,2} \dots G_{m,n}]$ and $R_l = [R_{l,1}, R_{l,2} \dots R_{l,H}]$. In other words, the first specification contains pre-defined structural breaks dependent on the state of the U.S. economy.

The second specification contains non-defined structural breaks conditional on the different states of the market index (bull and bear regimes). We relate HF returns to the market factor since our objective is to capture the different conditions in the market. We apply a regime-switching Markov model (Hamilton, 1989) like other studies which endogenously determine or measure the structural breaks of HF returns and volatility (see Akay, et al., 2013; and Teulon, et al., 2014; Meligkotsidou and Vrontos, 2014). However, in this study we measure the exposures of HF returns, considering the states of the market index, the Wilshire 5000 TRI, including dividends and, more specifically, the bull and bear regimes as described below in this section. This index is a better proxy for the entire market compared to the S&P500 index as it captures almost all firms actively traded in the US.

As with the first specification, within each regime of the market index a stepwise regression technique is applied to limit the final list of factors for each HF group (following Jawadi and Khanniche, 2012) and we do not rely on a single model simply adding factors on existing models. We use specific criteria to select the loading factors (see methodology and data section).

Under the Markov switching model, systematic and unsystematic events may affect the dependent variable because of the presence of discontinuous shifts in the average market return and volatility. The change in regime is regarded as a random and unpredictable event. The model is as follows:

[6] For more details see https://www.nber.org/cycles/recessions.html; https://www.nber.org/cycles.html

$$r_{jt} = \alpha + \beta_{S_t} I_t + \omega u_t \tag{2}$$

$$I_t = \mu_{S_t} + \sigma_{S_t} \varepsilon_t \tag{3}$$

where $r_{j,t}$ is the return for HF j in period t, S_t is a Markov chain with *n* states and transition probability matrix P and u_t and ε_t are independent and normally distributed random variables with zero mean and unit variance.

Each state of the market index *I* has its own mean and volatility. HF returns are related to the states of the market index. They are defined by a parameter *α* plus a factor loading *β*, on the conditional mean of the factor. In addition, HF volatilities are related to the states of the market index *I*. They are defined by the factor loading *β* on the conditional volatility of the factor plus the volatility of the idiosyncratic risk factor *u*. In both cases, *β* could be different, conditional on the state of the risk factor *I*.

For *n* = 2 states, *n* takes the value one when we are in the bull regime and zero when we are in the bear regime.

$$r_t = \begin{cases} \alpha + \ \beta_0 I_t + \omega u_t \, , & when \ S_t = 0 \\ \alpha + \ \beta_1 I_t + \omega u_t \, , & when \ S_t = 1 \end{cases} \tag{4}$$

where the state variable *S* depends on time *t*, and *β* depends on the state variable *S* as:

$$\beta_{S_t} = \begin{cases} \beta_0 \, , & when \ S_t = 0 \\ \beta_1 \, , & when \ S_t = 1 \end{cases} \tag{5}$$

The Markov chain S_t is described by the transition probability matrix P (for two states):

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$$

where p_{ij} the transition probability from regime *i* to regime *j* with $p_{00} = 1 - p_{01}$ and $p_{11} = 1 - p_{10}$; where p_{00} and p_{11} stand for the probability of being in the bear regime, given that the system was in the bear regime during the previous period, and the probability of being in the bull regime, given that the system was in the bull regime during the previous period, respectively. The method used by investors to forecast different market conditions, although an interesting research question, is not the focus of this study.

We form portfolios for all HFs according to their size, age and lockup redemption restrictions to examine HFs at a fundamental level. Moreover, we form sub-portfolios for each of the 11 HF strategies to examine HFs at a mixed level (see below in this section). Although it is beyond the scope of this paper, other candidate drivers of HF performance and risk could be, for example, management and performance fees, use of leverage and use of the high-water mark.

3.2 Data

We build a sample of monthly data from EurekaHedge and the BarclayHedge databases from January 1990 (similar to Denvir and Hutson, 2006; Harris and Mazibas, 2010; and Giannikis and Vrontos, 2011) to March 2014. The area under study is North America, where we can identify three full business cycles since 1990. Most of the databases came into existence from the early/mid 1990s, with a few exceptions, such as the EurekaHedge and BarclayHedge databases, which came earlier. The used sample contains both live and dead funds before 1994; hence, it does not suffer from survivorship bias. In the robustness tests we exclude the period before 1994; we also use only the period before 1994 to test the validity of our results.

We use specific algorithms for the database merging and cleaning processes and specific select statements for funds that invest primarily in North America were used.[7] The survivorship and instant history bias are minimized by including dead/ceased reporting funds and by eliminating the first 12 months of each HF. For more details about HF bias, see Fung and Hsieh (2004). Following the literature (see Ramadorai, 2012) we “winsorise” the outliers at the top and bottom by 0.50%.

Multiple share classes of funds are treated as separate funds (see Ramadorai, 2013) to make the selection bias correction robust against the variations in liquidity restrictions, returns and fee structures that describe different share classes of the same fund. So, after merging 29,326 funds of all types, we end up with a dataset containing 6,373 funds with returns net of fees. We map the fundamental characteristics data with the relevant funds to construct portfolios, as described below.

[7] Regarding the merger and cleaning process, we consider (i) administration data (for instance, HF name/legal structure, management company/legal structure, manager name, inception date), and (ii) quantitative data (for instance return correlations). We eliminate records that contain null, N/A, and consecutive zero returns. We focus on HFs that invest in the North America region (geographical focus/mandate).

We use the strategies that fund managers report in the underlying databases and proceed to a mapping between these database strategies in a way similar to other authors (see Joenväärä et al., 2012). The dataset contains 11 HF strategies: Short Bias (SB), Long Only (LO), Sector (SE), Long Short (LS), Event Driven (ED), Multi Strategy (MS), Global Macro (GM), Relative Value (RV), Market Neutral (MN), strategies of Commodity Trading Advisor (CTA) funds, and Others (OT).[8] We classify these 11 strategies as directional (absolute values of the correlation coefficient above 0.5), semi-directional (absolute values of the correlation coefficient between 0.22 and 0.49) and non-directional (absolute values of the correlation coefficient between 0 and 0.21) strategies, according to their correlation with the market index Wilshire 5000TRI, including dividends. Hence, the SB, LO, LS, and SE are directional strategies; the ED, MS, OT, and GM are semi-directional strategies; and the RV, MN, and CTA non-directional strategies.

Table 1 presents the 14 used loading factors using Datastream and the Fama and French online library, according to specific criteria, such as their availability, the collinearity between them and the correlation with strategies, and what factors have been used previously in the literature based on their significance. The underlying risk factors have an impact on hedge fund performance as the hypothetical abnormal returns of HFs can be explained partially to the exposures of HFs to these factors. In other words, HF managers exploit, to a large extent, risk premia when claiming that they provide abnormal returns to investors. This implies that investors pay high incentive fees that do not reflect fund managers' skills. We have classified these factors to broader categories such as equity factors (used by Dor et al., 2006; Billio et al., 2012; Patton and Ramadorai, 2013); credit factors (used by Billio et al., 2012; Ibbotson et al., 2011; Giannikis and Vrontos, 2011; and Bali et al., 2011); and commodity factors (used by Capocci and Hubner, 2004). However, others, such as Giannikis and Vrontos, 2011; and Jawadi and Khanniche, 2012 use a total commodity index; others, such as Billio et al., 2012 use gold-only indices); real estate factor; currency factor (used by Capocci, 2009); and option factor (used by Billio et al., 2012). The VIX index is currently investable through various exchange-traded fund (ETF) products. We do not consider lookback straddles that are more appropriate to the CTA strategies (Fung and Hsieh, 2001) due to data availability for the early part of the period (the early 1990s) under examination.

[8] *CTA*s use systematic trading or make extensive use of derivatives and commodity trading. The *Others* strategy uses different styles / tools (e.g. private investment in public equity, close-ended) or even allocations (e.g. start-ups) not widely used by other HF strategies.

[Insert Table 1]

3.2.1 Fundamental characteristics and strategies

The objective is to examine the difference between small versus large funds, young versus old funds, and funds with lockup periods versus funds without lockup periods regarding their performance (alpha and exposures). Our analysis considers all the HF strategies except for CTAs, examined separately due to its uniqueness as a strategy.

We follow a large/small and a young/old classification according to the literature (see Harri and Brorsen, 2004; Meredith, 2007; Frumkin and Vandegrift, 2009; Joenväärä et al., 2012). The industry has grown over time; however, this does not mean that small funds will be in the early years only as the number of HFs has increased significantly in recent years.[9]

The median AUM of all HFs, is US$34.4m; and form and track two portfolios of funds during the period under study: those that were below US$34.4m, classifying them as small, and those above US$34.4m, classifying them as large. We compute the median age in months since the inception of each fund, which is 62 months. We form two portfolios of funds: those aged less than 62 months, classifying them as young, and those aged more than 62 months, classifying them as old.

For lockup periods we form two portfolios: those with funds with lockup restrictions, and those without restrictions, following the literature (see Aragon, 2007; Joenväärä et al., 2012, Schaub and Schmid, 2013; Hong, 2014). Within the data sample, about half of the funds do not have an explicit lockup period. There are other implicit restrictions, such as the redemption frequency or the redemption notice period, which can be considered as "soft" restrictions. However, too many records were missing to enable further analysis.

We form six sub-portfolios for each of the 11 strategies (fundamental level), a total of 66 portfolios at mixed level: the size portfolios (small and large funds), the age portfolios (young and old funds), and lockup portfolios (funds with and without lockup periods).

[9] This is also the case for other studies mentioned in the literature review section.

4 Empirical results

In this section we present the basic statistics at strategy/fundamental level, and the market classification into broad categories of HF strategies. We also give details of the regime switches and we report the results from the multi-factor models regarding alphas and exposures.

4.1 Summary Statistics

We provide basic statistics on raw returns for each of the 11 strategies and then statistics for each of the six portfolios regarding all the HFs. Table 2 panel A presents the summary statistics of the raw (net of fees) returns for the 11 HF strategies, where each strategy is a time series of averages with respect to its relevant HFs. We use equal weights in the averaging procedure to avoid biases against large funds. At the top left are the most directional strategies and at the bottom right are the most non-directional strategies.

On average, directional strategies — with the exception of the CTA strategy — have more volatile returns than all non-directional strategies since they are more aggressive. More specifically, some strategies (e.g. Sector, Long Short) deliver high monthly mean returns (at least 1.10%), being more aggressive than non-directional strategies (e.g. Market Neutral). There are also strategies (e.g. Short Bias) that deliver low monthly mean returns (0.10%). The Short Bias strategy has a high negative correlation to the market index of -0.924, whereas strategies like Market Neutral and CTA have low correlation to the market index.

Table 2 panel B presents the statistics for all HFs based on the fundamental characteristics. Each fundamental group is a time series of averages with respect to its relevant HFs. In absolute returns, large funds, old funds and funds with lockups outperform their peers.

[Insert Table 2]

We consider different business cycles and market conditions. During the period January 1990 - March 2014, there are three official business cycles as denoted by NBER; hence, there are four growth periods (01/1990–07/1990, 04/1991–03/2001, 12/2001–12/2007 and 07/2009–03/2014) and three recession periods (08/1990–03/1991, 04/2001–11/2001 and 01/2008–06/2009).

A Markov switching process determines the different market conditions (bull and bear regimes) based on the mean and volatility of the Wilshire 5000TRI. The value of a Markov switching model is that the switch of state is determined by an unobservable (state) variable. These are often based on the past state plus some random probability of switching state. Thus, the regime can be dependent on predetermined data rather than, having an ex post classification of the state variable. We perform a unit root test with breaks and the Augmented Dickey-Fuller t-statistic results in value -16.4; we reject the null hypothesis of a unit root, as the p-value is less than 1%. The return coefficients for the bull and bear regimes are 1.58 and -8.65 respectively, which are significant; the transition probability from a bear to a bull regime is 61.90%, while the transition probability from a bull to a bear regime is as low as 5.32%.

We also examine the transition probabilities. At time t, when we are in the down regime, the probability at time t+1 of staying in the same regime is 0.40%. When we are in the up regime the transition probability to the down regime is 7.50%. We further test for inverse roots of autoregressive polynomials and no root lies outside the unit circle.

There are two selected categories of regimes to enable us to compare with the business cycles. Hence, the period under examination is divided into four bull regimes (01/1990–06/1990, 11/1990–10/2000, 10/2002–05/2008 and 03/2009–03/2014) and three bear regimes (07/1990–10/1990, 11/2000–09/2002 and 06/2008–02/2009). We later classify the market conditions from the most favourable to the least favourable overlapping state as: bull regimes, growth periods, recession periods and bear regimes.

4.2 Alpha Analysis

In the next paragraphs we conduct an alpha analysis for different market conditions and states of economic activity. We also, consider fundamental characteristics and group strategies.

4.2.1 Different market conditions

Table 3 panel A shows the alpha results for the growth and recession periods. We measure alpha as the monthly excess return, expressed in percentages. Within growth periods, when grouped according to each of the fundamental characteristics, all HFs deliver alphas, significantly different from zero. The highest alpha is 1.322 and the lowest is 0.823, delivered from funds that impose redemption restrictions and funds that do not impose redemption restrictions respectively. The former perform better as they are able to exploit liquidity premia for higher returns and also have protection against redemptions. Within recession periods, on average, HFs do not provide significant alphas to investors, irrespective of their characteristics.

Table 3 panel B presents the alpha results for the bull and bear regimes. During bull regimes all HFs deliver significantly strong alphas or excess returns. Again, the highest alpha of 0.507 is delivered from funds that impose redemption restrictions, since they are able to exploit liquidity premia and also have protection against redemptions. The lowest alpha of 0.301 is delivered from young funds, since they are not well established. During bear, regimes HFs, irrespective of their fundamental characteristics, do not provide significant alphas to investors. Table 3 offers also the statistical tests for the difference between alphas across different groups of HFs (see Paternoster et al., 1998). There are statistically significant differences in alphas. Panel C presents information regarding the adjusted R-square and F-statistics.

[Insert Table 3]

4.2.2 Different states of economic activity

Table 4 reports the average performance of the different groups within "good" and "bad" times. Small funds outperform large funds during "good" times. However, during "bad" times the results are insignificant for every fund characteristic. Young funds outperform old funds during all conditions, especially during "good" times, since they can exploit the timing advantage. We mention that the impact of age on performance is dependent on bull/bear or good/bad market conditions.

As expected, funds with lockup periods outperform funds without lockup periods during the "good" times due to the illiquidity premia exploitation. However, during "bad" times, funds without lockup periods slightly outperform funds with lockup periods. It seems that funds with lockup periods cannot successfully exploit the illiquidity premia during "bad" times, for instance by investing in real estate. This is in contrast to funds without lockup periods that try to be more efficient, for instance investing in counter-cyclical industries.

We further study the behaviour of alpha in each of the four different states of economic activity. We classify and rank four different states of economic activity, from the most desirable to the least desirable state. Based on the Markov switching model, the worst or most severe state is the bear regime, because it captures market downturns accompanied with great volatility. The next less severe state is the recession, as during this period there are mostly negative market returns due to general low economic activity. The growth period comes third, during which there are mostly positive market returns. Finally, the most favourable state is the bull regime, due to very high market returns.

Table 4 also shows that in the most favourable state, HFs do not provide the highest excess returns to investors, as HFs are actually exploiting the upward market conditions by increasing their exposures to the market factor. This means that HFs do not always deserve the excess fees that they receive from investors. Large compared to small funds perform very well during extremely good conditions, such as the bull regimes (0.476). The opposite happens with small funds with 0.313 in the extremely good states. It appears that in extremely good conditions, large funds are better known. So, the larger a HF is, the better known it is, and the more information external investors have about it, increasing their will to invest in it. However, in extremely negative conditions, large funds do not have the flexibility to adapt. Moreover, the impact of size on performance is conditional on bull/bear or good/bad market conditions.

Old funds perform better than young funds, meaning that in extremely good market conditions reputation is more important than the timing advantage. Especially for those funds that have a good proven track record and remain in the market for a relatively long time. Funds with lockup periods outperform funds without lockup periods during "good" times, 0.507 and 1.322 for the best (bull regime) and good (growth) states respectively, as these funds are exploiting illiquidity premia. However, we cannot study the significance of the differences in alphas in each pair (small/large, young/old, and funds with and without lockup periods) due to the small number of observations, i.e. eight observations (states) for each pair.

One reasonable explanation for why the large and old HFs outperform their peers is that large funds and old funds enjoy the benefits of their size and their long establishment (reputation), respectively. Although the formal test of how HF reputation can be linked to the alpha is an interesting future direction, it is beyond the scope of this paper. However, we find that this does not work when conditions are just good (growth), when there might be fluctuations in market returns and investing opportunities are less frequent.

[Insert Table 4]

4.2.3 Fundamental characteristics and group strategies

In this section we provide an alpha analysis, taking into account the strategy groups and the fundamental factors. As previously mentioned, there are three broad groups of strategies: directional, semi-directional and non-directional and Table 5 present their results.[10]

Large directional funds outperform small directional funds in both “good” and “bad” conditions as they can benefit from the upward market movement and avoid the downward market movement by exploiting their size, since external investors have better information on that HF. The same applies to all young directional funds, except those, which follow the Short Bias strategy, as they may not have a reputation, but are nevertheless able to exploit the timing advantage as opposed to old directional funds. All funds that follow directional strategies with lockup restrictions outperform the directional strategies without lockup restrictions, except those, which follow the Short Bias strategy. The reasons are the illiquidity premia exploitation in “good” market conditions and the lockup protection during “bad” times; directional strategies are more exposed during “bad” times.

The semi-directional large funds outperform small funds during “good” market conditions (due to better exploitation of the upward market movement), whereas during “bad” market conditions small semi-directional strategies outperform large funds due to their flexibility. All old semi-directional strategies outperform young semi-directional funds in all market conditions due to their experience and market establishment. Moreover, semi-directional strategies with lockup restrictions outperform those without lockup restrictions in “good” market conditions (due to the illiquidity premia), whereas the opposite is true during “bad” market conditions. One explanation is that funds with no redemption restrictions (that survive) during “bad” times should be more innovative and efficient than their peers as fund managers feel high pressure.

The small non-directional funds outperform large funds during “good” times as small funds use some market exposure to benefit from the upward market movement, and this also explains why during “bad” times small funds underperform the large funds. Old non-directional funds outperform young funds because of their market establishment, whereas young funds outperform during “bad” times due to the timing advantage. All non-directional funds with lockup restrictions

[10] There is a gradual classification from extreme directional strategies (e.g. Short Bias strategy) to the extreme non-directional strategies (e.g. CTAs).

outperform funds without lockup restrictions in all market conditions as fund managers exploit illiquidity premia during "good" times and the protection of the redemption restrictions during "bad" times.

[Insert Table 5]

Table 6 presents the results for the best (worst) two strategy funds with specific fundamental characteristics during "good" and "bad" times. Investors should be aware of these strategies - not only to have high abnormal returns but also to avoid strategies that are harmful when considering them into their asset and portfolio allocation decisions. Thus, they can avoid paying high fees for poor or even negative alphas. In other words, to avoid losing money. During "good" times, the top performers are Sector young and Long Short young funds in terms of excess returns, with significant results of 4.18% and 2.86%, respectively, on a monthly basis. One explanation is that both strategies are directional, and another is that both funds are young, which in general provide superior returns to old funds. Sector funds have a deeper knowledge of specific cyclical sectors. It is conceptually easy to understand but difficult to implement a Long Short strategy; hence, fund managers with superior stock-picking abilities can benefit from such a strategy.

During "bad" times, the top performers are small and old funds that follow the Others strategy and deliver high and statistically significant excess returns of 4.14% and 2.64% respectively; this strategy invests mainly in start-ups with high yields. During "bad" times, the bottom performers are funds without redemption restrictions that follow the Long Only strategy and young funds that follow the Multi Strategy and deliver significantly negative alphas. This poor performance can be explained by the fact that Long Only funds without restrictions do not have investing alternatives and they are not protected from redemptions. Young funds that follow the Multi Strategy seem to lack the necessary experience of implementing this type of complex strategy, which is a combination of other strategies.

From the previous discussion, we reject H1 that at the fundamental level, small and young funds, and funds with redemption restrictions, deliver higher alpha with respect to their peers. This is because that relationship is questionable when we consider 'bad' times. In other words, H1 is true only during 'good' market conditions. We also reject H2 that HFs are able to deliver positive alpha to investors at all times, irrespective of their fundamental characteristics. It seems that HFs are more vulnerable than they are supposed to be during 'bad' times. We accept H4 that HF strategies with specific fundamental characteristics within specific market conditions deliver negative alpha to investors. We found that the Long Only strategy funds with no redemption restrictions and the Multi Strategy for young funds deliver significant negative alphas in "bad" times. The negative alpha is a result similar to that of Teo (2011), although he concentrates on funds with the lowest exposures to liquidity risk. We focus jointly on specific fund strategies and characteristics.

[Insert Table 6]

4.3 Exposure Analysis

In the next paragraphs we present an exposure analysis for different market conditions and states of economic activity. We also, consider fundamental characteristics and group strategies.

4.3.1 Different market conditions

Table 7 panel A shows that, during growth periods, the most common exposures are MAI, SMB, and then MOM and DEF in absolute terms (portfolio allocations). MAI has the highest exposure for all fund groups when compared with the other exposures. The exposure to MAI ranges from 0.355 for funds with lockups to 0.394 for old funds. The exposure to SMB ranges from 0.127 for small funds to 0.173 for funds with lockups and these exposures are statistically significant at 1% the level. Young funds have the highest exposure to the MOM factor (0.103) which is almost twice the MOM exposure for old funds. For the other groups, there are no large differences in exposure to the MOM factor. Moreover, all groups present negative exposure to DEF that ranges from -1.406 for young funds to -0.491 for large funds and these exposures are statistically significant at the 1% level. In total, there are 37 exposures to the various asset classes. Overall, within the growth period, HFs have relatively high asset allocation exposures for higher returns, irrespective of their fundamental characteristics.

Table 7 panel B shows that exposures for recessions are fewer compared to the growth periods in terms of asset and portfolio allocation. The most common exposures are MAI and COAG. The exposure to MAI is the most important for all fund groups although, overall, is lower compared to growth periods as fund managers try to minimize their risk. Large funds, old funds, and funds with lockup restrictions have COAG exposures -significant at the 5% level- equal to 0.086, 0.091, and

0.084, respectively which are higher compared to their peers. In total, there are 20 exposures to asset classes compared to 37 during growth periods. This means that fund managers try to minimise their exposures at the expense of lower alphas during recessions. Panel C gives information regarding the adjusted R-squared and F-statistics.

[Insert Table 7]

Table 8 panel A shows that during bull regimes, the most important exposures are MAI and MOM. Compared to the other exposures, the exposure to MAI is the most important. The highest is 0.410 for small funds and the lowest is 0.367 for funds with no lockups and are statistically significant at the 1% level. MOM exposures range from 0.052 to 0.070 and are statistically significant at the 1% level, for all the groups. Similarly to the growth periods there is, as expected, no wide distribution of exposures in HFs in terms of asset allocations. In total, there are 32 asset class exposures across all strategies. In general, fund managers during “good” times try to exploit the upward market movement and increase their exposures.

Table 8 panel B shows that during bear regimes there are fewer exposures compared to growth periods in terms of asset allocation and portfolio allocation. MAI, SMB and then COIM are the most common exposures. The MAI exposure is the most important compared to the other exposures. In bull regimes, fund managers try to reduce their MAI exposure to minimize their risk. The exposures for small funds (0.237), young funds (0.223), and funds with lockups (0.196) are higher than their peers. The exposures to SMB for the large funds (0.193), old funds (0.159), and fund with redemption restrictions (0.206) are higher than their peers and are statistically significant. The exposures to the COIM factor range from 0.113 (young funds) to 0.086 (funds with lockups) and are statistically significant. The total number of exposures during the bear regimes is 26 across all HF strategies. During bear regimes, fund managers try to minimise their exposures in a similar way to recessions. Panel C shows information regarding the adjusted R-squared and F-statistics.

[Insert Table 8]

In the following paragraphs we give a brief outline of the most important findings for each of the six fundamental groups based on Tables 7 and 8.

During "good" market conditions, the most important exposures for both small and large funds are the market, Small minus Big and Momentum. Both groups try to exploit the upward market movement, providing significant alpha to investors. They also have a statistically significant negative default premium exposure, as the DEF premium is negative during "good" times. On average, small funds appear to have larger exposures to these factors, and deliver higher statistically significant alpha than large funds, as we discuss below.

During stressful market conditions (recessions or bear regimes), both small and large funds decrease their exposures and do not deliver significant alpha to investors. Market exposure is still the most important for both groups, although exposures to energy and agriculture commodities are also statistically significant as fund managers switch to these during stressful market conditions. Large funds seem to be more successful than small funds in minimising their risk as they have a small number of exposures.

Overall, small funds are more successful in terms of alpha than large funds (although according to our H1, there is not enough evidence to further support this during stressful market conditions). This can be explained by assuming that the most talented fund managers build experience in large funds and then self-select to start their own firms. Another explanation is the stellar small-fund performance. Small funds have better niche opportunities than large funds because as a fund increases in size, fund managers have to adopt less profitable opportunities to accommodate their large investments – the well documented effect of diseconomies of scale in HF literature (see, for example, Joenväärä et al., 2012). Moreover, in small funds there is higher pressure due to lower AUM and, therefore, lower associated management fees. Another explanation is that the larger the fund, the further away the fund managers are from security-level analysis.

During "good" times, both young and old funds exploit upward market movement by increasing their exposures, with young funds being more successful because of the timing advantage, as we have already discussed (see earlier in this section). The most important statistically significant exposures are the market, Momentum, and the Small minus Big factor. During "bad" times, neither group provides significant alpha to investors; instead managers try to minimise their risk. The most important exposures are the market, and the energy and agriculture commodities exposures.

Moreover, both groups have statistically significant negative High minus Low exposure during "bad" times. However, young funds appear to have higher exposure to this factor. It is worth mentioning that young funds, by definition, have a timing advantage over old funds. This is because young funds tend to be formed at times that are advantageous for specific strategies. An example is funds that specialise in securitised credit strategy after a recession in response to opportunities in this area. In addition, young funds appear to be more return driven because they are not yet established.

During "good" times, funds with and without redemption restrictions deliver significant alpha to investors, although funds that impose lockup restrictions are more successful because they can exploit liquidity premia. The most important statistically significant factors for both groups are the market, Small minus Big, Momentum, and the default spread (negative). Overall, funds that impose redemption restrictions are riskier, having higher exposure in terms of asset allocations than funds that do not impose restrictions. During "bad" times, both groups reduce their exposure, although funds with no lockups appear to have slightly lower exposure. In general, it seems that funds that impose lockup restrictions are more successful as they are protected from withdrawal risk, and can, therefore, have higher exposure than their peers and also exploit more illiquidity premia (e.g. new premia or exploit better the existing premia). However, during stressful conditions, funds with no restrictions (that survive) are more successful than funds with restrictions.

Table 9 provides the different exposures for all HFs, taking into account only the fundamental characteristics and different economic states. We focus on MAI and then on SMB, HML, and MOM which are four of the most common exposures. As it was expected, all groups, on average, decrease their MAI exposures during stressful market conditions. There is a large decrease in exposures across all groups during bear regimes. However, during recessions, large and old funds, and funds without lockup periods, do not significantly change their exposures, meaning that recessions are less fierce than bear regimes for HFs. All groups decrease their MOM exposures during stressful market conditions. This is not surprizing because MOM is a vital factor during "good" times when fund managers keep up their investments' momentum. Regarding HML, during 'bad' times, most groups not only reduce their exposures but even reverse some exposures from positive to negative. All groups reduce their exposures to SMB, from growth to recession periods. During bear regimes, all groups increase their exposures except small funds.

We also examine the MAI behaviour of the underlying groups within different states. We classify and rank four different states of economic activity, from the most desirable to the least desirable state (see earlier in this section). The groups have the highest market exposures during the best state, and in almost all cases, these exposures gradually diminish when moving closer to the worst state. Small funds have higher exposures in extreme good and bad financial conditions compared to large funds. Young funds have higher exposures in extremely good and bad conditions compared to old funds. Funds with lockup periods provide higher exposures during "good" times, whereas in the bad and worst states this group provides higher and lower exposures, respectively, compared to funds without redemption restrictions. However, we cannot study the significance of the differences in alphas in each pair (small/large, young/old and funds, with and without lockup periods) due to the small number of observations, i.e. eight observations (states) for each pair. For MOM, SMB, and HML, due to many insignificant figures, we cannot draw sound conclusions about their behaviour within different states of the economic activity. However, within best states (bull regimes) the underlying exposures seem in general higher compared to the good states (growth periods). Table 9 also offers the statistical tests for the difference between market, size, high minus low, and momentum exposures across different groups of HFs (see Paternoster et al., 1998). There are statistically significant differences especially in market exposures.

[Insert Table 9]

4.3.2 Fundamental characteristics, group strategies

We follow a market analysis taking into account the strategy groups and the fundamental characteristics to offer a broader perspective. Table 10 panel A presents the results for the directional strategies and the fundamental characteristics. All funds, regardless of their characteristics, lower their exposures during recessions as compared to growth periods since they try to protect themselves against negative market movements. Large and old funds, and funds without lockup restrictions, decrease their exposures during bear regimes. Young funds have the timing advantage (they enter the market when it is in their interest) and funds with lockup restrictions are protected from the withdrawal risk.

Table 10 panel B shows the results for the semi-directional strategies and the fundamental characteristics. The majority of funds in this group do not lower their exposures during recessions. This means that all funds, regardless of their characteristics, do not strictly follow the market index.

However, when we study bull and bear regimes, all the funds in this group change their exposures against the market index, as the bear regimes are severer than recessions. One exception is the funds with lockup restrictions that do not suffer from redemptions. This seems to work for these funds as the excess returns are among the highest.

Table 10 panel C shows the results for the non-directional strategies and the fundamental characteristics. There is no large difference in exposures among growth and recession periods for these HFs. This is because non-directional strategies, are not correlated with the market index. When we study bull and bear regimes, some groups decrease their exposures substantially. It appears that during bear regimes HFs are trying not only to minimise, but even to have negative exposures to the market index to protect themselves from the systematic risk. From the previous discussion we accept H3 that during stressful market conditions HFs, on average, decrease their market exposures, irrespective of the fundamental characteristics.

[Insert Table 10]

4.4 Discussion of Results

The relationship between size and performance is negative and this result is in agreement with the academic literature (Meredith, 2007; Joenväärä et al., 2012). Our results also agree with practitioners' literature (Pertrac Corporation, 2012). However, our study shows that the relationship between size and performance is not static and changes with market conditions and HF strategies. Although this negative relationship holds for "good" times, during "bad" times it is statistically insignificant.

The relationship between age and performance is negative as well, and this result is again in agreement with the literature (Meredith, 2007; Frumkin, and Vandegrif, 2009; Pertrac Corporation, 2012). However, in this study we proceed further and stress test this relationship for "good" and "bad" market conditions and different HF strategies. We find that this holds for "good" times, but for "bad" times it is insignificant.

The relationship between lockup restrictions and performance is positive and this result is again in agreement with the literature (Aragon, 2007; Joenväärä et al., 2012). However, we show that this relationship is not static as this negative relationship holds only during "good" times; during "bad" times, it is insignificant. This study facilitates investors in their decision process as redemption restrictions do not necessarily mean high expected returns, particularly during "bad" times. We deal with the omitted variable bias (for specific commodity factors) and we stress-test previous studies. It is shown that the relationship between fund characteristics and fund performance is not static.

Finally, we investigate HFs at mixed level (strategies and fund-specific characteristics at the same time). We find that directional strategies with specific characteristics (such as young and small funds) provide high returns to investors. On the other hand, non-directional strategies, especially those with no redemption restrictions, and young funds, suffer during "good" times. We also find that directional strategies (for example, strategies similar to traditional investments taking Long Only positions) with no redemption restrictions present significantly negative alpha. Young funds that follow less directional strategies also present significantly negative alpha due to lack of experience. The findings are important because investors can know what to expect from HFs at the mixed level during "bad" times, and might avoid paying high fees for significantly negative alpha during these "bad" times.

4.5 Robustness Checks

In this section, we examine the robustness of our main results. We first regress the HF returns only on the Wilshire 5000 TRI risk factor, conditional on the different regimes. The statistical significance of the proposed model is almost the same as the simple market model with only the Wilshire 5000 TRI risk factor. Hence, the analysis performed above is robust for the inclusion of other factors that may affect hedge index returns.

During stressful market conditions, there is no significant alpha to HFs, on average, irrespective of fundamental fund factors. This is in agreement with the analysis at mixed level where during "good" times almost all funds deliver significant excess returns and during "bad" times the majority of funds do not deliver significant excess returns.

We also estimate our model excluding the first 48 months (1/1990–12/1993) and implement the proposed specification again at the fundamental level. All the regressors have the same sign and are mostly statistically significant, making our findings robust. Moreover, we confirm the relative performance between funds with different characteristics. We also confirm that HFs deliver significant alpha only during "good" times, as opposed to "bad" times, where fund managers are concerned with minimising their risks, irrespective of the fundamental factors. We also estimate our model for the first 48 months (1/1990–12/1993) and the results are qualitatively comparable. The Newey-West estimator is used for any unknown residual autocorrelation and heteroscedasticity, and the results are still valid. Finally, we perform an out-of-sample test for our model at the fundamental level and also at the mixed level. Half of our data length is tested (in-sample data) and the other half is reserved (out-of-sample) for business cycles and different market conditions separately, and our results still hold.[11]

5 Conclusions

We examine HF performance considering their fundamental characteristics under different business cycles and market conditions covering multiple financial crisis and credit events. We further analyse HF strategies at the mixed level, namely fundamental characteristics, at the same time. We also use the Markov switching model to identify the structural breaks conditional on the different states of the market. Finally, we use stepwise regressions to adjust to the different conditions. To study the impact of the fundamental on HF performance, we form portfolios based on HF characteristics: age, size and whether lockup periods exist or not. We further examine the impact of these fundamentals at strategy group level; to help investors in their asset and portfolio allocations, avoiding high fees for poor or even negative alphas.

We deal with the omitted variable bias that existed in previous studies and we offer a number of interesting findings that contribute significantly to the HF literature. First, at the fundamental level, small and young funds, and funds with redemption restrictions, deliver higher alpha with respect to their peers, during 'good' only market conditions. During 'bad' times, the results related to previous studies should be further examined. More specifically, during "bad" times, small funds suffer more than large funds, young funds continue to outperform old funds, and funds that do not impose redemption restrictions (and survive) outperform funds with lockups, but these results are insignificant.

Second, during "good" times HFs deliver significant excess returns, irrespective of the underlying fundamental characteristics. However, none of the underlying characteristics were able to significantly assist in delivering excess returns during 'bad' times. The results show that HFs

[11] The robustness tests are available upon request.

are more vulnerable than they are supposed to be during 'bad' times. Third, during stressful conditions, HFs decrease their market exposures, irrespective of their fundamental characteristics. Fourth, within specific fundamental characteristics that follow specific strategies, HFs deliver significant negative alpha to investors during 'bad' times. For instance, the Long Only strategy funds with no redemption restrictions, and the Multi Strategy for young funds, deliver significant negative alphas in "bad" times. On the other hand, the Others strategy for small and old funds provides extraordinary excess returns to investors during "bad" times.

Our findings assist investors in having a better understanding of what to expect from HFs with different characteristics, considering business cycles and market conditions. They can have a guide and construct a portfolio according to their needs. We reveal that some HFs can even deliver negative alpha to investors (e.g. Long Only strategy funds with no redemption restrictions, and the Multi Strategy young funds, deliver significant negative alphas in 'bad' times). Investors are now aware that they may pay high fees for HFs that provide negative alpha. The controversial view that HFs always produce positive alpha to investors is challenged. Fund of fund managers can consider the different exposures of different funds with different characteristics and can build portfolios, which are balanced according to their needs.

Declaration-of-interest Disclosure Statement

The work has not been published previously and it is not under consideration for publication elsewhere. Its publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

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Acknowledgements

We wish to thank the participants of the BAFA 2017 Conference for their valuable comments. We also wish to thank Prof. Mike Tsionas, Prof. Mahbub Zaman, Dr. Keith Anderson, Dr. Mark Rhodes, Dr. Moshfique Uddin and Dr. Harry Venables for their valuable comments. The usual disclaimer applies. We acknowledge financial support to purchase the database used in this project from the York Management School, UK.

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Table 1
Hedge Fund Factors

Variable	Descriptor
MAI	Market factor: Wilshire 5000 Total Return Monthly Index
GEMI	Global market factor: Morgan Stanley Capital International (MSCI) world index Excluding US (Total Return Index)
SMB	Size factor: Small Minus Big
HML	High minus Low factor: High minus Low book-to-market capitalization
MOM	Momentum factor
TERM	Term spread premium: the spread between ten-year US government bonds and 3-month US treasury rate
DEF	Default premium: Differences in Promised Yields which is the spread between Moody's corporate AAA and BAA bond yields
COEN	Energy factor: S&P GSCI Energy (Total Return Index)
COPM	Precious metals factor: S&P GSCI Precious Metal (Total Return Index)
COIM	Industrial metals factor: S&P GSCI Industrial Metals (Total Return Index)
COAG	Agriculture factor: S&P GSCI Agriculture (Total Return Index)
RLE	Real estate factor: DJ US Select Real Estate Securities – Tot Return Index
EXCH	Currency factor: US Trade-Weighted Value of US Dollar against Major Currencies
DVIX	Option factor: CBOE S&P500 Volatility Index (VIX) (Price Index)

Notes: This Table describes the factors used in this study. We classify them into six categories. Equity factors: MAI, GEMI, SMB, HML, and MOM. Credit factors: TERM, and DEF. Commodity factors: COEN, COPM, COIM, and COAG. Real estate factors: RLE. Currency factor: EXCH. Option factor: DVIX. The factors MAI, GEMI, COEN, COPM, COAG, and RLE are excess risk-free rates. The risk-free rate is the one-month Treasury bill rate from the Fama and French online data library.

Table 2

Hedge Fund Raw Returns Summary Statistics and Market Correlations

Panel A

Strategy	Mean	Standard Deviation	Correl. Coefficient	Strategy	Mean	Standard Deviation	Correl. Coefficient
Short Bias	0.05%	5.197	-0.924**	**Others**	1.35%	1.091	0.232**
Long Only	1.00%	3.437	0.707**	**Global Macro**	0.93%	2.017	0.223**
Sector	1.15%	3.259	0.637**	**Relative Value**	0.82%	1.238	0.211**
Long Short	1.13%	2.663	0.550**	**Market Neutral**	0.53%	0.874	0.059**
Event Driven	0.94%	1.839	0.338**	**CTA**	1.18%	3.415	0.048**
Multi Strategy	1.06%	1.713	0.271**				

Panel B

Fundamen-tal Group	Mean	Standard Deviation	Funda-mental Group	Mean	Standard Deviation
Size Small	0.92%	2.069	**Size Large**	1.02%	2.022
Lockup-Yes	1.07%	2.269	**Lockup-No**	0.91%	1.884
Age Young	0.77%	2.336	**Age Old**	0.99%	2.040

Notes: Panel A reports summary statistics of monthly raw returns for each HF strategy and its correlation with the Wilshire 5000TRI, including dividends for the entire period under examination 01/1990-03/2014. We use the correlation of each strategy with the market index and we group the strategies as follows: a) directional (absolute values of the correlation coefficient above 0.5): Short Bias, Long Only, Sector and Long Short; b) semi-directional (absolute values of the correlation coefficient between 0.22 and 0.49): Event Driven, Multi Strategy, Others, and Global Macro; c) non-directional (absolute values of the correlation coefficient between 0 and 0.21): Relative Value, Market Neutral, and CTA. Each strategy is a representative-average time series of all the relevant HFs; ** denotes correlation significance at the 1% level. Panel B reports summary statistics of monthly raw returns for each of the six portfolios – size small, size large, age young, age old, lockup-yes, lockup-no (detailed descriptive statistics - raw and excess risk free returns along with histograms – for the HF strategies are not presented here but they are available upon request).

Table 3

Alphas of HFs during growth, recessions, bull and bear regimes

Dep. Variable	Small	Large	Young (Y)	Old (O)	Lockup Yes	No Lockup (N)
Panel A						
Growth – Constant	1.219**	0.906**	1.709**	1.002**	1.322**	0.823**
	(4.833)	(4.332)	(3.740)	(5.007)	(5.195)	(4.444)
Z-value of difference		0.957		1.418†		1.586†
Recession - Constant	0.252	0.404	0.307	0.342	0.246	0.385
	(1.300)	(1.534)	(1.961)	(1.484)	(0.953)	(1.949)
Z-value of difference		-0.467		-0.126		-0.426
Panel B						
Bull Regime - Constant	0.313**	0.476**	0.301**	0.428**	0.507**	0.372**
	(4.280)	(8.211)	(2.650)	(7.814)	(7.390)	(7.223)
Z-value of difference		-1.740*		-1.010		1.578†
Bear Regime - Constant	0.211	0.073	0.359	0.082	0.037	0.097
	(1.143)	(0.276)	(1.924)	(0.361)	(0.142)	(0.500)
Z-value of difference		0.427		0.942		-0.186
Panel C						
Growth - Adj. R-square:	0.742	0.790	0.639	0.821	0.773	0.807
Recession - Adj. R-square:	0.837	0.781	0.916	0.818	0.789	0.843
Bull - Adj. R-	0.705	0.774	0.606	0.804	0.749	0.791
Bear - Adj. R-	0.873	0.759	0.898	0.811	0.808	0.824
Each Prob (F-stat):	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This Table shows the Jensen's alphas and exposures of the multi-factor model during growth/recession periods (Panel A), and bull/bear regimes (Panel B) at fundamental level (size, age, and lockup). HF 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. * and ** denote significance at 5% and 1% level respectively. The t-statistics are in parentheses. Z-values of the differences of the alpha coefficients among groups are presented. More specifically, the differences Small-Large, Young-Old and Yes-No. †,* and ** denote significance at 10%, 5% and 1% level respectively - (see, Paternoster et al., 1998). Empty cells mean that there is no significant exposure to these factors.

Table 4

Alphas for all groups between different states of the economy

Fundamental Group	Bull regimes (Best state)	Growth periods (Good state)	"Good" market conditions	Recessions (Bad state)	Bear regimes (Worst state)	"Bad" market conditions
Size Small	0.313**	1.219**	0.766	0.252	0.211	0.232
Size Large	0.476**	0.906**	0.691	0.404	0.073	0.239
Age Young	0.301**	1.709**	1.005	0.307	0.359	0.333
Age Old	0.428**	1.002**	0.715	0.342	0.082	0.212
Lockup-Yes	0.507**	1.322**	0.915	0.246	0.037	0.142
Lockup-No	0.372**	0.823**	0.598	0.385	0.097	0.241

Notes: This Table reports the excess returns for all groups (size, age, and lockup) between different states of the economy. The excess returns during "good" market conditions is the average of the excess returns during bull regimes and the excess returns during growth periods. The excess returns during "bad" market conditions is the average of the excess returns during bear regimes and the excess returns during recessions. ** denotes significance at 1% level.

Table 5

Alphas for directional, semi-directional and non-directional strategies

	Directional		Semi-Directional		Non-Directional	
	Bull and Growth	**Recession and Bear**	**Bull and Growth**	**Recession and Bear**	**Bull and Growth**	**Recession and Bear**
Size Small	0.656	0.090	0.638	0.842	0.357	0.578
Size Large	1.081	0.368	0.735	0.531	0.262	0.708
Age Young	1.236	0.163	0.524	0.242	0.204	0.788
Age Old	0.711	0.027	0.773	0.464	0.411	0.383
Lockup-	0.746	0.403	0.718	0.671	0.776	0.450
Lockup-No	0.628	-0.414	0.685	0.823	0.255	0.362

Notes: This Table shows the average alphas for all groups (size, age, and lockup) belonging to the directional (absolute values of the correlation coefficient above 0.5), semi-directional (absolute values of the correlation coefficient between 0.22 and 0.49) and non-directional (absolute values of the correlation coefficient between 0 and 0.21) strategies during growth and recession periods as well as the bull and bear regimes. Overall for the mixed cases, during "good times" alphas are statistically significant whereas during "bad times" most results are not statistically significant.

Table 6
Bottom/Top Performers

"Good Conditions"		"Bad" Conditions	
Sector – Young Funds	4.175**	**Others - Small Funds**	4.142**
Long Short -Young Funds	2.586**	**Others - Old Funds**	2.462**
Market Neutral – Young Funds	-0.036	**Long Only – Lockup-No Funds**	-3.524**
Relative Value – Lockup-No Funds	-0.225	**Multi-Strategy – Young Funds**	-1.316*

Notes: This Table shows the two top and bottom performers during "good" and "bad" conditions. * and ** denote significance at 5% and 1% level, respectively.

Table 7
Multi-Factor Model During Growth and Recession Periods

Panel A - Dep. Variable	Small	Large	Young	Old	Lockup	No Lockup
Market Index - MAI	0.376**	0.383**	0.393**	0.394**	0.430**	0.355**
	(23.580)	(27.686)	(14.960)	(29.873)	(25.631)	-29.015
Small minus Big - SMB	0.127**	0.154**		0.152**	0.173**	0.128**
	(6.602)	(9.093)		(9.461)	(8.435)	-8.581
Momentum - MOM	0.063**	0.048**	0.103**	0.050**	0.047**	0.060**
	(4.186)	(3.868)	(4.657)	(4.269)	(3.099)	-5.483
Commodity Energy - COEN	0.026**	0.021**	0.029*	0.022**	0.022**	0.021**
	(3.298)	(3.134)	(2.299)	(3.424)	(2.775)	-3.662
Default Spread - DEF	-0.941**	-0.491*	-1.406**	-0.652**	-0.921**	-0.515*
	(-3.393)	(-2.146)	(-3.033)	(-2.971)	(-3.297)	(-2.540)
Commodity Previous Metals - COPM	0.046**			0.032**	0.035*	
	(3.290)			(2.917)	(2.469)	
High minus Low - HML		0.094**	-0.081*	0.084**	0.082**	0.064**
		(5.048)	(-2.478)	(4.745)	(3.616)	(3.886)

Panel B - Dep. Variable	Small	Large	Young	Old	Lockup	No Lockup
Market Index – MAI	0.228**	0.380**	0.294**	0.368**	0.277**	0.347**
	(5.467)	(8.936)	(11.211)	(9.913)	(4.988)	(10.886)
Commodity Energy - COEN	0.048**		0.044*			
	(3.514)		(2.757)			
Change in VIX - DVIX	-0.027*				-0.034*	
	(-2.456)				(-2.359)	
Commodity Agriculture - COAG	0.060*	0.086*	0.053*	0.091**	0.084*	0.081**
	(2.060)	(2.309)	(2.500)	(2.821)	(2.297)	(2.926)
High minus Low - HML		-0.190*	-0.253**	-0.142*		-0.131*
		(-2.544)	(-6.352)	(-2.180)		(-2.348)

Panel C

Growth, Adj. R-square:	0.742	0.790	0.639	0.821	0.773	0.807
Growth, F-statistic:	123.910	161.734	60.422	168.379	125.836	179.299
Growth, Prob (F-stat):	0.000	0.000	0.000	0.000	0.000	0.000
Recession, Adj. R-square:	0.837	0.781	0.916	0.818	0.789	0.843
Recession, F-statistic:	43.203	40.253	69.276	50.505	42.190	59.907
Recession, Prob (F-stat):	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This Table shows exposures of the multi-factor model during growth (Panel A) and recession (Panel B) periods, at fundamental level (size, age, and lockup). HF 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. * and ** denotes significance at 5% and 1% level respectively. The t-statistics are in parentheses; panel C reports adjusted R-squared and F-statistics for growth and recession periods; empty cells mean that there is no significant exposure to these factors.

Table 8
Multi-Factor Model during Bull and Bear Regimes

Panel A-Dep. Var.	Size Small	Size Large	Age Young	Age Old	Lockup-	Lockup-No
Market Index - MAI	0.410**	0.390**	0.403**	0.399**	0.422**	0.367**
	(17.309)	(26.012)	(14.590)	(28.150)	(23.774)	(27.542)
Commodity Energy - COEN	0.033**	0.027**	0.034**	0.028**	0.030**	0.026**
	(3.864)	(3.929)	(2.681)	(4.195)	(3.682)	(4.285)
Small minus Big - SMB	0.133**	0.151**		0.149**	0.165**	0.127**
	(5.932)	(8.094)		(8.424)	(7.443)	(7.684)
Momentum - MOM	0.070**	0.052**	0.112**	0.052**	0.066**	0.053**
	(4.640)	(4.131)	(5.356)	(4.417)	(4.499)	(4.767)
Commodity Precious Metals - COPM	0.044**			0.032**	0.035*	
	(3.081)			(2.880)	(2.520)	
High minus Low - HML	0.069**	0.100**		0.095**	0.095**	0.080**
	(2.624)	(4.591)		(4.606)	(3.684)	(4.119)
Change in VIX - DVIX	0.010*					
	(2.033)					
Panel B-Dep. Var.	**Size Small**	**Size Large**	**Age Young**	**Age Old**	**Lockup-**	**Lockup-No**
Market Index - MAI	0.237**	0.149*	0.223**	0.175**	0.196**	0.165**
	(6.025)	(2.467)	(7.111)	(3.369)	(3.313)	(3.718)
Exchange Rate - EXCH	-0.193*					
	(-2.553)					
High minus Low - HML	-0.070*		-0.176**			
	(-2.268)		(-6.171)			
Commodity Energy - COEN	0.043**					
	(3.754)					
Change in VIX – DVIX	-0.021*	-0.032*		-0.028*	-0.034**	-0.023*
	(-2.421)	(-2.517)		(-2.579)	(-2.801)	(-2.483)
Small minus Big – SMB	0.103*	0.193**	0.142**	0.159**	0.206**	0.140**
	(2.378)	(3.079)	(3.226)	(2.956)	(3.347)	(3.052)
Commodity Industrial Metals – COIM		0.097**	0.113**	0.100**	0.086*	0.087**
		(2.811)	(4.466)	(3.362)	(2.521)	(3.428)
Panel C						
Bull, adj. R-square:	0.705	0.774	0.606	0.804	0.749	0.791

Bull, F-statistic:	87.702	174.727	84.061	174.787	127.063	193.394
Bull, Prob (F-stat):	0.000	0.000	0.000	0.000	0.000	0.000
Bear, adj. R-	0.873	0.759	0.898	0.811	0.808	0.824
Bear, F-statistic:	41.054	28.619	69.312	38.602	37.866	41.951
Bear, Prob (F-stat):	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This Table reports the exposures of the multi-factor model for the bull (Panel A) and bear (Panel B) regimes, at fundamental level (size, age, and lockup). HF 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 library (Ibbotson Associates). MAI, GEMI, COEN, COPM, COIM, COAG and RLE are excess RF returns. * and ** denote significance at 5% and 1% level respectively. The t-statistics are in parentheses; panel C reports adjusted R-squared and F-statistics; empty cells mean that there is no significant exposure to these factors.

Table 9
MAI, SMB, HML, and MOM Analysis by Fundamental Group and State

Market Index –MAI	Growth (Good State)	Recession (Bad State)	Difference (Base Growth)	Bull regimes (Best state)	Bear regimes (Worst State)	Difference (Base Bull)
MAI, Size Small (S)	0.376**	0.228**	-39.40%	0.410**	0.237**	-42.31%
MAI, Size Large (L)	0.383**	0.380**	-0.68%	0.390**	0.149**	-61.85%
MAI, Z-value of difference (S-L)	-0.342	-2.565**		0.723	1.220	
SMB, Size Small (S)	0.127**			0.133**	0.103*	-22.72%
SMB, Size Large (L)	0.154**			0.151**	0.193**	27.80%
SMB, Z-value of difference (S-L)	-1.056			-0.611	-1.183	
HML Size Small (S)				0.069**	-0.070*	-201.01%
HML, Size Large (L)	0.094**	-0.190*	-301.59%	0.100**		
HML, Z-value of difference (S-L)				-0.903		
MOM, Size Small (S)	0.063**			0.070**		
MOM, Size Large (L)	0.048**			0.052**		
MOM, Z-value of difference (S-L)	0.478			0.927		
MAI, Age Young (Y)	0.393**	0.294**	-25.09%	0.403**	0.223**	-44.77%
MAI, Age Old (O)	0.394**	0.368**	-6.43%	0.399**	0.175**	-56.24%
MAI, Z-value of difference (Y-O)	-0.022	-1.626†		0.128	0.791	
SMB, Age Young (Y)					0.142**	
SMB, Age Old (O)	0.152**			0.149**	0.159**	6.99%
SMB, Z-value of difference (Y-O)					-0.240	
HML, Age Young (Y)	-0.081**	-0.253**	211.95%		-0.176**	
HML, Age Old (O)	0.084**	-0.142*	-268.85%	0.095**		
HML, Z-value of difference (Y-O)	-4.435**	-1.458†				
MOM, Age Young (Y)	0.103**			0.112**		
MOM, Age Old (O)	0.050**			0.052**		
MOM, Z-value of difference (Y-O)	2.096**			2.488**		
MAI, Lockup-Yes (Y)	0.430**	0.277**	-35.44%	0.422**	0.196**	-53.35%
MAI, Lockup-No (N)	0.355**	0.347**	-2.39%	0.367**	0.165**	-55.06%
MAI, Z-value of difference (Y-N)	3.577**	-1.085		2.491**	0.422	
SMB, Lockup-Yes (Y)	0.173**			0.165**	0.206**	24.92%
SMB Lockup-No (N)	0.128**			0.127**	0.140**	10.46%

SMB, Z-value of difference (Y-N)	1.744*			1.356†	0.849
HML, Lockup-Yes (Y)	0.082**			0.095**	
HML, Lockup-No (N)	0.064**	-0.131*	-304.36%	0.080**	
HML, Z-value of difference (Y-N)	0.620			0.477	
MOM, Lockup-Yes (Y)	0.047**			0.066**	
MOM, Lockup-No (N)	0.060**			0.053**	
MOM, Z-value of difference (Y-N)	-0.737			0.735	

Notes: This Table reports the market exposures of the proposed multi-factor model for all the groups (portfolios). Z-values of the differences of the MAI, SMB, HML, and MOM coefficients among groups, are presented. †,* and ** denote significance at 10%, 5% and 1% level respectively - (see, Paternoster et al., 1998). Empty cells mean that there is no significant exposure to these factors.

Table 10

MAI Analysis by Fundamental, Strategy Group, and State

MAI Exposures	Growth	Recession	Difference (Base Growth)	Difference (% Base Growth)	Bull	Bear	Difference (Base Bull)	Difference (% Base Bull)
Panel A. Directional Strategies								
Size Small	0.276	0.234	0.042	15.28%	0.279	0.134	0.145	51.88%
Size Large	0.238	0.172	0.066	27.69%	0.238	0.162	0.076	31.84%
Age Young	0.278	0.084	0.194	69.73%	0.271	0.295	-0.024	8.87%
Age Old	0.230	0.135	0.095	41.27%	0.223	0.110	0.113	50.74%
Lockup-Yes	0.169	0.094	0.075	44.58%	0.150	0.162	-0.012	7.83%
Lockup-No	0.252	0.144	0.108	42.90%	0.239	0.112	0.126	52.87%
Panel B. Semi-Directional Strategies								
Size Small	0.301	-	-	-	0.261	0.215	0.046	17.72%
Size Large	0.226	0.220	0.007	2.94%	0.222	0.173	0.049	22.14%
Age Young	0.223	0.274	-0.052	-23.15%	0.280	0.248	0.031	11.18%
Age Old	0.241	0.301	-0.059	-24.75%	0.232	0.174	0.058	24.81%
Lockup-Yes	0.446	-	-	-	0.333	0.514	-0.181	54.29%
Lockup-No	0.219	0.411	-0.192	-88.04%	0.216	0.225	-0.009	3.97%
Panel C. Non-Directional Strategies								
Size Small	0.131	0.063	0.068	52.06%	0.193	-	0.219	113.42%
Size Large	0.096	-	-	-	0.101	-	-	-
Age Young	0.139	0.174	-0.035	-24.91%	0.095	-	-	-
Age Old	0.103	0.077	0.026	25.69%	0.101	-	-0.258	-255.06%
Lockup-Yes	0.115	0.316	-0.202	-175.52%	0.114	-	-	-
Lockup-No	0.102	0.060	0.042	41.50%	0.082	-	-0.290	-354.12%

Notes: This Table presents the average exposures to the MAI market index for all groups (size, age, and lockups) that are directional-Panel A (absolute values of the correlation coefficient above 0.5), semi-directional-Panel B (absolute values of the correlation coefficient between 0.22 and 0.49) and non-directional strategies-Panel C (absolute values of the correlation coefficient between 0 and 0.21) during growth and recession periods as well as the bull and bear regimes. Since the growth periods and bull regimes are the longest, we use them as the base to measure the percentage difference of the exposure (MAI exposure for each mixed case is statistically significant from zero). The fourth (eighth) column gives the difference of the growth period (up regime) return minus the recession period (down regime) return. The fifth (ninth) column shows the percentage difference of the growth period (up regime) return minus the recession period (down regime) return.