Measuring Hedge Fund Performance: A Markov Regime-Switching with False Discoveries Approach *

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February 2, 2016

Preliminary version

Abstract

We propose a Markov regime-switching approach accounting for false discoveries in order to measure hedge fund performance. It enables us to extract information from both time-series and cross-sectional dimensions of panels of individual hedge fund returns in order to distinguish between skilled, unskilled and zero-alpha funds for a given state of the economy. Applying our approach to individual hedge funds belonging to the Long/Short Equity Hedge strategy, we find that their performance cannot be explained by luck alone, and that the proportion of zero-alpha funds in the population decreases when accounting for alpha regime dependence. However, the proportion of truly skilled funds is higher during expansion periods, while unskilled funds tend to be more numerous during recession periods. Moreover, sorting on regime dependent alphas instead of unconditional alphas improves investors' ability to select funds that outperform their benchmarks in both regimes of the economy, and thus maximizes the performance persistence effect of top performer fund portfolios.

JEL classification: C51, C52, G12

Keywords: Hedge fund performance, Markov regime-switching factor models, false discovery rates, business cycles, portfolio choice.

*We gratefully acknowledge financial supports from the chair of the QUANTVALLEY/Risk Foundation: Quantitative Management Initiative, as well as from the project ECONOM&RISK (ANR 2010 blanc 1804 03).

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1 Introduction

Hedge Fund managers are not constrained to publicly report their portfolio holdings implying a high level of opacity on the drivers of fund returns. Since either the risk exposures of hedge fund strategies or the style drifts are not directly known, the question whether these alternative investment vehicles really add value after controlling for risk exposures and fees is closely related to the comprehension of the determinants of hedge fund returns, whose number or nature is uncertain and time-varying even for funds belonging to the same investment strategy. In other words, to measure hedge fund net performances (i.e., hedge fund alphas), one should both control for the relevant common risk factors and implement a suitable methodology accounting for statistical particularities of hedge fund return dynamics. More specifically, the evaluation of hedge fund performance is subject to many difficulties. First, the complexity and the opacity of hedge fund strategies increases the risk of model misspecification. Second, since the top performers are drawn from a large cross-section of hedge funds, some managers seem to generate positive net performances only by chance. Third, hedge fund managers implement dynamic trading strategies implying that fund risk exposures, as well as their risk profile are time-varying and dependent on the macroeconomic conditions. A related consequence is that hedge fund performances do not follow parametric normal distributions but display option-like payoffs.

On the one hand, the growth of the hedge fund industry has reoriented the factor modeling effort toward alternative returns offered by hedge funds. A wide literature deals with the particularities of hedge fund risk exposures. A first stream in the literature proposes nonlinear and/or strategy-based factors in order to capture nonlinearities of hedge fund returns as well as style heterogeneity while using linear regression methods. For instance, Agarwal and Naik (2004), Mitchell and Pulvino (2001), Fung and Hsieh (2001) focus on option-based factors, while Fung and Hsieh (2004) propose strategy-based risk exposures. A second stream focuses on exogenous time-varying risk exposures. For instance, Hasanhodzic and Lo (2007) implement rolling-period analysis to capture the dynamics of hedge fund risk exposures, while Roncalli and Teiletche (2008) focus on the Kalman filter framework to deal with this same issue. In addition, based on an approximate latent risk factor analysis, Darolles and Mero (2011) deal with the time-varying hedge fund risk profile as well as the factor selection issue. Fung and Hsieh (2004), Agarwal et al. (2011) and Fung et al. (2008) consider breakpoints in factor exposures, introducing dynamic betas and time-varying performances. A third stream in the literature deals with endogenous hedge fund style drifts. For instance, Billio et al. (2012), Blazsek and Downarowicz (2013), Saunders et al. (2010), Erlwein and Muller (2013) propose regime-dependent risk exposures of several hedge fund indexes.

On the other hand, the recent economic crisis, starting with the liquidity dry up situations faced by the traders in August 2007, followed by the subprime crisis exacerbated by the failure of the Lehman Brothers (September 2008), and the sovereign debt turmoil, have particularly impacted the hedge fund industry. In this new context of stressed economic environment, a natural question is whether hedge funds really add value after controlling for risk reward and fees, and if so, whether the hedge fund managers generate extra profits during recession periods, which are often characterized by poor performances of other more traditional asset classes. From this perspective, the efforts of the practitioners as well as academic research during the past few years have concentrated on the net performance of hedge fund returns, i.e., the net returns after controlling for common risk exposures and fees. Investors are interested in selecting the true top performer funds in order to optimize their portfolios. The academics try to deal with the dynamic patterns of hedge fund alphas, and, thus, provide the investors with the appropriate econometric tools in order to efficiently pick up the truly skilled managers, especially during crisis periods. Numerous papers in the literature deal specifically with hedge fund net performances by focusing on different aspects of their return generating process. Billio et al. (2012), Bollen and Whaley (2009), Patton and Ramadorai (2013) and Criton and Scaillet (2014) concentrate on dynamic risk exposures, Sadka (2010) and Cao et al. (2013) investigate liquidity exposures, Ang et al. (2011) concentrate on leverage, Bollen and Pool (2009) and Jagannathan et al. (2010) analyze misreporting of returns, Titman and Tiu (2011) and Sun et al. (2012) concentrate on low R^2 and low risk exposures, Kosowski et al. (2007) control for luck in hedge fund performances and deal with alpha non-normality as well as short sample issues, and Billio et al. (2014) propose a Markov regime-switching approach applied to individual hedge funds in order to assess the performance of several investment strategies through aggregation.

In this paper, we propose a generalized Markov regime-switching (MRS) framework accounting for false discovery rate (FDR) in order to measure hedge fund net returns after controlling for risk reward and fees. It enables us to extract information from both time-series and cross-sectional dimensions of panels of individual hedge fund returns belonging to the same investment strategy in order to distinguish between skilled, unskilled and zero-alpha funds for a given state of the economy. For this purpose, we combine two approaches which have been developed independently in the literature and have been applied to mutual fund returns: the FDR approach of Barras et al. (2010) applied to a large cross-section of mutual fund returns, and the MRS model with time-varying transition probabilities of Kosowski (2011) applied to mutual fund Index returns. The MRS part of our framework allows us to estimate regime-dependent alphas for individual hedge funds. As suggested by Kosowsky (2011), we let the transition probabilities vary conditional on the lagged values of the composite leading index (CLI), i.e., a macroeconomic indicator commonly used to forecast the future state of the economy. This allows us to endogenously account for the regime-dependence of hedge fund net performance by linking it directly to the information set available to fund managers, which is likely to underlie their decision making process. Based on the filtered probabilities of each state, we then separate the full time-series of returns for each fund into two subsequences in order to control for luck in the hedge fund performance conditional on the state of the economy. For this purpose, we apply the FDR approach of Barras et al. (2010) to the population of fund alphas for a given state of the economy. In this sense, the FDR part of our approach presents the advantage of clearly defining the frontiers between skilled, unskilled and zero-alpha fund populations for a given economic regime.

Controlling for either luck or regime-dependence of hedge fund performances is not new in the literature. For instance, Kosowski et al. (2007) propose a Bayesian and bootstrap analysis in order to measure individual hedge fund alphas. The non-parametric bootstrap part of their method allows one to control for luck in the hedge fund performance since it minimizes model misspecification, as well as accounts for alpha non-normality [see Kosowski et al. (2006)]. The Bayesian estimation part deals with short sample problem and improves the precision of the estimated alphas [see Pastor and Stambaugh (2002)]. However, this approach presents several limitations. First, it does not account for dynamic regime-dependent hedge fund trading strategies; for example Long-Short strategies are more likely to be long equity during up-markets and short equity during down-markets. Second, it does not assess the hedge fund industry as a whole by distinguishing between zero-alpha, skilled and unskilled funds; the frontier between zero-alpha and (un)skilled funds is not well defined. Third, it does not tell how to locate skilled funds in the right tail of the cross-sectional performance distribution. In contrast, our framework deals with each one of these three limitations and, in this sense, it can be considered as complimentary of that of Kosowski et al. (2007). As discussed above, the MRS part of our framework allows us to endogenously account for the regime-dependence of hedge fund net performance, while the FDR part of our approach used to control for luck in the cross-section of hedge fund performances presents the advantage of clearly delimitating the subsamples of skilled, unskilled and zero-alpha funds. We can thus analyze the population of hedge funds as a whole by reporting the proportion of skilled, zero-alpha and unskilled funds for a given state of the economy, and, more importantly, we can locate the truly skilled funds in the right tail of the cross-sectional performance distribution conditional on the state of the economy, which has direct implications for portfolio management.

Criton and Scaillet (2014) use a time-varying coefficient model (TVCM) to estimate dynamic alphas and betas depending on time. Then, they apply the FDR approach of Barras et al. (2010) in order to control for luck in the hedge fund performance both during the overall period and during two particular stressed events, the LTCM and the internet bubble crisis . To assess the fund performance during the overall period, the authors average the track of each fund alpha through the whole time period. However, even if they use time-varying instead of static alphas, averaging them through time still may offset some aspects of the true fund performance. In particular high alphas during some periods of time and low alphas during other time points for the same fund may offset each other. Instead, our MRS approach allows us to distinguish between expansions and recessions and provide regime-dependent alphas. For each fund, these two alphas represent two synthetic indicators of the manager skills during a given state of the economy. The FDR approach can thus be implemented conditional on the state of the economy in order to estimate the portion of truly skilled funds. Note also that the authors focus, ex post, on two isolated crisis events of length 3 months each and estimate the portion of funds whose managers have done well during these events. Instead, we propose a more global approach allowing us to distinguish, ex ante, between expansion and recession periods with transition probabilities being endogenously determined by the data and closely related to the macroeconomic predictors of the state of the economy such as the CLI. The length and the occurrence of the recession periods is not chosen arbitrarily ex post but is rather determined by the data. We can thus estimate the portion of truly skilled and unskilled managers during recessions and expansions. In addition, our approach has a predictive extent since the regimes are endogenously related to the lagged values of the CLI which is a good predictor of the future state of the economy.

As for Billio et al. (2014), they are the first to apply a MRS framework to investigate individual hedge fund performances. For each fund, the authors first control for several common risk factor effect on its returns. Then they inject the static estimated alpha on the residuals and apply a MRS framework to estimate a regime dependent alpha; the unconditional regime-weighted alpha for each fund is obtained by averaging its two regime-dependent alphas by the respective smoothed probabilities for each state. Finally, the authors aggregate these individual fund unconditional alphas across all funds belonging to a given strategy by weighting them by the relative AUM, and compare these aggregated alphas, for each strategy, with the static aggregated alphas obtained by the standard OLS regressions. Our approach differs from that of Billio et al. (2014) regarding three main aspects. First, the authors are specifically interested on the magnitude of the aggregated alphas for a given hedge fund strategy and not on their cross-sectional patterns for a given state of the economy. Their approach can be considered as a more accurate alternative of the other one applying the MRS regression model directly to several hedge fund strategy Indexes. This is motivated by previous literature suggesting that when linear dynamic models [Pesaran (2003)] and non-linear models [Van Garderen et al. (2000)] are used, aggregating after the parameter estimation produces better forecasts in the mean square sense than estimating the same parameters after aggregation. In contrast, we focus on the cross-sectional patterns of the individual fund performance distribution within a given strategy. Unlike Billio et al. (2014), we control for luck, and assess a given hedge fund strategy as a whole by distinguishing between zero-alpha, skilled and unskilled fund population. By doing so, our MRS with FDR approach allows us to locate truly skilled funds, for a given strategy, in the right tail of the cross-sectional performance distribution conditional on the state of the economy, and, as such, has direct implications for portfolio management purposes. Second, instead of using static transition probabilities as in Billio et al. (2014), we allow for them to vary conditional on the lagged changes of the CLI, which are commonly used to forecast the future state of the economy. The interest in using time-varying transition probabilities depending on the lagged changes of the CLI is twofold: i) it allows us to account for manager information set underlying their investment decision making process; ii) the regime-dependent time series across funds are driven by the same macroeconomic indicator (i.e., the CLI), so that we expect the regimes to be homogenous across individual funds belonging to the same investment strategy. Third, the authors do not account for switching exposures to systematic factors, since the short life of most hedge funds in the database could be responsible for high risk of over-parameterization. Here, we account for regime-dependent alphas as well as betas, and use bootstrapped t-statistics instead of standard ones in order to deal with model misspecification and parameter non-normality, thus, implicitly reducing the risk of over-parametrization inherent to short samples.

The contribution of this paper is twofold. *i)* We are the first to combine the MRS and FDR approaches to model the dynamics of hedge fund alphas. We, thus, propose a unified and generalized framework in order to extract valuable information on hedge fund performances from both time-series and cross-sectional dimensions. The time-series dimension of individual hedge funds enables us to estimate regime-dependent alphas, which are endogenously related to the macroeconomic variables driving the investment decisions of fund managers according to the state of the economy. The cross-sectional dimension, allow us to estimate the portion of truly skilled, unskilled or zero-alpha funds conditional on the state of the economy. Indeed, some managers may outperform their benchmarks during a given state of the economy, while underperforming them during the other. For instance, as reported by Kosowsky (2011), the mutual fund managers outperform their benchmarks during recessions, but their net performance is flat during expansions. Our framework reconciles and completes several previous and less general articles, which can be considered as special cases. For instance, in the absence of the regime-dependent pattern of the hedge fund performance, we obtain the Kosowski et al. (2007) case. In addition, omitting for the FDR part of our approach would prevent us to control for luck in the cross-section of fund performances; in this case, our framework would reduce to either those based on hedge fund indexes instead of individual funds [Billio et al. (2012), Blazsek and Downarowicz (2013), Saunders et al. (2010), and Erlwein and Muller (2013) among others], or to that of Billio et al. (2014) who use the cross-section dimension to simply obtain better estimates of the aggregated alphas without distinguishing between the truly good (or bad) performers and the lucky (or un lucky) ones.

ii) Our framework allows us to analyze the population of hedge funds as a whole by estimating the portion of skilled, zero-alpha and unskilled funds for a given state of the economy and, more importantly, to locate the truly skilled funds in the right tail of the cross-sectional performance distribution conditional on the state of the economy. In this sense, our approach has direct portfolio management implications since it provides investors with a useful tool in order to improve their ability to select funds outperforming their benchmarks in both regimes of the economy, and thus maximize the out-of-sample performance persistence effect of top performer fund portfolios.

Applying our approach to individual hedge funds belonging to Long/Short Equity Hedge (LSEH) strategy, we find that their performance cannot be explained by luck alone, and that the proportion of zero-alpha funds in the population decreases when accounting for regime-dependence with time-varying transition probabilities. However, the proportion of truly skilled funds is higher during expansion periods, while unskilled funds tend to be more numerous during recession periods. Moreover, sorting on regime-dependent alpha instead of unconditional alpha improves the ability to select the truly good performing funds in both regimes of the economy, and thus maximize the out-of-sample net returns of top performer fund portfolios.

The rest of paper is organized as follows. In section 2, we present our framework. We start by a brief review of the main features of the FDR approach used to control for luck in the cross-section of hedge funds performances. Then, we present the MRS with FDR approach and discuss its implications for portfolio management. Section 3 describes the data. In section 4, we challenge our approach and discuss the main empirical results. In particular, we compare our results to those obtained by some competing procedures. We also report a performance persistence analysis in order to assess the empirical implications of our approach for portfolio management purposes. Finally, section 5 concludes the paper.

2 Our framework

We first present the factor model used to estimate hedge fund alphas. Then, we provide a brief review on how to control for luck in the cross-section of hedge funds performances based on the false discovery rate (FDR) approach. Finally, we present our Markov regime-switching with FDR approach and discuss its implications for portfolio choice.

2.1 How to measure hedge fund alphas?

The use of multifactor models in order to examine the abnormal performance of hedge funds is standard in the literature. We here provide a short resume of the linear factor model framework where the estimated coefficients are supposed to be time-invariant. Several hypothesis of this standard model are relaxed later on in this paper. Let R_{it} be the net-of-fee excess return (i.e., after controlling for fees and the risk-free rate) of fund i ($i = 1, ..., N$) at date t ($t = 1, ..., T$), and F_j a ($T \times 1$) vector of the excess returns of the j^{th} common factor used to explain hedge fund performance ($j = 1, ..., K$).

The factors F_j ($j = 1, ..., K$) represent the common shocks that drive the variations of asset returns. When dealing with hedge funds, the K factors can be considered as a set of buy-and-hold, as well as dynamic portfolios commonly used as underlying benchmarks for a given hedge fund strategy. Here, we use a set of seven common factors in order to compute the net performances of individual funds belonging to the Long/Short Equity (LSE) hedge fund strategy. This set includes the three equity-oriented risk factors of Fama and French (1993) together with that of Carhart (1997) in order to capture the common risks inherent to market portfolio, size, value and momentum effects, respectively; two bond-oriented factors in order to account for common risks related to fixed income markets; and one option-based risk factor proposed by Agarwal and Naik (2004) in order to capture non-linear risk exposures characterizing the dynamic trading strategies implemented by hedge fund managers.[1]

The standard static factor analysis consists in simply estimating the following time-series OLS regression for a given hedge fund i:

$$R_{it} = \alpha_i + \sum_{j=1}^{K} \beta_{ij} F_{jt} + \epsilon_{it}. \tag{2.1}$$

In this equation, β_{ij} represents the risk exposure of fund i to the common factor j, and α_i corresponds to the abnormal performance of fund i, i.e., the net performance after controlling for risk reward, fees and risk-free rate. In this article, we focus on the estimated α_i for the whole population of individual LSE hedge funds of our sample. The question of interest is whether LSE hedge funds really add value after controlling for luck and the dependence of manager skills on the business cycles. To answer this question, we first control for luck in the cross-section of fund estimated alphas. The FDR approach used for this purpose is presented in the following subsection. Then, we combine the FDR approach (initially applied to a static factor model framework) with a Markov regime-switching factor model in order to estimate the portion of truly skilled and unskilled funds conditional on a given state of the economy (i.e., recession versus expansion economic regimes). Our Markov regime-switching with FDR approach is presented in subsection 2.3.

[1] A detailed description of the factors is provided in section 3.

2.2 Accounting for false discoveries in the cross-section of hedge fund alphas

We first discuss why is it important to control for luck in the cross-section of hedge fund net performances. Then, the FDR approach is briefly introduced by emphasizing its benefits in analyzing the net performances of a large cross-section of hedge funds belonging to the same investment strategy.

2.2.1 False discoveries and hedge fund abnormal returns

In order to investigate whether a fund manager generates abnormal returns after controlling for risk reward and fees, we need to analyze the α_i parameter of equation (2.1).[2] According to their alpha, we can distinguish three categories of fund: *i*) the unskilled funds exhibiting truly negative alphas; *ii*) the skilled funds characterized by truly positive alphas; *iii*) the zero-alpha funds whose alphas are not economically different from zero.

Since the true alpha of a given fund cannot be observed, it should be estimated by running the regression (2.1). The interest in estimating hedge fund α is twofold. First, based on the estimated α, denoted by $\hat{\alpha}$, hedge fund investors can identify the outperforming funds to be included in their portfolios. Second, the estimation of individual fund alphas allows us to assess the performance of a given fund universe by appreciating the prevalence of the skilled funds in the entire population. One simple way to do this is to count for the number of funds with statistically significant $\hat{\alpha}$ at a given confidence level, i.e., funds with (alpha) t-statistics being higher (in absolute value) than the significance threshold implied by the considered level of confidence. However, this methodology does not account for the fact that some fund positive $\hat{\alpha}$ may be due to luck while their true α is zero. To illustrate this point, let us consider a population of funds whose true alphas are not economically different from zero. At the usual significance level of 5%, 5% of these funds are expected to exhibit statistically significant estimated alphas while the true ones equal to zero. These zero-alpha funds presenting statistically significant estimated alphas are called "false discoveries"; some of them will be lucky (i.e., $\hat{\alpha} > 0$ while $\alpha = 0$), and the others will be unlucky ($\hat{\alpha} < 0$ while $\alpha = 0$). As discussed by Barras et al. (2010), if one does not control for false discoveries, she risks to overstate the prevalence of (un)skilled funds in the population, since some truly zero-alpha funds can be falsely included in the (un)skilled fund category.

In other words, a given fund population can be considered as a mixture or three distinct categories: skilled, zero-alpha and unskilled funds. Since we do not observe the true α, we do not know with certainty whether a significant positive estimated alpha is due to luck or manager skills. Thus, accounting for false discoveries allows us to isolate the skilled (or unskilled) funds among those exhibiting statistically significant and positive (or negative) $\hat{\alpha}$. For this purpose, it is crucial to allow for the three fund categories to present different distribution patterns of the estimated alphas. For instance, according to Barras et al. (2010), the whole population of hedge fund estimated alphas can be considered as a mixture of three normal distributions differing from their mean parameter values. Chen et al. (2012) extend the idea of Barras et al. (2010) by considering instead a mixture of three distinct distributions for the estimated alphas. In this paper, we focus on the FDR approach of Barras et al. (2010) whose main features are summarized in the next paragraph.

2.2.2 Controlling for luck based on the FDR approach of Barras et al. (2010)

Consider a population of M funds assumed to be a combination of three distinct performance groups: skilled, zero-alpha and unskilled funds. Since the true fund alphas are not observed,they should be estimated together with their associated t-statistics. Let $\hat{\alpha}_i$ be the estimated alpha for fund i and $\hat{t}_i = \hat{\alpha}_i / \hat{\sigma}_{\hat{\alpha}_i}$ be the estimated t-statistic. Barras et al. (2010) focus on $\hat{t}_i$ in order to infer the prevalence

[2] Recall that in this equation we implicitly controll for the risk-free rate as well since we work with hedge fund returns in excess of the risk-free rate.

of each group in the entire population.[3] The entire population of fund t-statistics is considered to be a mixture of three distinct normal distributions differing from their mean parameter values. However, after estimating the fund t-statistics for the whole fund universe under consideration, what we really observe is the empirical distribution of $\hat{t}_i$. Without controlling for false discoveries, we are unable to tell whether a statistically significant $\hat{t}_i$, at a given significance level γ, is due to (un)luck or to (un)skilled manager.[4] The main objective here is to control for false discoveries in the cross-sectional distribution of fund alpha t-statistics, thus, being able to estimate the prevalence of skilled and unskilled funds in the entire population.

Let π_0, π_A^+ and π_A^- be the proportion of zero-alpha, skilled and unskilled funds in the population, respectively. Then, $E(F_\gamma^+)$ and $E(F_\gamma^-)$ represent the expected proportion of lucky and unlucky funds for a given γ, and can be computed as follows:[5]

$$E(F_\gamma^+) \quad = \quad E(F_\gamma^-) = \pi_0 \frac{\gamma}{2}. \tag{2.2}$$

Let $E(S_\gamma^+)$ and $E(S_\gamma^-)$ be the expected proportion of funds with significantly positive and negative estimated alphas, respectively. The quantities of interest after controlling for luck are the expected proportions of skilled and unskilled funds, denoted by $E(T_\gamma^+)$ and $E(T_\gamma^-)$, respectively:[6]

$$E(T_\gamma^+) = \hat{\pi}_A^+ \quad = \quad E(S_\gamma^+) - E(F_\gamma^+) = E(S_\gamma^+) - \pi_0 \frac{\gamma}{2}. \tag{2.3}$$

$$E(T_\gamma^-) = \hat{\pi}_A^- \quad = \quad E(S_\gamma^-) - E(F_\gamma^-) = E(S_\gamma^-) - \pi_0 \frac{\gamma}{2}. \tag{2.4}$$

Note that, the true proportion π_0 of zero-alpha funds in the population is not observed and should be estimated. As suggested by Barras et al. (2010), we compute its empirical counterpart, $\hat{\pi}_0$, based on a two-step procedure. The first step consists in running the OLS regression (2.1) for each fund i in order to estimate $\hat{\alpha}_i$ parameters and the related t-statistics for the entire population of hedge funds. Then, the associated p-values are obtained using the bootstrap procedure of Kosowski et al. (2006).[7] The second step consists in estimating the proportion of zero-alpha funds by extrapolation, based on the bootstrapped p-values obtained in step 1.[8] Once $\hat{\pi}_0$ has been estimated, the empirical versions of

[3]In particular, as discussed by Kosowski et al. (2006), $\hat{t}_i$ exhibits better statistical properties than $\hat{\alpha}_i$ since the former adjusts for differing precision of $\hat{\alpha}_i$ across funds.

[4]Based on Monte-Carlo simulations, Barras et al. (2010) show that the proportion of skilled funds is overestimated because it includes some lucky zero-alpha funds.

[5]Note that, at a given significance level γ, a zero-alpha fund has a probability of $\gamma/2$ to exhibit an alpha t-statistic higher (or lower) than the significance threshold implied by γ. For instance, if $\gamma = 10\%$, there is a probability of 5% to get a t-statistics higher (or lower) than 1.65 (or -1.65) for a zero-alpha fund.

[6]As discussed by Barras et al. (2010), the chosen γ determines the segment of the tail related to lucky versus skilled (or unlucky versus unskilled) funds. As γ increases, $\hat{\pi}_A^+$ and $\hat{\pi}_A^-$ converge to π_A^+ and π_A^-, thus minimizing Type II error (failing to locate truly skilled or unskilled funds). In order to determine the location of truly skilled (unskilled) funds, equation (2.3) (or 2.4) should be evaluated for different values of γ. $E(S_\gamma^+)$ and $E(F_\gamma^+)$ increase with γ. However the amplitude of $E(T_\gamma^+)$ increase will depend on the increase of $E(S_\gamma^+)$ relative to $E(F_\gamma^+)$. When the skilled funds are located in the extreme right tail, the increase of γ (say from 10% to 20%) will result in small increase in $E(T_\gamma^+)$ since most of additional significant-alpha funds will be lucky funds. When the skilled funds are dispersed throughout the right tail, the increase of γ will result in a larger increase in $E(T_\gamma^+)$. In the first case, skilled funds can be more easily distinguished than in the second case.

[7]As discussed by Kosowski et al. (2006), the non-normality of the estimated alphas can characterize both the cross-section and the time-series dimensions. The cross-sectional non-normality can be addressed by using estimated Newey and West (1987) t-statistics instead of estimated alphas. However, the non-normality of the estimated alphas at the individual fund level still affects the cross-sectional distribution of the estimated t-statistics. To address this point, the authors apply the bootstrap procedure to Newy-West t-statistics instead of the estimated alphas to estimate p-values for a given level of confidence γ. For more details on the bootstrap methodology see Kosowski et al. (2006).

[8]As discussed by Barras et al. (2010), zero-alpha funds satisfy the null hypothesis $H_{0,i} : \alpha_i = 0$ implying that their p-values are uniformly distributed over the interval $[0, 1]$. Skilled and unskilled fund p-values tend to be very small because their estimated t-statistics tend to be far from zero. This information can thus be exploited to estimate π_0 without knowing the exact distribution of the p-values of the skilled and unskilled funds. It follows that a vast majority of estimated p-values larger than a sufficiently high threshold λ^*, say $\lambda^* = 0,6$, come from zero-alpha funds. Then, the proportion of the area on the right of the λ^* is measured as $\hat{W}(\lambda^*)/M$, with $\hat{W}(\lambda^*)$ being the number of funds having p-values higher than λ^*. Finally, extrapolating this area over the entire region between 0 and 1 allows us to estimate the proportion of zero-alpha

equations (2.2), (2.3) and (2.4) for a given γ are:

$$\begin{aligned} \hat{F}_{\gamma}^{+} &= \hat{F}_{\gamma}^{-} = \hat{\pi}_0 \frac{\gamma}{2}, \\ \hat{T}_{\gamma}^{+} &= \hat{S}_{\gamma}^{+} - \hat{\pi}_0 \frac{\gamma}{2}, \\ \hat{T}_{\gamma}^{-} &= \hat{S}_{\gamma}^{-} - \hat{\pi}_0 \frac{\gamma}{2}. \end{aligned}$$

Finally, the proportions of skilled and unskilled funds in the entire population are obtained, for a given γ^*, as follows:[9]

$$\hat{\pi}_A^{+} = \hat{T}_{\gamma^*}^{+}, \qquad \hat{\pi}_A^{-} = \hat{T}_{\gamma^*}^{-}. \tag{2.6}$$

2.3 A Markov regime-switching with FDR approach to assess hedge fund performance

The FDR approach presented above relies on static alphas and does not account for non-stationarities in the risk-adjusted performance measures. To deal with this issue, we propose an extended framework combining the Markov regime-switching analysis of Kosowsky (2011) with the standard FDR approach. In this subsection, we first discuss the biases arising when working with static instead of time-varying alphas depending on the economic conditions in order to assess whether hedge funds truly outperform their benchmarks. Then, we focus on the Markov regime-switching version of equation (2.1) and provide a brief review of the estimation procedure. Finally, we show how to control for luck in the cross-section of fund alphas conditional on the state of the economy.

2.3.1 Why does regime-switching matter when assessing hedge fund performance?

There are two main drivers of hedge fund risk-adjusted performance: manager asset selection skills and common risk exposures. On the one hand, manager asset picking skills may either depend on the regime of the economy [Basac et al. (2006), Avramov et al. (2011)] or be closely related to time-varying information asymmetries between corporate and fund managers, which seem to increase during recession and decrease during expansion periods [Shin (2003), Kothari et al. (2009)].[10] On the other hand, hedge fund managers implement dynamic trading strategies based on style drifts and benchmark timing skills, which depend on their expectations of future market fluctuations and macroeconomic conditions. This implies that hedge fund risk exposures as well as their risk profile are time-varying and depend on the state of the economy. Several articles focus on time-varying hedge funds betas and show that dynamic factor modeling approaches perform better than their static counterparts in estimating hedge fund risk exposures. For instance, Hasanhodzic and Lo (2007) implement rolling-period analysis to capture the dynamics of hedge fund risk exposures, Roncalli and Teiletche (2008) focus on the Kalman filter framework to deal with this same issue, Darolles and Mero (2011) use an approximated latent factor analysis in order to account for time-varying hedge fund betas as well as their risk profile, Fung and Hsieh (2004), Agarwal et al. (2011) and Fung et al. (2008) consider breakpoints in factor exposures, and Billio et al. (2012), Blazsek

funds as follows:

$$\hat{\pi}_0(\lambda^*) = \frac{\hat{W}(\lambda^*)}{M(1-\lambda^*)} \tag{2.5}$$

[9]Note that γ^* represents a sufficiently large significance level for $\hat{\pi}_A^{+}$ and $\hat{\pi}_A^{-}$ to converge to the true π_A^{+} and π_A^{-}, and is selected via a bootstrap procedure in order to minimize $\widehat{MSE}$ of $\hat{\pi}_A^{+}$ and $\hat{\pi}_A^{-}$.For more details regarding this technical point, see Barras et al. (2010)

[10]For a more detailed discussion and literature review see Kosowsky (2011) and Avramov et al. (2011).

and Downarowicz (2013), Saunders et al. (2010), Erlwein and Muller (2013) propose regime-dependent risk exposures for several hedge fund indexes.[11]

It follows that, the dynamic patterns of asset selection manager skills and hedge fund risk exposures can explain the time-variability of risk-adjusted fund performance as well as its dependance on the economic conditions. For instance Avramov et al. (2011) show that asset selection as well as benchmark timing skills of hedge fund managers vary as a function of market conditions, and that the lagged values of macroeconomic variables such as the credit spread or the VIX help predict hedge fund performance. Generally speaking, the estimated static (unconditional) alpha in equation (2.1) is not an accurate measure of hedge fund abnormal performance for two main reasons. First, the constant (unconditional) alphas are not truly risk-adjusted when obtained based on time-invariant betas because the true risk exposures of hedge funds are driven by dynamic trading strategies. Second, the constant alphas make abstraction of the dynamic character of manager asset selection skills, which in turn seem to depend on the market conditions [Avramov et al. (2011)].[12]

A direct consequence of working with static instead of dynamic alphas is that a fund appearing to belong to a zero-alpha category may yield a positive alpha during a specific regime of economy which may be offset by a bad abnormal performances during another regime. More importantly, when assessing the hedge fund industry as a whole, unconditional static alphas may understate the prevalence of outperforming funds in the entire population. Several papers in the literature deal with this issue. For instance, Criton and Scaillet (2014) use a time-varying coefficient model to estimate hedge fund alphas while controlling for the dynamics of their betas. Billio et al. (2014) implement a Markov regime-switching model to compute regime-dependent alphas for a given hedge fund strategy through aggregation. Kosowsky (2011) apply a Markov regime-switching procedure with time-varying transition probabilities to portfolios of mutual funds and find that fund managers tend to underperform their benchmarks during expansion periods and outperform them during recessions.

In this article, we deal with both the dynamic pattern of hedge fund net performances and the presence of false discoveries in the cross-section of fund alphas. We start by assuming that hedge fund alhas are regime dependent and that, for each state of the economy, we are in the presence of a mixture of three different normal distributions for the estimated (regime-dependent) alphas, which differ from their mean parameters.[13] We then propose e unified two-step approach combining the FDR framework of Barras et al. (2010) with the Markov regime-switching analysis of Kosowsky (2011).

In the first step, we rely on Kosowsky (2011) framework and use a Markov regime-switching approach factor model with time-varying transition probabilities to estimate individual hedge fund alphas. In particular, instead of using static transition probabilities as in Billio et al. (2014), we allow for them to vary conditional on the lagged changes of the composite leading index (CLI), which are commonly used to forecast the future state of the economy. This enables us to account for information being available to managers and underlying their investment decision making process. The second step consists in estimating the proportion of zero-alpha, skilled and unskilled funds conditional on the state of the economy. The following two paragraphs deal with each one of these two steps, respectively.

[11] Note that, making abstraction of time-varying risk exposures may induce important biases when estimating fund risk-adjusted performances. **?** and Kosowsky (2011)

[12] For a more detailed discussion, see Kosowsky (2011), who use the Grinblatt and Titman (1989) model of information and portfolio choice to illustrate the biases arising from applying unconditional performance measures to regime-dependent performance and risk processes.

[13] As discussed by Barras et al. (2010), the average alpha is positive, zero or negative for the population of skilled, zero-alpha and unskilled funds, respectively.

2.3.2 Estimating Markov regime-switching hedge fund alphas

In the first step of our approach, we focus on the Markov regime-switching (MRS) version of equation (2.1) with time-varying transition probabilities in order to estimate regime-dependent alphas and betas of individual hedge funds. Following Kosowsky (2011), we assume that there are two possible regimes, a recession and an expansion one, and allow for the transition from one state of the economy to the other to be endogenously determined by the data.[14] In fact, recession periods are inherent to events that occur periodically and have in common several patterns − such as increasing inflation rate and market volatility − which are likely to similarly impact the investment decision making process of hedge fund managers. In this sense, the MRS approach allows us to capture the effects of changing economic conditions on hedge funds' alpha, risk exposures as well as expected returns.

One alternative way to separate recession from expansion period effects on hedge fund returns would be to either use several state indicators such as production rate or NBER recession dates to identify the regime of the economy for each time observation, or to perform *ex post* sub-period analysis in order to separate recession from expansion periods. However, these approaches are purely descriptive and exogenous, and do not contain any predictive power since they rely on stale information (i.e., information which becomes known after the fact). In contrast, the MRS approach is forward looking and provides one-step-ahead state probabilities conditional on the available information at a given time point; as such, it enables us to perform accurate predictions regarding the conditional expected fund returns. Another possibility to capture the dynamics of fund abnormal returns and risk exposures is to use rolling period analysis [Hasanhodzic and Lo (2007), Darolles and Mero (2011)], Kalman filter procedure [Roncalli and Teiletche (2008)], or time-varying coefficient (semi-parametric) approache relying on kernel density estimations (Criton and Scaillet (2014)) in order to estimate time-varying alphas and betas. However, unlike the MRS framework, these approaches are unable to provide regime-dependent alphas and betas.

We now present the uni-variate MRS specification applied to equation (2.1) in order to estimate regime-dependent alphas and betas for a given individual hedge fund.[15] To distinguish between recession and expansion regimes, we consider a latent state variable, s_t, taking 2 possible values ($s_t = 1$ or $s_t = 2$). The MRS model given below allows the regressions coefficients of equation (2.1) to be state-dependent by takin two possible values, indexed by s_t for a given fund i, i.e., α_{i,s_t} and β_{ij,s_t}, with $i = (1, ..., N)$, $j = (1, ..., K)$, and $s_t = (1, 2)$:

$$\begin{aligned} R_{it} &= \alpha_{i,s_t} + \sum_{j=1}^{K} \beta_{ij,s_t} F_{jt} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma_{s_t}^2), \\ R_{it}|s_t &\sim N(\mu_{s_t,\sigma_{s_t}^2}), \quad s_t = 1, 2 \end{aligned} \tag{2.7}$$

Recall that, R_{it} represents the net-of-fee return of fund i at month t in excess of the risk-free rate. The parameters α_{i,s_t} and β_{ij,s_t} reflect manager asset selection and benchmark timing skills, respectively. They are indexed by s_t since they depend on manager expectations of the future state of the economy conditional on the available information.

[14]The MRS framework of Kosowsky (2011) relies on that of Hamilton (1989) who was the first to introduce regime-switching models in order to deal with endogenous regime shifts occurring repeatedly and reflecting asymmetric effects of business cycles.

[15]Note that, Kosowsky (2011) also develop a multi-variate MRS approach in order to estimate regime-dependent alphas and betas for a few number of mutual fund portfolios simultaneously. This multi-variate formulation has the advantage to allow the regime-dependent estimated parameters be the function of a single latent state variable S_t, which is not the case in the uni-variate framework. However, this multi-variate approach is not suitable in our framework relying on individual fund estimations because of the high number of the estimated parameters it would induce. For this reason, we focus on the uni-variate MRS approach. As it will discussed later on, conditioning the transition state probabilities for each fund by the same macroeconomic variable, i.e., the composite leading index (CLI), ensures homogeneity in the conditional state probabilities across all individual funds.

Let us now concentrate on the state transition probabilities inherent to the MRS specification given in (2.7). In order to account for hedge fund manager's information set underlying their investment decisions, one should make the transition probabilities depend on a macroeconomic indicator that helps forecast the future state of the economy. For this reason, instead of using static state transition probabilities as in Billio et al. (2014), we allow for them to vary according to the lagged changes of the composite leading index (CLI), as suggested by Kosowsky (2011).[16] For this purpose, the state transition probabilities are assumed to follow a first-order Markov chain:

$$p_t = Pr(s_t = 1|s_{t-1} = 1, \Delta c_{t-2}), \tag{2.8}$$

$$1 - p_t = Pr(s_t = 2|s_{t-1} = 1, \Delta c_{t-2}), \tag{2.9}$$

$$q_t = Pr(s_t = 2|s_{t-1} = 2, \Delta c_{t-2}), \tag{2.10}$$

$$1 - q_t = Pr(s_t = 1|s_{t-1} = 2, \Delta c_{t-2}), \tag{2.11}$$

with Δc_{t-2} representing the two-month lagged changes of the CLI. More specifically, the transition probabilities p and q are related to the two-month lagged changes of the CLI as follows:

$$p_t = \phi(d_1 \Delta c_{t-2}), \tag{2.12}$$

$$q_t = \phi(d_2 \Delta c_{t-2}), \tag{2.13}$$

where $\phi(.)$ represents the cumulative density function of a standard normal variable.[17]

For each individual fund, we use maximum likelihood procedure to estimate the vector of parameters $\Psi_i = [\alpha_{i,1}\ \alpha_{i,2}\ \beta_{ij,1}\ \beta_{ij,2}\ d_{i,1}\ d_{i,2}]$ implied by the model formulation (2.7)-(2.13) together with the conditional state probabilities $Pr(s_t = h|\Omega_{t-1}, \Psi_i)$, i.e., the probability of being in state s_t $(h = 1, 2)$ at time t given Ψ_i and the available information Ω_{t-1} at time $t - 1$.[18]

2.3.3 Accounting for FDR in the cross-section of regime-dependent alphas

The second step of our approach consists in estimating the prevalence of zero-alpha, skilled and unskilled funds in the entire population, conditional on the state of the economy. For this purpose, we combine the FDR approach of Barras et al. (2010) with the MRS framework of Kosowsky (2011).

First, given the conditional state probabilities $Pr(s_t = h|\Omega_{t-1}, \Psi_i)$ which are filtered in the previous step of our approach, we decompose the time series dimension for each fund into two state dependent time subsequences. The decision criterion for inferring the state of the regime at each time point t is that the regime has filtered probability above $0, 5$.[19] Let $\delta_{i,1t}$ and $\delta_{i,2t}$ be two indicator variables taking two possible values for a given time t $(t = 1, ..., T)$ and fund i $(i = 1, ..., N)$:

$$\delta_{i,1t} = 1 \; and \; \delta_{i,2t} = 0 \quad if \quad Pr(s_t = 1|\Omega_{t-1}, \Psi_i) > 0.5,$$
$$\delta_{i,1t} = 0 \; and \; \delta_{i,2t} = 1 \quad if \quad Pr(s_t = 1|\Omega_{t-1}, \Psi_i) < 0.5.$$

Given the values of $\delta_{i,1t}$ and $\delta_{i,2t}$, we decompose the time series of interest – i.e., the fund i net-of-fee returns $\{R_{it}\}_{t=1}^{T}$ and common factor returns $\{F_{jt}\}_{t=1}^{T}$ (for $j = 1, ..., K$) – into two state dependent subsequences, denoted by $\{R_{it_1}\}_{t_1=1}^{T_1}$ and $\{F_{jt_1}^{(i)}\}_{t_1=1}^{T_1}$ for state 1 and $\{R_{it_2}\}_{t_2=1}^{T_2}$ and $\{F_{jt_2}^{(i)}\}_{t_2=1}^{T_2}$ for state

[16] For a detailed discussion regarding the benefits of allowing state transition probabilities to vary over time as a function of the composite leading index, see Kosowsky (2011).

[17] Kosowsky (2011) omits the constant in the transition equations (2.12) and (2.13) in order to avoid for outliers to be classified into high volatility states as suggested by Perez-Quiros and Timmermann (2001).

[18] The maximum likelihood estimation procedure applied to (2.7)-(2.13) is not reported here. For a detailed review of this procedure, see the appendix B in Kosowsky (2011).

[19] Dates with filtered probability equalling 0,5 are thus excluded from the analysis. However, very few dates with filtered probabilities have $0, 5$ values.

2. Note that a given vector of time t observations $[R_{it}\ F_{1t}\ ...\ F_{Kt}]$ is assigned to the first subsequence ($t \to t_1$) when $\delta_{i,1t} = 1$ and to the second subsequence ($t \to t_2$) when $\delta_{i,2t} = 1$. The length of each time subsequence is $T_1 = \sum_{t=1}^{T} \delta_{i,1t}$ and $T_2 = \sum_{t=1}^{T} \delta_{i,2t}$, respectively. Generally speaking, for each fund i, we obtain two regime-dependent time subsequences of net-of-fee returns and risk factor returns: $[\{R_{it_1}\}_{t_1=1}^{T_1}\ \{F_{1t_1}^{(i)}\}_{t_1=1}^{T_1}\ ...\ \{F_{Kt_1}^{(i)}\}_{t_1=1}^{T_1}]$ for state 1, and $[\{R_{it_2}\}_{t_2=1}^{T_2}\ \{F_{1t_2}^{(i)}\}_{t_2=1}^{T_2}\ ...\ \{F_{Kt_2}^{(i)}\}_{t_2=1}^{T_2}]$ for state 2. Note that, the time subsequences of risk factor observations are also indexed by i since the uni-variate MRS specification used in this paper is estimated separately for each individual fund of our sample, making the (filtered) conditional state probabilities fund-specific. However, since the state transition probabilities for all the funds of our sample are driven by the same economic indicator, commonly used to forecast the future state of the economy, i.e., the CLI, we should expect the regime assignment process to be homogenous across individual funds. In this sense, the computation of regime-specific alphas enables us to appreciate whether a given fund manager is truly skilled or not during each of the two states of the economy considered separately.

Second, considering the fund population as a whole, we can compute the prevalence of truly skilled and unskilled funds conditional on the state of the economy. For this purpose, we implement the FDR approach of Barras et al. (2010) conditional on the state of the economy. To do so, we start by running the OLS regression (2.1) for each fund i based on each one of its two regime dependent subsequences in order to estimate regime dependent alphas and their associated t-statistics.[20] Then, the associated p-values are obtained by applying the bootstrap procedure of Kosowski et al. (2006) for each fund i conditional on the state of the economy. These procedure yields two cross-sectional distributions of fund bootstrapped (alpha) p-values (i.e., two $1 \times N$ vectors of fund bootstrapped (alpha) p-values), one for each state of the economy. Finally, we estimate the proportion of zero-alpha funds for a given regime by extrapolation, based on the regime-dependent bootstrapped p-values.[21] The estimated proportion of zero-alpha funds for a given state of the economy is now denoted $\hat{\pi}_0^{s_t}$ with $s_t = (1,\ 2)$. Moreover, the empirical regime-dependent versions of equations (2.2), (2.3) and (2.4) for a given γ become:

$$\begin{aligned}
\hat{F}^{+}_{\gamma,s_t} &= \hat{F}^{-}_{\gamma,s_t} = \hat{\pi}_0^{s_t}\frac{\gamma}{2}, \\
\hat{T}^{+}_{\gamma,s_t} &= \hat{S}^{+}_{\gamma,s_t} - \hat{\pi}_0^{s_t}\frac{\gamma}{2}, \\
\hat{T}^{-}_{\gamma,s_t} &= \hat{S}^{-}_{\gamma,s_t} - \hat{\pi}_0^{s_t}\frac{\gamma}{2}.
\end{aligned}$$

Similarly, the proportions of skilled and unskilled funds in the entire population conditional on the state of the economy are obtained, for a given γ^*, as follows:

$$\hat{\pi}^{+}_{A,s_t} = \hat{T}^{+}_{\gamma^*,s_t}, \qquad \hat{\pi}^{-}_{A,s_t} = \hat{T}^{-}_{\gamma^*,s_t}. \tag{2.14}$$

Note that, being able to estimate $\hat{\pi}^{+}_{A,s_t}$ and $\hat{\pi}^{-}_{A,s_t}$ for $s_t = (1,\ 2)$ allows us to appreciate the prevalence of skilled and unskilled managers within the considered hedge fund population conditional on the state of the economy. The benefits of controlling for false discoveries based on regime dependent alphas instead of static alphas will be discussed in section 4.

[20] Recall that the time subsequences of the variables of interest for a given fund i are $[\{R_{it_1}\}_{t_1=1}^{T_1}\ \{F_{1t_1}^{(i)}\}_{t_1=1}^{T_1}\ ...\ \{F_{Kt_1}^{(i)}\}_{t_1=1}^{T_1}]$ for state 1, and $[\{R_{it_2}\}_{t_2=1}^{T_2}\ \{F_{1t_2}^{(i)}\}_{t_2=1}^{T_2}\ ...\ \{F_{Kt_2}^{(i)}\}_{t_2=1}^{T_2}]$ for state 2.

[21] For each regime-dependent panel of fund bootstrapped (alpha) p-values, we implement the methodology of Barras et al. (2010) in order to estimate the proporion of zero-alpha funds.

3 The Data

In this article, we focus on individual Long Short Equity (LSE) hedge fund monthly net-of-fee returns extracted from TASS Database. The sample period runs from January 1983 until May 2009. Alive as well as dead LSE hedge funds are considered in order to address the survivorship bias. We drop funds that: do not report net-of-fee returns; report returns in currencies other than the U.S. dollar; report returns less frequently than monthly; have less than 60 monthly returns observations. These filters yield a final sample of 1060 funds.

The choice of the LSE hedge strategy is motivated by two main reasons. First, the number of funds belong to the LSE hedge strategy is quite large which is crucial to the statistical efficiency of the FDR approach based on the cross-sectional distribution of individual fund alphas. Second, this strategy involves quite homogenous equity-oriented funds investing on both the long and the short sides of the market. The common variations of LSE hedge fund returns can be explained by a set of equity, bond and option oriented benchmarks which is clearly identified by previous research and has become quite standard in the literature. Being able to select the relevant risk factors is crucial when dealing with fund alphas. On the one hand, if some relevant risk factors are missing, one should incorrectly conclude that some funds exhibit positive alphas while they are in fact due to the omitted risk factors. On the other hand, the inclusion of irrelevant risk factors for a given strategy increases the estimation error. Based on a cross-sectional asymptotic approach, Darolles and Mero (2011) show that the variation of LSE hedge fund returns can accurately be explained by the set of seven risk factors we use in this article. In addition, since these risk factors are represented by effectively traded benchmark portfolios, our approach has direct empirical implications in practice. More precisely, the risk factors used in this study in order to compute the net performances of individual LSE hedge funds are:

i) Four equity-oriented buy-and-hold risk factors, which are extracted from the website of Kenneth French:[22] 1) MKT: the excess return of the market value-weighted portfolio consisting of all the CRSP stocks in the US which are listed on the NYSE; the two risk factors of Fama and French (1993): 2) SMB (small minus big): the spread between the average return of the three small-stock portfolios and the average return of the three big-stock portfolios; 3) HML (high minus low): the spread between the average return of the two value portfolios and the average return of the two growth portfolios; 4) MOM (momentum): the short-term reversal factor of Carhart (1997) representing the spread between the average return of the two high prior return portfolios and the average return of the two low prior return portfolios.

(*ii*) Two bond-oriented buy-and-hold risk factors: 5) $BOND$: the monthly change in the treasury constant yield available at the Board of Governors of the Federal Reserve System; 6) $SPREAD$: the monthly change in the Moody's BAA yield less the 10-year treasury constant yield, which are extracted from Bloomberg.

iii) One option-based risk factor proposed by Agarwal and Naik (2004) in order to capture non-linear risk exposures directly provided by Vikas Agarwal: 7) SPP_a: the monthly returns of a strategy consisting in buying an at-the-money European put option on the S&P 500.[23]

[22]Note that these factors are computed based on equity data extracted from the Center for Research in Security Prices (CRSP) of the University of Chicago.

[23]Note that, Agarwal and Naik (2004) propose four option-based factors based on at-the-money (ATM) and out-of-the-money (OTM) European call and put options on the S&P 500. The use of options with different degrees of moneyness allows a flexible piecewise linear risk-return relation. The process of buying an ATM call option on the S&P 500 index consists of purchasing, on the first trading day of each month, an ATM call option on the S&P 500 that expires in the next month and selling the call option bought in the first day of the previous month. This procedure provides time series of returns on buying an ATM call option on the S&P 500. Similar procedures are used to get time series of returns for ATM put option, as well as OTM call and put options on the S&P 500. The ATM call (put) options on the S&P 500 are denoted by SPC_a (SPP_a), and the OTM call (put) options are denoted by SPC_o (SPP_o). However, as discussed by Darolles and Mero (2011), the Agarwal-Naik factors are highly correlated both among each other and with the S&P 500 index. To avoid some important drawbacks due to factor collinearity, such as beta instability, only the SPP_a option-based

Note that Fung and Hsieh (2004) proposed an alternative set of seven common factors in order to explain hedge fund returns. As documented by the empirical literature, these two sets of factors yield similar results [see for instance, Fung and Hsieh (2004), Kosowski et al. (2007), Criton and Scaillet (2014)].

Finally, we acknowledge that considering the overall sample period, the time series of individual fund returns are sparsely overlapping, which might be an issue when dealing with cross-sectional distribution of fund alphas. To address this issue while keeping the number of funds included in the analysis large, we implement our approach based on rolling subperiods as well; for each rolling window, only funds having full sample data are included in the analysis.

4 Empirical Results

The first subsection provides some preliminary results obtained by applying our MRS with FDR approach to the aggregated LSE hedge fund index. We characterize the features of each regime as well as the performance patterns of the LSE hedge fund industry conditional on the state of the economy. In subsection 2, we apply the MRS with FDR approach to individual LSE hedge funds in order to estimate the proportion of unskilled, zero-alpha and skilled funds in the entire population. Our results are compared with those obtained from the FDR approach of Barras et al. (2010) based on static alphas. Finally, in subsection 3 we analyze the out-of-sample performance of a portfolio formed by sorting funds based on their regime dependent instead of unconditional alphas and show that this maximizes the performance persistence effect of top performer fund portfolios.

4.1 Regime characteristics and LSE hedge fund index conditional performance

In this subsection, we characterize the two regimes of the economy into recession and expansion periods by discussing their impact on the statistical patterns of the LSE hedge fund industry as well as its related benchmarks. We also focus on the net-of-fee returns of the LSE hedge fund equally-weighted index in order to examine the time-series properties of this equity-oriented strategy by emphasizing the dependence of its performance and risk exposures on the state of the economy.

We start by performing an *ex post* descriptive analysis based on the NBER dummy variable in order to distinguish between recession and expansion dates.[24] Table 1 reports summary statistics for LSE hedge fund index and benchmark returns over the 1983-2009 period, as well as NBER recession and expansion subperiods. Two main remarks can be drawn. First, the LSH hedge funds perform better, on average, during expansion periods. Indeed, the equally-weighted LSE hedge fund index generates an average annualized net-of-fee return of 19% during expansion periods against 0.5% during recessions.[25] Moreover, the annualized standard deviation of the index returns is almost the same during both regimes, what explains the important gap between regime dependent annualized Sharpe ratios, whose values are 1.26 during expansion against -0.21 during recession periods. Second, Table 1 shows that the annualized average returns of the market proxy, the book-to-market factor and the monthly change in the treasury constant yield (BOND) are lower in recession periods than in expansion periods. However, the opposite

factor is used in our analysis. In fact, based on an approximate latent factor model framework, Darolles and Mero (2011) assess the relevance of these four factors in explaining the covariation of LSE hedge fund returns, and conclude that the SPP_a factor is the most relevant one.

[24]The dummy variable used her is provided by the Federal Reserve Bank of St. Louis. This indicator is an interpretation of US Business Cycle Expansions and Contractions data provided by The National Bureau of Economic Research (NBER) at http://www.nber.org/cycles/cyclesmain.html, and is composed of dummy variables that represent periods of expansion and recession. A value of 1 is a recessionary period, while a value of 0 is an expansionary period.

[25]The annualized average performance of the LSE hedge fund index reported in Table 1 does not account for the risk-free rate, but only for several management and performance fees.

is true for the size factor (SMB), the momentum factor (MOM), the option-based factor (SPPa) as well as the credit spread factor (SPREAD).

	Mean			Standard Deviation			Sharpe Ratio		
	All periods	Recessions	Expansions	All periods	Recessions	Expansions	All periods	Recessions	Expansions
LSEH Index	0.176	0.005	0.196	0.118	0.124	0.117	1.085	-0.212	1.258
MKT	0.055	-0.124	0.076	0.157	0.235	0.145	0.048	-0.659	0.184
SMB	-0.023	0.064	-0.033	0.113	0.118	0.112	-0.622	0.276	-0.734
HML	0.059	-0.039	0.071	0.109	0.123	0.107	0.108	-0.573	0.200
MOM	0.157	0.291	0.141	0.163	0.299	0.139	0.670	0.871	0.659
SPPa	-0.019	0.018	-0.023	0.032	0.040	0.030	-2.093	-0.321	-2.389
BOND	-0.003	-0.005	-0.002	0.009	0.010	0.009	-5.387	-3.618	-5.606
SPREAD	0.001	0.010	-0.000	0.006	0.013	0.005	-7.735	-1.669	-10.780
Δc_{t-2}	-0.016	-0.317	0.020						

Table 1: This table reports the summary statistics for LSE hedge fund index returns (row 1), benchmark returns (rows 2 to 8), as well as the lagged changes of the composite leading index (last row). Based on the NBER dummy variable whose value equals to 1 for recessionary month and 0 for expansionary months, we separate each considered time-series into two time subsequences corresponding to recession and expansion regimes, respectively. Then, we compute the means, standard deviations and Sharpe ratios for each variable based on (i) its overall time-series, (ii) its recessionary time subsequence, (iii) its expansionary time subsequence.

In order to assess the determinants of the LSE hedge fund index performance, we need to compute the regime-dependent risk-adjusted performance (or alpha) as well as the regime-dependent factor loadings. These two components measure respectively the contribution of the manager asset-picking skills and the risk-reward component of the raw performance. Allowing for the risk-adjusted performance and factor loadings to vary according to the state of the economy enables us to better understand what generates the average raw (net-of-fee) performance of the LSE hedge fund industry. For instance, the higher performance observed during expansion periods may be due to increasing manager asset-picking skills, better benchmark timing skills, or both. For this purpose, we use the MRS approach with time-varying transition probabilities initially developed by Kosowsky (2011) to estimate the regime dependent alphas and betas. Note that we could estimate regime dependent alphas and betas by running simple OLS regressions including the NBER dummy variable in order to distinguish between recession and expansion periods. However, this approach is purely descriptive and exogenous, and does not contain any predictive power since it relies on stale information (i.e., information which becomes known after the fact). In contrast, the MRS approach is forward looking and provides one-step-ahead state probabilities conditional on the available information at a given time point; as such, it enables us to perform accurate predictions regarding the conditional expected fund returns.

We allow for the state transition probabilities to vary according to the two month lagged changes of the CLI, Δc_{t-2} commonly used to forecast the state of the economy. To assess the predictive power of CLI, reported are in the last row of Table 1 the average values of the Δc_{t-2} variable. As expected the average value of Δc_{t-2} is negative during recession periods and positive during expansions. Moreover, the correlation coefficient between Δc_{t-2} and NBER dummy variables is -0.49 and is statistically significant at the 99% level of confidence, meaning that positive (negative) lagged changes of the CLI can be significantly associated with current expansion (recession) periods.[26] To ensure that the MRS with time-

[26]Recall that the NBER dummy variable equals to 1 during recessionary months and 0 during expansionary months.

varying transition probabilities used here allows us to correctly describe the regime dependent patterns of the fund performance, we have applied the MRS approach (2.7)-(2.13) to the equally-weighted LSE hedge fund index returns, and used the filtered conditional transition probabilities to distinguish, *ex ante*, between recession and expansion periods. A given month is considered to be recessionary (expansionary) if the filtered state 1 (state 2) probability is higher than a given threshold, say 0.9. Table 2 reports the summary statistics for LSE hedge fund index returns over the 1983-2009 period, NBER recession and expansion subperiods (row 1), as well as recession and expansion subperiods identified using the filtered state probabilities for 0.90 and 0.80 thresholds (rows 2 and 3, respectively).[27] These results show that the statistical patterns of the regime dependent average returns and Sharpe ratios of the LSE hedge fund index remain basically the same when the filtered state probabilities arising from the MRS approach are used to distinguish between recession and expansion periods. Again, the LSH hedge funds seem to perform better, on average, during expansion periods. For instance, for a given filtered probability threshold of 0.9, the annualized average return of the LSE hedge fund index is 23% during expansion periods against 8.3% during recessions. However, the annualized standard deviation of the index returns is approximately twice more important during expansion than recession periods. This explains why the difference between regime dependent annualized Sharpe ratios is lower when the filtered probabilities instead of the NBER dummies are used to distinguish between the two states of the economy. The slight disparity between the results obtained based on both regime classification criteria (i.e. NBER dummy variable versus filtered state probabilities) arises from the fact that the NBER dummy variable does not account for the intensity of the regime while the filtered probabilities do.[28] The high threshold levels used here allow us to select particularly severe recessionary and intense expansionary months, which increases the dispersion between the two regimes in terms of annualized average returns and standard deviations.

Generally speaking, the results reported in Table 2 show that the first state of the economy $-$ which is endogenously determined by the data when applying the MRS factor model to the LSE hedge fund index returns $-$ in inherent to recession periods, while the second one can be assimilated to expansion periods. In fact, when we use the filtered state probabilities to distinguish between recessionary and expansionary months, we obtain similar regime dependent descriptive statistics for equally-weighted LSE hedge fund index returns. Similarly, the average values of the Δc_{t-2} variable for each of the two states are -0.256 and 0.026, respectively (when the threshold of the filtered probability is 0.80), and -0.384 and 0.025, respectively (when the retained threshold is 0.90). We have also plotted in Figure 1 the time series of Δc_{t-2} variable and the filtered state 1 probability for the period 2005-2009.[29] Figure 1 shows that the filtered probabilities associated to state 1 are negatively correlated to the lagged changes of the CLI index, meaning that the state 1 is inherent to recession periods. Indeed, the correlation coefficient between the Δc_{t-2} and the filtered state 1 probability, during the entire test period 1983-2009, is -0.40 and is statistically significant at the 99% level of confidence.

Finally, reported are in Table 3 the regime dependent alphas (row 1) and betas (rows 2 to 8) estimated by applying the MRS approach to the equally-weighted LSE hedge fund index returns for the overall test period. These results show that the risk-adjusted performance of this equity-oriented hedge fund industry is slightly higher during expansion periods. In addition, the risk profile of the LSE hedge fund index varies from one regime to the other as (i) the estimated betas for a given factor present different signs and/or orders of magnitude during the two regimes, and (ii) the LSE hedge fund strategy is not

[27] Note that only months with strong values of the filtered conditional probabilities are considered in order to better capture the effect of each state of the economy on the hedge funds performances by avoiding periods whose attribution to a given regime is not clear enough given the moderate values of the associated filtered conditional probability.

[28] Note that the NBER indicators are a binary classification thus failing to capture important phenomena such as economic growth slowdowns.

[29] For a better visibility of the negative correlation between the two variables, we focus on a subperiod running from Jan. 2005 to May 2009.

	Mean			Standard Deviation			Sharpe Ratio		
	All periods	Recessions	Expansions	All periods	Recessions	Expansions	All periods	Recessions	Expansions
NBER Recession Dates	0.176	0.005	0.196	0.118	0.124	0.117	1.085	-0.212	1.258
Filtered Probabilities Threshold 0.9	0.238	0.083	0.337	0.205	0.099	0.247	0.911	0.399	1.133
Filtered Probabilities Threshold 0.8	0.212	0.107	0.335	0.175	0.099	0.231	0.923	0.625	1.208

Table 2: This table reports the summary statistics for LSE hedge fund returns based on the NBER classification (row 1) as well as the filtered state probabilities (rows 2 and 3). First, based on the NBER dummy variable whose value equals to 1 for recessionary month and 0 for expansionary months, we separate the considered time-series of LSE hedge fund index returns into two time subsequences corresponding to recession and expansion regimes, respectively. Then, we compute the means, standard deviations and Sharpe ratios based on (i) the overall time-series of LSE hedge fund index returns, (ii) the related recessionary time subsequence, (iii) the related expansionary time subsequence. Second, we apply the MRS approach (2.7)-(2.13) to the LSE hedge fund index returns, and use the filtered conditional transition probabilities to distinguish between recession and expansion periods. A given month is considered to be recessionary (expansionary) if the filtered state 1 (state 2) probability is higher than a sufficiently high threshold in order to focus only on pure recession and expansion periods. We consider two thresholds, 0.9 and 0.8. For a given filtered probability threshold, we compute the means, standard deviations and Sharpe ratios based on (i) the overall time-series of LSE hedge fund index returns, (ii) the related recessionary time subsequence, (iii) the related expansionary time subsequence. The results are reported in rows 2 and 3, respectively.

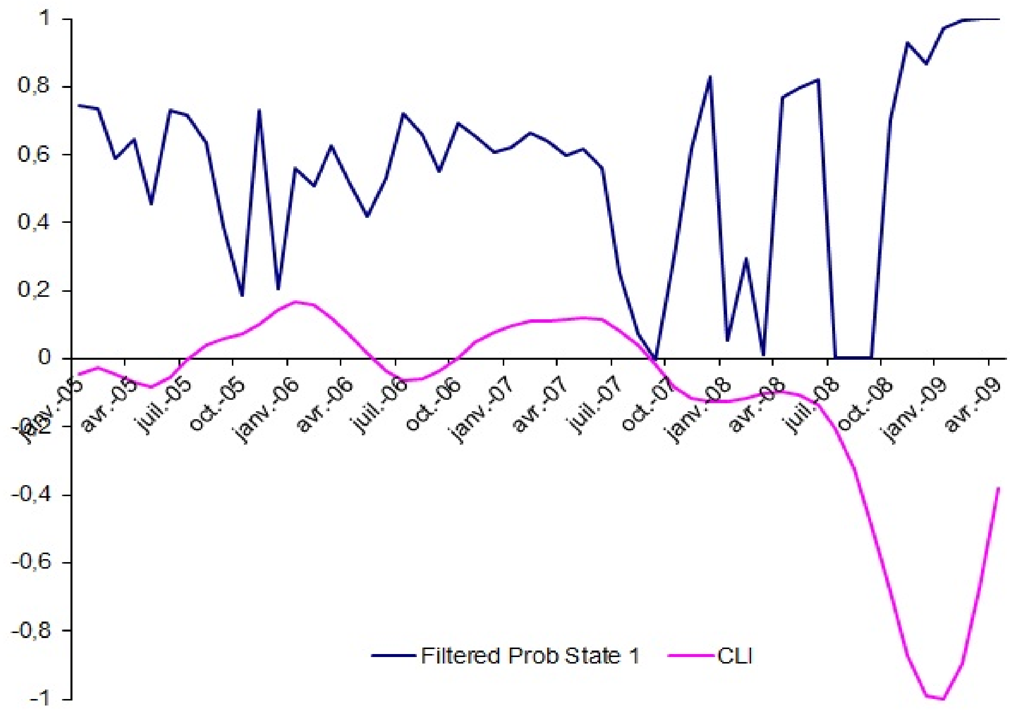

Figure 1: This figure plots the fluctuations of the two-month lagged changes of the CLI (pink curve) and the filtered conditional probability associated to state 1 (blue curve), which is directly filtered by applying the MRS framework to the equally-weighted LSE hedge fund index. For a better visibility of the negative correlation between the two variables, we focus on a subperiod running from Jan. 2005 to May 2009.

exposed to the same risk factors during recession and expansion periods. Some beta shifts across the two regimes emphasize the good benchmark timing skills of fund managers: the beta associated to the market

	State 1 (Recession)	State 2 (Expansion)
Alpha (year)	0.1249**	0.1312**
MKT	0.3772**	0.6625**
SMB	0.2566**	0.0736
HML	0.0032	-0.0940*
MOM	0.0033	0.2512**
SPPa	-0.1665	-0.3303*
BOND	-0.5788**	-0.8337*
SPREAD	-1.1249**	-0.7486
di	-3.8532**	0.2164

Table 3: This table reports the regime dependent alphas and betas estimated by applying the Markov regime switching (MRS) factor model with time-varying transition probabilities to the equally-weighted LSE hedge fund index returns. The estimated conditional alphas are reported in the first row. The associated conditional factor loadings are reported in rows 2 to 8. The last row contains the estimated parameters of equations (2.12)-(2.13) capturing the sensibility of state transition probabilities to the two month lagged changes of the CLI. The parameters denoted by "**" and "*" are statistically significant at the 95% and 90% levels of confidence, respectively.

(SMB) factor is higher during expansion (recession) periods allowing the managers to efficiently capture the increase of the risk premium associated to the market (SMB) factor during expansion (recession) periods. Some other beta shifts – such as those related to HML and MOM factors – reflect poor manager benchmark timing skills.[30] Note also that the d_i parameters ($i = 1, 2$) reported in the last row of Table 3 capture the sensibility of state transition probabilities to the two-month lagged changes of the CLI as given in equations (2.12)-(2.13). The estimated d_1 parameter is negative while d_2 is positive, which is coherent with the characterization of both regimes as recessionary and expansionary, respectively.[31]

To summarize, the MRS analysis applied to the LSE hedge fund index provides some preliminary insights regarding the regime dependent patterns of the performance and risk profile of the LSE hedge fund industry. Regarding the total net-of-fee performance, our results suggest that LSE hedge fund index performs better during expansion periods as indicated by an increasing Sharpe ratio. As for the determinants of this total performance, Table 3 shows (i) that the risk adjusted performance (i.e., alpha) of the LSE hedge fund index is slightly higher during expansion periods and (ii) that the fund managers partly succeed in timing their benchmarks (good benchmark timing skills for the market and size factors). However, this stage of our analysis based on the time series dimension of the aggregated LSE hedge fund index, leaves us with many unanswered questions regarding the contribution of individual hedge funds into the global industry performance conditional on the state of the economy. In particular, we are interested in estimating the proportion of unskilled, zero-alpha and skilled funds conditional on the state of the economy in order to appreciate the dispersion of the (un)skilled managers across the two regimes and, thus, emphasize the interest in working with conditional instead of static alphas in order to select

[30] In particular, the the beta relative to the HML factor is negative during expansion periods characterized by a positive HML risk premium. In addition, the loading on the MOM factor is smaller during expansion than recession periods, while the opposite is true regarding the MOM factor premium.

[31] More precisely, the negative value of d_1 means that the decrease of the two-month lagged values of the CLI can be associated to an increasing probability of being in state 1 (recession) currently.

the truly skilled managers. For this purpose, we go further in the analysis by focussing on individual funds instead of their aggregated index and apply our two step approach presented in section 3 in order to estimate the proportion of skilled, zero-alpha and skilled funds in the population of hedge funds belonging to the LSE hedge strategy. Our results are discussed in the two consecutive subsections.

4.2 Controlling for luck in the cross-section of fund alphas conditional on the state of the economy

The MRS framework applied to the aggregated LSE hedge fund index exploits the information filtered from the time-series dimension in order to examine how the manager asset-picking and benchmark timing skills vary conditional on the state of the economy. The results presented in the previous subsection show that the LSE hedge fund industry seems to generate, on average, regime dependent risk-adjusted returns having similar orders of magnitude. The main question arising here is whether this average risk-adjusted aggregated performance, seemingly the same across the two regimes, is governed by the same drivers. For instance, two different situations can explain the same observed results at the aggregated fund level: (i) A positive risk-adjusted performance at the aggregated fund level may be explained by a high proportion of skilled managers offsetting the negative effect of the less numerous unskilled managers. (ii) However, the same results may be obtained from a population of funds combining only skilled and zero-alpha funds. Thus, in order to better understand the determinants of the aggregated risk-adjusted performance, we need to exploit the cross-sectional dimension of individual hedge funds belonging to the same LSE hedge fund universe. The MRS with FDR approach presented in section 3 allows us to combine both time-series and cross-sectional dimensions in order to analyze the drivers of risk-adjusted performance conditional on the state of the economy. Here, we present our results obtained by applying this approach to the entire population of individual LSE hedge funds.

We begin by estimating the proportion of unskilled, zero-alpha and skilled funds based on the unconditional FDR approach of Barras et al. (2010) using the overall test period 1983-2009. Note that only funds with at least 60 monthly observations are included in the analysis. We implement the methodology proposed by Barras et al. (2010) to compute the standard deviations of the estimated parameters, and find that the estimated proportion of zero-alpha and skilled funds are statistically significant.[32] These results, reported in Table 4, suggest that the population of individual LSE hedge funds in composed by zero-alpha and skilled manager funds ($\hat{\pi}_0 = 0.69$ and $\hat{\pi}_A^+ = 0.31$, respectively), while the unskilled managers in the considered population during the overall test period are nonexistent ($\hat{\pi}_A^-$).

	$\hat{\pi}_A^-$	$\hat{\pi}_0$	$\hat{\pi}_A^+$
Proportion	0	0.690	0.310
Number of funds	0	731	329

Table 4: This table displays the estimated proportion of unskilled, zero-alpha and skilled funds ($\hat{\pi}_A^-$, $\hat{\pi}_0$ and $\hat{\pi}_A^+$) in the entire population of LSE hedge funds (1060 funds). These proportions are estimated by applying the FDR approach of Barras et al. (2010) to individual fund returns observed during the overall test period 1983-2009. Only funds with at least 60 monthly observations are included in the analysis. We implement the methodology proposed by Barras et al. (2010) to compute the standard deviations of the estimated parameters, and find that the estimated proportion of zero-alpha and skilled funds are statistically significant.

Second, we estimate the proportion of unskilled, zero-alpha and skilled funds conditional on the state of the economy based on the MRS with FDR approach developed in this paper, and using the overall

[32]These standard deviations are not reported here but are available upon request.

test period 1983-2009.[33] The results are displayed in Table 5. Two main remarks can be drawn. (i) The proportion of zero-alpha funds presents the same order of magnitude across the two regimes (0.34 and 0.33, respectively), but it is twice lower than its unconditional counterpart (0.69). Moreover, the proportion of skilled funds for both regimes is higher than the proportion of skilled managers obtained by the FDR approach of Barras et al. (2010). More importantly, our results show that the proportion of unskilled managers is statistically significant during both recession and expansion periods, meaning that some managers underperform their benchmarks during at least one of the two regimes of the economy. Thus our approach enables us to identify such managers. (ii) Table 5 also shows that the proportion of skilled funds is higher during expansion periods while the unskilled funds tend to be more numerous during recession periods.

	$\hat{\pi}_A^-$	$\hat{\pi}_0$	$\hat{\pi}_A^+$
State 1 (Recession)			
Proportion	0.2609	0.3403	0.3989
Number of funds	276	360	422
State 2 (Expansion)			
Proportion	0.1638	0.3308	0.5054
Number of funds	174	350	535

Table 5: This table displays the estimated regime dependent proportions of unskilled, zero-alpha and skilled funds ($\hat{\pi}_A^-$, $\hat{\pi}_0$ and $\hat{\pi}_A^+$) in the entire population of LSE hedge funds (1060 funds). These proportions are estimated by applying the the MRS with FDR approach developed in this paper to individual fund returns observed during the overall test period 1983-2009. Only funds with at least 60 monthly observations are included in the analysis. We implement the methodology proposed by Barras et al. (2010) to compute the standard deviations of the estimated parameters, and find that the estimated proportion of unskilled, zero-alpha and skilled funds are statistically significant.

Finally, we have estimated the proportion of unskilled, zero-alpha and skilled funds based on twelve 15-month rolling subperiods, in order to check for the consistency of the results obtained using the overall period. The first subperiod extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. Only funds with at least 60 monthly observations for a given subperiod are included in the analysis. For each subperiod, we have applied both, the FDR approach of Barras et al. (2010) and our MRS with FDR approach. The results are reported in Tables 6 and 7, respectively. Three main reparks can be drawn. (i) The subperiod results obtained based on static alphas are similar to those obtained using the overall period. The proportion of unskilled funds is always economically insignificant. As in the overall period case, the zero-alpha and skilled funds represent almost two-thirds (one third) of the entire population of LSE hedge funds, respectively. (ii) When accounting for the regime dependence of the estimated parameters, the proportion of zero-alpha funds is lower than in the unconditional case for all subperiods (see Figure 2). Moreover, the proportion of unskilled funds becomes statistically significant for all subperiods, while the proportion of skilled funds increases as compared to the unconditional case, for almost all subperiods (see Figure 3). (iii) The proportion of unskilled funds is, in general higher during recession than expansion subperiods (for 8 out of 12 subperiods), which corroborates the results obtained from the overall period case.

[33] Again, only funds with at least 60 monthly observations are included in the analysis. We implement the methodology proposed by Barras et al. (2010) to compute the standard deviations of the estimated parameters, and find that the estimated regime dependent proportions of unskileld, zero-alpha and skilled funds are statistically significant. These standard deviations are not reported here but are available upon request.

	$\hat{\pi}_A^-$	$\hat{\pi}_0$	$\hat{\pi}_A^+$	Fund Number
Overall period	**0.00**	**0.68**	**0.32**	1060
Subperiod				
1	0.00	0.57	0.43	117
2	0.00	0.65	0.35	158
3	0.00	0.50	0.50	202
4	0.00	0.67	0.33	263
5	0.00	0.72	0.28	345
6	0.00	0.75	0.25	424
7	0.00	0.67	0.33	503
8	0.00	0.68	0.32	589
9	0.00	0.69	0.31	705
10	0.00	0.74	0.26	825
11	0.00	0.68	0.32	922
12	0.00	0.72	0.28	1006

Table 6: This table displays the estimated proportion of unskilled, zero-alpha and skilled funds ($\hat{\pi}_A^-$, $\hat{\pi}_0$ and $\hat{\pi}_A^+$) obtained for each of the twelve 15-month rolling subperiods by applying the FDR approach of Barras et al. (2010). The first subperiod extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. Only funds with at least 60 monthly observations for a given subperiod are included in the analysis. The number of funds for each subperiod is reported in the last column. The first row displays the estimated parameters obtained based on the overall period 1983-2009. We implement the methodology proposed by Barras et al. (2010) to compute the standard deviations of the estimated parameters, and find that the estimated proportion of zero-alpha and skilled funds are statistically significant for all the considered subperiods.

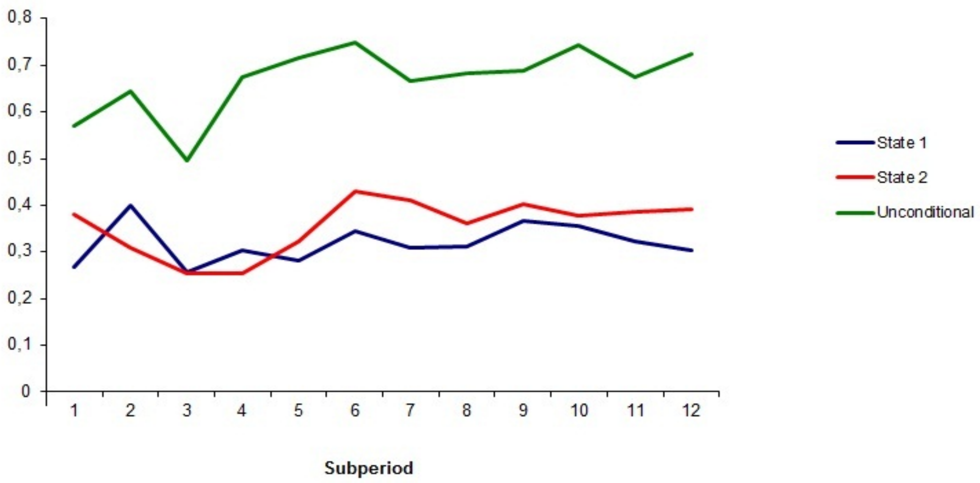

Figure 2: This figure displays the estimated proportion of zero-alpha funds obtained for each of the twelve 15-month rolling subperiods by applying both the MRS-FDR approach developed in this paper and the FDR approach of Barras et al. (2010). The first subperiod extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. The estimated proportion of zero-alpha funds obtained by the FDR approach is represented by the green curve (Unconditional). The remaining curves represent the state dependent proportions of zero-alpha funds obtained by the MRS-FDR approach.

Generally speaking, our results highlight the importance of accounting for the regime dependence of the estimated alphas in order to assess the proportion of skilled and unskilled funds in the entire population of a considered strategy. On the one hand, when using static alphas, the underperformance of some unskilled managers during a particular regime of the economy may be offset by their outperformance during the other regime, which artificially increases (decreases) the proportion of zero-alpha (unskilled)

	Panel A: State 1 (Recession)				Panel B: State 2 (Expansion)			
	$\hat{\pi}_A^-$	$\hat{\pi}_0$	$\hat{\pi}_A^+$	Fund Number	$\hat{\pi}_A^-$	$\hat{\pi}_0$	$\hat{\pi}_A^+$	Fund Number
Overall period	**0,26**	**0,34**	**0,40**	1058	**0,16**	**0,33**	**0,51**	1058
Subperiod								
1	0.22	0.27	0.51	117	0.19	0.38	0.43	117
2	0.19	0.40	0.41	158	0.24	0.31	0.45	158
3	0.23	0.26	0.51	202	0.22	0.25	0.52	202
4	0.19	0.30	0.51	263	0.19	0.25	0.55	263
5	0.20	0.28	0.52	345	0.17	0.32	0.51	345
6	0.17	0.34	0.49	424	0.17	0.43	0.40	424
7	0.16	0.31	0.53	503	0.17	0.41	0.42	503
8	0.16	0.31	0.53	589	0.19	0.36	0.45	589
9	0.18	0.37	0.46	705	0.20	0.40	0.40	705
10	0.22	0.36	0.43	825	0.23	0.38	0.39	825
11	0.21	0.32	0.47	921	0.18	0.39	0.43	921
12	0.25	0.30	0.44	1004	0.17	0.39	0.44	1004

Table 7: This table displays the regime dependent proportion of unskilled, zero-alpha and skilled funds ($\hat{\pi}_A^-$, $\hat{\pi}_0$ and $\hat{\pi}_A^+$) obtained for each of the twelve 15-month rolling subperiods by applying the MRS with FDR approach developed in this paper. Panel A displays the parameters of interest relative to state 1, while the panel B deals with state 2. The first subperiod extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. Only funds with at least 60 monthly observations for a given subperiod are included in the analysis. The number of funds for each subperiod is reported in the last column of each panel. The first row displays the estimated parameters obtained based on the overall period 1983-2009. We implement the methodology proposed by Barras et al. (2010) to compute the standard deviations of the estimated parameters, and find that the estimated proportion of zero-alpha and skilled funds are statistically significant for all the considered subperiods.

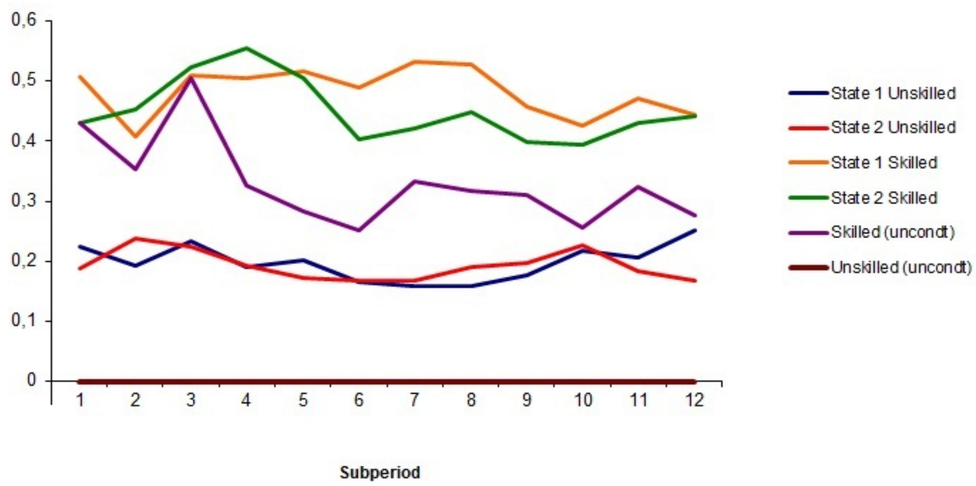

Figure 3: This figure displays the estimated proportion of skilled and unskilled funds obtained for each of the twelve 15-month rolling subperiods by applying both the MRS-FDR approach developed in this paper and the FDR approach of Barras et al. (2010). The first subperiod extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. The estimated proportions of skilled funds obtained by the FDR approach is represented by the violet curve named "Skilled (uncondt)". The proportion of unskilled funds ("Unskilled (uncondt)") arising from this same approach is not statistically different from zero, for all the considered subperiods. The remaining curves represent the state dependent proportions of skilled and unskilled funds obtained by the MRS-FDR approach.

funds. On the other hand, some managers may outperform their benchmarks during a specific regime of the economy while being flat during the other. In this case, the static FDR approach generates artificially higher zero-alpha funds at the expense of artificially lower skilled funds. Finally, our results show that the regime dependent proportion of unskilled funds is economically important for the LSE hedge fund strategy during both regimes, and it seems to be more important during recession periods thus questioning the ability of fund managers to beat the market when it matters the most to investors.

4.3 Out-of-sample performance of a fund selection strategy based on our approach

Here, we examine the out-of-sample performance of a portfolio comprising individual LSE hedge funds whose managers outperform their benchmarks during both, recession and expansion periods. We compare the out-of sample performance of this portfolio with that of another one formed by selecting the skilled funds based on the FDR approach of Barras et al. (2010). More precisely, we examine the out-of-sample performance of two portfolios. The first one (Unconditional Portfolio) is formed by selecting, for each rolling subperiod, the skilled funds based on their unconditional alphas; the static alphas are here estimated using the FDR approach of Barras et al. (2010). The second one (Conditional Portfolio) includes, for a given rolling period, only funds whose managers generate positive alphas during both regimes of the economy; the regime dependent alphas are here estimated using our MRS with FDR approach. We consider twelve 15-month rolling periods: the first one extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. For a given subperiod, we form the two portfolios and compute their net-of-fee returns in excess of the risk-free rate for the twelve months following the portfolio formation period, which leaves us with two time series (one for each portfolio) of out-of-sample performances of length 137 months.[34] We implement these procedure for different levels of FDR targets ($z^+ = 1\%, 2\%, 3\%, 4\%, 5\%, 7.5\%, 10\%, 15\%, 20\%, 30\%$).[35] For each portfolio (Unconditional and Conditional) and each FDR target level z^+, we compute the annual mean returns and standard deviations as well as the annualized Sharpe ratios. We also estimate the annual seven-factor alphas, the standard deviation of residuals, as well as the annualized information ratios. These results are reported in Table 8.

Our results show that the Conditional Portfolio arising from our MRS with FDR approach outperforms the one obtained from the FDR approach of Barras et al. (2010) in terms of total and risk-adjusted net-of-fee returns. Indeed, for most of the target levels z^+, the Sharpe ratios are higher for the Conditional Portfolio as compared to those of the Unconditional Portfolio. Moreover, the seven-factor risk-adjusted alphas are statistically significant only for the Conditional Portfolio and for most of target levels z^+. The information ratio (IR) as well is higher for the Conditional Portfolio. These results emphasize the interest in accounting for the regime dependence of the estimated alphas in order to maximize the performance persistence of portfolios of good performers, which has direct implications in practice. It would be interesting lo link the performance of the Conditional and Unconditional portfolios to the market liquidity and funding liquidity factors in order to assess the determinants of their performance, conditional on the regime of the economy. These results will be available in a forthcoming version of this article.

[34] Our sample period ends on May 2009.

[35] We implement the methodology of Barras et al. (2010) to form portfolios of good performers. Basically, we first estimate alpha bootstrapped p-values for each fund and for both regimes. Then, we estimate the FDR in the right tail, $F\hat{D}R^+$ over a range of γ: $F\hat{D}R^+_\gamma = \frac{\hat{F}^+_\gamma}{\hat{S}^+_\gamma} = \frac{\hat{\pi}_0\gamma/2}{\hat{S}^+_\gamma}$. For a given FDR target level z^+, $\gamma(z^+)$ is the one that yields a $F\hat{D}R^+_\gamma$ as close possible to this target. Only funds with bootstrapped p-values lower than the respective $\gamma(z^+)$ (one for each regime) are selected. For more details, see Barras et al. (2010).

Panel A: Unconditional Portfolio

Target (z+)	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.075**	**0.1**	**0.15**	**0.2**	**0.3**
Mean Returns	0.0931	0.0830	0.0887	0.0891	0.0908	0.0911	0.0911	0.0911	0.0911	0.0911
Std of Returns	0.0957	0.0996	0.1065	0.1081	0.1093	0.1094	0.1094	0.1094	0.1094	0.1094
Sharpe Ratio	0.9725	0.8339	0.8331	0.8245	0.8310	0.8326	0.8326	0.8326	0.8326	0.8326
Alpha	0.0345	0.0309	0.0317	0.0337	0.0344	0.0342	0.0342	0.0342	0.0342	0.0342
Std of residuals	0.0581	0.0526	0.0525	0.0530	0.0522	0.0519	0.0519	0.0519	0.0519	0.0519
IR	0.5934	0.5867	0.6038	0.6366	0.6596	0.6576	0.6576	0.6576	0.6576	0.6576

Panel B: Conditional Portfolio

Target (z+)	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.075**	**0.1**	**0.15**	**0.2**	**0.3**
Mean Returns	0.0801	0.0778	0.0838	0.0869	0.0899	0.0960	0.0922	0.0927	0.0907	0.0908
Std of Returns	0.0665	0.0687	0.0705	0.0757	0.0799	0.0832	0.0843	0.0893	0.0903	0.0903
Sharpe Ratio	1.2039	1.1336	1.1896	1.1484	1.1260	1.1531	1.0939	1.0378	1.0041	1.0056
Alpha	0.0255	0.0227	**0.0335**	**0,0375**	**0.0398**	**0.0458**	**0.0430**	**0.0411**	**0.0392**	**0.0391**
Std of residuals	0.0423	0.0422	0.0422	0.0433	0.0432	0.0436	0.0442	0.0445	0.0450	0.0451
IR	0.6038	0.5376	0.7931	0.8655	0.9211	1.0506	0.9720	0.9233	0.8701	0.8679

Table 8: This table displays out-of-sample performance parameters for two portfolios. The first one (Unconditional Portfolio) is formed by selecting, for each rolling subperiod, the skilled funds based on their unconditional alphas; the static alphas are here estimated using the FDR approach of Barras et al. (2010). The second one (Conditional Portfolio) includes, for a given rolling period, only funds whose managers generate positive alphas in both regimes of the economy according; the regime dependent alphas are here estimated using our MRS with FDR approach. We consider twelve 15-month rolling periods: the first one extends from Jan. 1983 to Dec. 1997, the second from Jan. 1984 to Dec. 1998, and so on. For a given subperiod, we form both portfolios and compute their net-of-fee returns in excess of the risk-free rate for the twelve months following the portfolio formation subperiod, which leaves us with two time-series (one for each portfolio) of out-of-sample performances of length 137 months. We implement these procedure for different levels of FDR targets ($z^+ = 1\%, 2\%, 3\%, 4\%, 5\%, 7.5\%, 10\%, 15\%, 20\%, 30\%$). For each portfolio (Unconditional and Conditional) and each FDR target level, we compute the annual mean returns and standard deviations and the annualized Sharpe ratios. We also estimate the annual seven-factor alphas, the standard deviation of residuals, as well as the annualized information ratios. The statistically significant alphas at the 95% level of confidence are given in bolded values.

5 Concluding remarks

We propose a Markov regime-switching approach accounting for false discoveries in order to measure hedge fund performance. It enables us to extract information from both time-series and cross-sectional dimensions of panels of individual hedge fund returns in order to distinguish between skilled, unskilled and zero-alpha funds for a given state of the economy. Applying our approach to individual hedge funds belonging to the LSE hedge strategy, we find that their performance cannot be explained by luck alone, and that the proportion of zero-alpha funds in the population decreases when accounting for alpha regime dependence. However, the proportion of truly skilled funds is higher during expansion periods, while unskilled funds tend to be more numerous during recession periods. Moreover, sorting on regime dependent alphas instead of unconditional alphas improves investors' ability to select funds that outperform their benchmarks in both regimes of the economy, and thus maximizes the performance persistence effect of top performer fund portfolios.

The next step of our work would be to apply our approach to other hedge fund strategies in order to highlight the risk-adjusted performance profile conditional on the state of the economy for strategies having different risk profiles. It would also be interesting to examine the characteristics of the populations of unskilled and skilled funds conditional on the state of the economy, such as their regime dependent risk exposures. It would also be interesting to assess whether the shifts of the market liquidity and funding liquidity risk across the two regimes significantly impact the proportion of unskilled and skilled funds in the entire population. These results will be available shortly, in a forthcoming version of this article.

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