MUTUAL FUND PERFORMANCE AND CHANGES IN FACTOR EXPOSURES

Abstract: This paper examines whether active mutual funds that markedly change their exposures to systematic risk factors subsequently outperform. We propose a new returns-based approach to assess the degree to which mutual funds adjust their risk exposures, with the benefit of not requiring periodically updated information related to funds' portfolio holdings. Applying this measure to active US mutual funds from 1990 to 2016, we provide evidence that mutual fund managers exhibiting substantial changes in their risk exposures generate alphas which are significantly greater than those with limited exposure variation. These findings are not explained by other characteristics such as fund tracking errors, fund size and investment style, or by holdings-based measures. Analyzing the longer-term persistence of active management, we provide evidence that the indicated outperformance is attributable to managers' skill rather than to luck. Our findings contribute to the body of evidence which suggests that active management may, in some cases, produce short-term performance persistence.

Keywords: Mutual funds, performance, active management, fund exposures

JEL Classification: G11, G20, G23

1. Introduction

Superior mutual fund performance depends upon optimal asset-allocation decisions, which requires setting ex-ante an optimized fund exposure to those risk factors delivering the highest abnormal risk premium ex-post. Consequently, a portfolio managers' performance can be attributable to skill, and not luck, if the ex-post realized returns of the portfolio holdings are persistently higher than those of passively managed or randomly selected portfolios investing in the same asset universe. Persistently outperforming an appropriate benchmark is, however, a difficult endeavor as most evidence from the asset management industry and related literature suggests that mutual funds do not deliver persistent outperformance to investors and that outperformance in well-functioning financial markets is difficult to achieve (Berk and Green, 2004). Most of the empirical evidence is, however, based on longer-term equilibrium processes such as fund flows and manager changes (Bessler *et al*., 2018), but this does not preclude short-term persistence resulting from active management (Cremers and Petajisto, 2009). While acknowledging that profit opportunities often vanish when strategies become commonly known (McLean and Pontiff, 2016), we consider a new perspective on active fund management, by investigating whether funds which alter their exposures to systematic factors the most achieve better performance.

The literature on measuring mutual fund performance has focused on many different approaches, which can be grouped according to two main methodologies: the characteristic-based and the return-based approaches. Characteristic-based performance analysis employs data on several characteristics or portfolio holdings to analyze returns. For instance, Daniel *et al*. (1997) observe the return of each stock held by a fund in excess of that of the average stock with similar characteristics and propose several ways to measure the stock picking and timing abilities of mutual fund managers. Kacperczyk *et al*. (2005) use portfolio weights to estimate an industry concentration index that measures the extent to which a fund differs from the market portfolio and find that funds that concentrate their investments in a few industries perform better. Cremers and Petajisto (2009) propose "Active Share" as a measure that analyzes how much funds differ from their benchmark in terms of their portfolio holdings and conclude that those which differ widely from their benchmark obtain greater alphas. Kacperczyk, Sialm and Zheng (2008) suggest that funds with a greater difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings, which they refer to as the return gap, subsequently outperform.

The characteristic-based methodologies have, however, a critical disadvantage as they largely depend on having access to exact portfolio holding information. Instead of requiring significant quantities of holdings data, which are only revealed periodically and may lag current portfolio holdings (Parida and Teo, 2018), return-based style analysis requires only portfolio returns to evaluate mutual fund performance (Cuthbertson *et al*. 2016; Hermann *et al*., 2013). Sharpe (1992) for instance, estimates the coefficients of a twelve-asset class model and shows that portfolio returns are exposed to traditional asset classes. In this context, some studies (Grinblatt and Titman, 1992; Malkiel, 1995; among others) analyze performance persistence by simply considering the returns in two consecutive periods, leading to the idea that managed funds that have previously earned superior returns may again generate an outperformance in the future. Other studies (Ferson and Schadt, 1996; Christopherson, Ferson and Glassman, 1998) propose conditional models to adjust fund performance to the information set that is available to the fund managers. In addition, multifactor models that extend the classic Capital Asset Pricing Model (CAPM) by including characteristic-based risk factors as explanatory variables are pervasive both in academia and the asset management industry as the standard to assess fund performance (Fama and French, 1993; Gruber, 1996; Carhart, 1997; and Fama and French, 2015; among others). These factors relate to average-return anomalies in the stock market such as size or momentum effects that the CAPM cannot explain but that could influence Jensen's alpha (Jensen, 1968). The application of these models is useful to detect whether fund managers are able to provide investors with superior returns compared to investing in a passive portfolio with exposure to these characteristic factors.

In this study, we build upon traditional return-based approaches, deriving and proposing a new measure for active management of equity mutual funds. This measure builds upon an extensive literature in Financial Economics, which focuses upon the regression coefficient of determination (R^2) as an estimate of explanatory power (See Roll (1988) and related literature). In contrast to Amihud and Goyenko (2013), where R^2 is used as a measure of how closely a mutual fund tracks its benchmark, we focus upon changes in funds' exposures to a set of common risk factors from one period to the next. Funds' exposures to the different asset classes or risk factors are determined by only using fund returns and comparable returns for a selected set of asset classes or factors, without requiring exhaustive data on portfolio holdings (Sharpe, 1992). Furthermore, the proposed approach allows for regular determination of fund exposure dynamics, as it does not require irregularly disseminated fund holdings, instead relying on information publicly available on a frequent basis.

We consider a six-factor model that consists of the recently proposed Fama and French (2015) five-factors augmented by the momentum factor (Carhart, 1997) to explain mutual fund performance. Instead of analyzing and using the betas of this model as indicative of the fund's exposures to the various risk factors, as in Sharpe (1992), we are interested in estimating the proportion of the variability of mutual fund returns that each characteristic risk factor explains. Hence, our focus is on the contribution of each risk factor to the fund's total R^2. The motivation for measuring these contributions to R^2 resides on a simple fact: Two different risk factors can have a similar and statistically significant sensitivity loading (beta) on fund returns, but one of them can contribute more to explaining the variation in fund returns than the other. Thus, the magnitude of beta explains the sensitivity but does not account for the economic significance of this risk factor with respect to portfolio risk contribution.

In the empirical analysis, we apply the optimal symmetric orthogonalization proposed by Löwdin (1950) in the context of the physical sciences to orthogonalize the Fama-French factors. The Löwdin symmetric transformation presents many benefits in terms of creating an orthonormal basis, not least the ability to decompose the coefficient of determination (R^2) into contributions associated with each factor (Klein and Chow, 2013). As documented in the literature, this orthogonalization method is preferable to other techniques such as sequential orthogonalization or Principal Component Analysis due to the maximal resemblance of the orthogonalized factors with the original factors. Other studies applying and providing empirical evidence of the benefits of this methodology include Bessler and Kurmann (2014) and Bessler *et al*. (2015).

Next, we provide an overview of our main empirical findings. For a large sample of actively managed US mutual funds for the period 1990 to 2016, we observe that, in aggregate, the market factor explains most of the variation of fund returns. This result is consistent with the values of R^2 often reported in studies that employ the CAPM. Other factors, especially size and momentum, are also found to contribute to R^2 in a relevant way. Of most importance to this work, these exploratory findings indicate that funds' exposures to the different orthogonal risk factors are time varying.

After decomposing the coefficient of determination of two consecutive and non-overlapping periods (e.g., t_0 and t_1), we estimate the overall change in a fund's factor exposures by simply comparing the change in relative contributions of each factor to the total R^2 of the fund between the beginning (t_0) and the end (t_1) of the period. Our main objective is to analyze whether active funds changing their risk factor exposures to a greater degree, i.e., highly actively managed funds, outperform funds that hardly adjust their exposures over time. The rationale underpinning this hypothesis is simple: fund managers with greater skill than the average manager in forecasting the evolution of a risk factor will adjust their portfolio holdings accordingly, leading to an overall change in fund risk exposures and a superior performance.

The empirical evidence provided in this study strongly supports our argument. We find that funds with the greatest change in exposures from one period to the next subsequently outperform by, on average, 198 basis points per annum, those mutual funds that reveal the smallest variation in factor exposures. Building on these initial insights, we investigate the performance of a strategy investing in those funds that performed best ex-post (highest alpha) and that, in addition, changed their exposures over the two most recent by the most. This strategy resulted in annualized alphas between 2.60% and 4.80%.

Building upon evidence provided by Amihud and Goyenko (2013), Chen *et al*. (2004), and Chan *et al*. (2002), we analyze whether a funds' tracking error, fund size and the manager's investment style, respectively, interact with a funds' tendency to change factor exposures. We also investigate whether the outperformance found for mutual funds that change their factor exposures more can be attributed to the holdings-based measures proposed by Cremers and Petajisto (2009) and Kacperczyk *et al.* (2008). Even after controlling for these well-studied characteristics, we find that funds that adjust their factor exposures to a larger degree still generate higher alphas than those that do not alter their exposures markedly. Finally, we document that a hypothetical portfolio investing in funds with the largest ex-ante adjustments in their factor exposures obtains a superior ex-post performance relative to a hypothetical portfolio that invests in funds with smaller exposure changes for periods of up to 12 months. This persistence implies that the larger alphas obtained by funds experiencing higher variations in their exposures is attributable to the managers' skill to shift risk exposures appropriately, rather than simply being a matter of luck.

This paper contributes to the literature on active management, using a simple returns-based approach to identify funds, which often shift their exposures between characteristic factors and introduces an innovative method to isolate fund factor exposures. This relates to but builds upon the literature on return-based style analysis, by exploiting the variation explained by characteristic factors to determine exposure changes. Relative to time series methods depending upon regression slopes, this has the advantage of providing an intuitive, bounded estimate of the relative importance of each factor. In comparison to the literature using holdings-based data to analyze and predict mutual fund performance, our methodology is easy to calculate and provides additional information useful in forecasting future performance. Our application of this methodology adds a new dimension to the recent literature focused on active management. Specifically, our novel time series-based approach provides evidence that investing in funds that vary their overall exposures to a greater degree generate larger alphas than those that have the lowest exposure variation. This relationship between changes in funds' exposures and subsequent performance is unrelated to other characteristics, such as the portfolio's tracking error, funds size, or the investment style implemented by the fund.

Evidence for the predictability of the equity market premium and characteristic factor returns has been well documented (for example, Wang and Xu (2015), Zakamulin (2013) and Welch and Goyal (2008)). Mutual fund managers who can accurately predict changes in factor returns are more likely to be amongst those with larger changes in their factor exposures. By preempting which factors are likely to have superior future performance and rotating the exposure of the fund towards these factors, such managers can outperform mutual funds realizing smaller changes in factor exposures as part of their investment strategy. Along with the results demonstrating performance persistence among managers who alter their factor exposures most, our findings provide evidence for skilled management among a subset of mutual fund managers.

The rest of the paper proceeds as follows. Section 2 describes our sample of US equity mutual fund and outlines the methodology used in the study. In Section 3, we introduce and derive our new measure for mutual fund risk exposures and explain how it changes over time. Section 4 presents the main results of our empirical analyses. Section 5 concludes.

2. Data and methodology

2.1. Performance methodology

We implement a six-factor model to measure the risk exposures and performance of mutual funds.[1] Given the evidence in Matallín-Sáez (2006) about the omission of relevant benchmarks, we apply the extended Fama and French (2015) five-factor model along with the Carhart (1997) momentum factor. This model is described in Equation (1):

$$R_{j,t} - R_{f,t} = \alpha_j + \beta_{1,j}RMRF_t + \beta_{2,j}SMB_t + \beta_{3,j}HML_t + \beta_{4,j}RMW_t + \beta_{5,j}CMA_t + \beta_{6,j}UMD_t + \varepsilon_{j,t} \quad (1)$$

where $R_{j,t}$ is the daily return of fund *j* during the day *t*, and $R_{f,t}$ is the return on the risk-free asset during the same day. *RMRF* is the daily market factor return minus the risk-free asset return. *SMB* (small-minus-big) and *HML* (high-minus-low) are the average returns on the size and value factor-mimicking portfolios, respectively. *RMW* (robust-minus-weak) and *CMA* (conservative-minus-aggressive) are the returns on the operating profitability and the investment factors, respectively. *UMD* (up-minus-down) is the difference in returns between portfolios previously reporting the highest and lowest prior return. The performance of fund *j* is the intercept of the model, which is an extended version of the well-known Jensen's alpha (α_j). This is the average return provided by a fund in excess of a passively-managed portfolio that replicates the slopes on the risk-factors considered in the model (Fama and French, 2010). The data on the risk factors are obtained from Kenneth French's website.[2]

[1] We also applied other multifactor models, such as the Fama and French (1993, 2015) three- and five-factor models, and the Carhart (1997) four-factor model, and reached very similar conclusions. Results, therefore, are not reported for the sake of brevity.

[2] The authors are grateful to Professor French for making this data publicly available. For more information, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2.2. Data

The initial sample consists of 17,773 US share-class funds primarily investing in US common equities. The sample period runs from January 1990 to December 2016, with data provided by Morningstar. Daily data, previously shown to provide better inference than monthly data in regard to fund performance (Coggins *et al.*, 2009), is employed. We obtain different fund characteristics such as the fund identifier and inception date, the Morningstar Category and dummy variables describing whether the fund is a passive index fund or a fund of funds. Furthermore, we obtain the daily return series for each fund, along with the monthly total net assets under management (TNA), the annual net expense ratio, and portfolio turnover. Daily net returns are computed using the daily return index. This index is the return to an investor who invested in one share at the inception date of the fund. Therefore, it reflects the total returns (included dividends, etc.) for an investor since inception.

After grouping all share-classes belonging to the same fund, we obtain a sample of 5,251 equity mutual funds. We exclude index funds, funds of funds, and funds that do not report data sufficient to calculate daily fund returns. We also exclude all funds with less than $15 million in assets under management, as these may result in a survivorship bias due to reporting conventions (Elton, Gruber, and Blake, 1996; Elton, Gruber, and Blake, 2001; Chen *et al*., 2004; and Amihud and Goyenko, 2013).

We require further that funds have at least 18 months of observations since inception to be included in the sample to avoid any incubation bias, and to reduce the number of funds that are likely to be cross-subsidized by their fund families (Evans, 2010; Yan, 2008, among others). To have a consistent dataset for our analysis, we also delete all funds with less than 30 daily return observations. The final sample consists of 2,360 actively managed US equity mutual funds. Some descriptive statistics for this sample are reported in Panel A of Table 1. Mean fund assets over the sample are $1,503.8 million, while the expense ratio is 1.29%. Relevant to this study, where we examine the performance of funds conditional upon changes of factor exposures, the average annual turnover of funds is 79.9%. The average annual net return associated with funds in the sample is 9.5%.

Some descriptive statistics for the returns on the factors in Equation (1) are presented in Table 1 (Panel B), and correlations between the risk factors are reported in Table 1 (Panel C). The market factor (RMRF) has the highest annualized return, following by the momentum factor (UMD). The size factor (SMB) displays the lowest annualized return over the period examined. All risk factors are significantly correlated with each other. For instance, SMB and the profitability (RMW) factors are negatively correlated (-0.353), while the correlation between the value (HML) and investment (CMA) factors is significantly positive (0.506). These correlations between factors motivate our use of an optimal orthogonal transformation to disentangle the attribution of each factor to overall explained variability.

(*INSERT TABLE 1 AROUND HERE*)

3. Funds' exposure to the risk factors

3.1. Decomposition of R^2

In this section, we analyze the exposure of mutual funds to the risk factors in Equation (1). The aim is to assess how much of the variation in individual mutual fund returns can be explained by returns of the asset classes related to these factors. Previous studies address this issue by regressing mutual funds' returns on several factors, estimating their beta coefficients. For instance, Sharpe (1992), in his classic study, implements a model with twelve asset-classes with some constraints[3] and considers the beta of each explanatory variable as the proportion of the portfolio invested in the related asset class. In addition, other studies (Chen*, et al.*, 2013; Bollen

[3] Sharpe (1992) requires each coefficient to lie between 0 and 100%, and the sum of all the coefficients to be equal to 100%.

and Busse, 2001; Volkman, 1999; among others) analyze the timing abilities of the mutual fund managers by employing the models such as those proposed by Treynor and Mazuy (1966), and Henriksson and Merton (1981). These studies try to identify whether funds increase or decrease their exposure to a specific factor-mimicking portfolio subsequent to positive or negative changes in a factor. These exposures are measured through the beta estimates.

In this study, we are interested in examining the contribution of each risk factor to mutual fund return variability and we do not focus on the slope estimates. The reason is as follows: We know that the exposure to the risk factors described are likely to have a significant impact on the returns of a mutual fund. Some factors will, however, contribute relatively more than others in explaining the variation in returns. To establish the relative importance of the risk factors in explaining mutual fund returns, we decompose the coefficient of determination (R^2), obtained after estimating the model in Equation (1), into the sum of the individual contributions of the specific risk factors. The primary challenge to decomposing R^2 into contributions associated with each of the risk factors is the common variation among factors. As highlighted in Table 1, correlations between the risk factors in this study vary from -0.37 to 0.51, making it difficult to disentangle the attribution of R^2.

To overcome this problem and to determine the contribution of each factor to overall R^2, we apply the optimal orthogonalization first developed by Löwdin (1950) and applied extensively in the natural sciences. While many approaches to orthogonalize a set of variables are available, this approach has the benefit of producing a set of orthogonal factors which are closest to the original factors in a least squares sense (Carlson and Keller, 1957).[4] This allows us to retain an economic interpretation, in terms of how the variation is attributed. Crucially, this approach treats all variables equally (symmetric), with the resultant benefit that there is no requirement to determine an a priori ordering of regression variables in order to isolate the

[4] Formally, the Löwdin symmetric transformation constructs a unique orthonormal basis which has maximal resemblance to the original basis in the nearest-neighbor sense.

attribution of variation. A further benefit of this approach is that the orthogonalized factors retain the same variation as the original factors. Finally, the intercept and the error terms in a regression model remain unchanged after the orthogonalization process, implying that the performance estimation results are not affected by using non-orthogonalized or orthogonalized risk factors.[5]

The orthogonalization procedure is structured as follows. Let us consider $\widetilde{F}_{TxK}$ as a demeaned matrix containing the returns of the *K* factor-mimicking portfolios (factors) during each period from 1 to *T*. The *K* factors are assumed to be uncorrelated with the error term of Model (1), $\varepsilon_{i,t}$, but not among each other. In order to isolate the contribution of each factor to the overall explained variation, we first orthogonalize the factors employing the optimal symmetric orthogonalization first proposed by Löwdin (1950).

In order to create a set of orthogonal factors, we employ a linear transformation, S_{KxK}, that allows us to generate the orthogonalized factors, $\tilde{F}_{TxK}^{\perp}$, from the original matrix $\widetilde{F}_{TxK}$

$$\tilde{F}_{TxK}^{\perp} = \widetilde{F}_{TxK} S_{KxK}. \tag{2}$$

The matrix $\tilde{F}_{TxK}^{\perp}$ will be orthonormal if:

$$\left(\tilde{F}_{TxK}^{\perp}\right)' \tilde{F}_{TxK}^{\perp} = \left(\tilde{F}_{TxK} S_{KxK}\right)' \left(\tilde{F}_{TxK} S_{KxK}\right) = S'_{KxK}\left(\tilde{F}'_{TxK}\tilde{F}_{TxK}\right) S_{KxK} = S'_{KxK} M_{KxK} S_{KxK} = I_{KxK}, \tag{3}$$

where M_{KxK} is the symmetric and positive definite Gram matrix associated with $\tilde{F}_{TxK}^{\perp}$. The general solution to Equation (2) is given by

$$S_{KxK} = M_{KxK}^{-1/2} U, \tag{4}$$

where U is an arbitrary unitary matrix. The Löwdin symmetric transformation is associated with the choice $U = I$, where I is the identity matrix.

To determine the inverse square root of M_{KxK}, we diagonalize the Gram matrix,

[5] See the Appendix A of Klein and Chow (2013) for a demonstration of this corollary.

$$M_{KxK} = O_{KxK} D_{KxK} O'_{KxK}, \tag{5}$$

where O_{KxK} is an orthogonal matrix formed by the *k* eigenvectors of the matrix M_{KxK}, and D_{KxK} is the diagonal matrix formed by the corresponding eigenvalues. Therefore:

$$S_{KxK} = M_{KxK}^{-1/2} = O_{KxK} D_{KxK}^{-1/2} O'_{KxK}. \tag{6}$$

The final step in the orthogonalization is to rescale the factors to their original variances,

$$S_{KxK} \longmapsto S_{KxK}\sqrt{T-1}\begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_K \end{bmatrix}, \tag{7}$$

where σ_k refers to the standard deviation of factor *K*. The orthogonalized factors, $F_{TxK}^{\perp}$, are then obtained by applying Equation (2). These orthogonalized factors are used as the explanatory variables in Equation (1) to estimate regression betas. Following the approach of Klein and Chow (2013), the coefficient of determination (R^2) can then be decomposed into components associated with each orthogonal factor, as follows:

$$R_j^2 = \sum_{k=1}^{K} R_{j,k}^2 = \sum_{k=1}^{K} \left(\hat{\beta}_{k_j}^{\perp} \frac{\sigma_k}{\sigma_j}\right)^2 \tag{8}$$

where R^2_j is the coefficient of determination estimated using the orthogonalized factor model for fund *j*. $R^2_{j,k}$ is the contribution of each orthogonalized factor *k* to the total R^2 of the estimated model. $\hat{\beta}_{k_j}^{\perp}$ is the estimated coefficient on the orthogonalized factor *k* in the fund *j*'s regression, and σ_j is the standard deviation of the returns of the same fund. See Adcock, Bessler and Conlon (2019) for evidence that the Lowdin (1950) transformation provides a higher correlation between the original and orthogonal variables than alternative orthogonalization methods.

3.2. Decomposition of Mutual Funds R^2

In this Section, we apply the Löwdin (1950) optimal orthogonalization to the set of factors under consideration and then decompose the R^2 associated with equation 1 into components associated with each factor (Klein and Chow, 2013) over the entire period. Ordinary least squares (OLS) time-series regressions are estimated for each fund in the sample, allowing the regression estimates to differ across funds. The mean and significance (t-statistics for an average coefficient significantly different from zero) of the estimates are presented in Table 2 along with the average factor contribution to the total R^2. The R^2 and the number of funds used in the analysis are also reported.

(*INSERT TABLE 2 AROUND HERE*)

In line with the previous literature, the average fund generates a significant negative performance of 110 basis points per year. In addition, the slope on the market factor is close to one, as the sample consists of equity mutual funds that invest primarily in US stocks and reflect, on average, the market index. As expected, this factor also explains most of the total variation (82.7%) in mutual funds' returns during the main period. Other factors, despite being statistically significant at any reasonable level, do not provide a large contribution to the explanation of the variability of the funds' returns during the entire period. For instance, the average coefficient on the investment factor, CMA, is significantly negative (coefficient of -0.170), with a t-statistic of -34.75, but its contribution to total R^2 is very low (contribution of 0.7%).

As all funds examined are actively managed, and given the evidence shown in previous studies (e.g., Matallín-Sáez, Soler-Domínguez and Tortosa-Ausina, 2016), we next analyze whether their exposures to the different risk factors are conditional upon the business cycle. According to the National Bureau of Economic Research (NBER), six different sub-periods are present in our sample period.[6] These sub-periods are classified as recessions (from August 1990 to March 1991, from April 2001 to November 2001, and from January 2008 to June 2009) or expansions (from April 1991 to March 2001, from December 2001 to December 2007, and from

[6] We do not include the first seven months because they are part of an expansion sub-period that started in December 1983. For more information on the NBER sub-periods, see http://www.nber.org/cycles/cyclesmain.html

July 2009 to December 2016). Similar to Table 2, Table 3 reports results of the aforementioned analysis for funds that existed in each of the NBER sub-periods. Recessions and expansionary sub-periods are shown in Panel A and Panel B, respectively.

(*INSERT TABLE 3 AROUND HERE*)

As expected, the average fund's exposures to the different risk factors is time varying. The market factor provides the highest contribution in explaining the variation in mutual funds' returns during the sub-periods. Its contribution, however, varies between 63.5% during the first expansionary sub-period and 83.8% during the most recent expansion sub-period. Contributions from the remaining factors are time varying as well. For instance, the contribution of the momentum factor to the total R^2 seems to be especially relevant during recessions (e.g., 12.3% during the dot-com bubble recession, and 11.8% during the recent 2008-2009 global financial crisis). These findings provide initial evidence that mutual fund managers change their risk factor exposures over time, indicating active fund management.

Due to the different lengths of the NBER sub-periods, and with the aim of inferring the average exposures of the mutual funds through time, we next employ a 252-day rolling window to estimate the contribution of each factor to the coefficient of determination for the period from 1990 to 2016. Figure 1 shows the plot of the overall results of this analysis.[7] Figure 1A presents the contribution of all the risk factors in the model, while Figure 1B omits the market factor to better visualize exposure changes for the remaining factors.

(*INSERT FIGURE 1 AROUND HERE*)

In line with the results in Table 2 and Table 3, the variability in mutual funds is primarily attributed to the market factor over time. Other factors (e.g., SMB, UMD), however, also play an important, but dynamic, role in explaining mutual fund returns. Nevertheless, some risk

[7] Each fund is required to present a minimum of 30 observations on daily returns in order to be included in the sample.

factors (e.g., CMA), despite being statistically significant, do not contribute substantially to explaining the variability in mutual fund returns since 2001.

In sum, using only returns data, we clearly demonstrate that the actively managed US mutual funds in our sample adjust their risk exposures on a short-term basis. In the next Sections, we propose a measure to quantify this change and study the relationship with ex-post mutual fund performance.

3.3. Change in the funds' exposures to the risk factors

Given the evidence for time-varying mutual fund exposures provided in the previous Section, we now develop a measure to capture the change in a funds' exposure to the different risk factors, defined as follows:

$$CFE_{j,t} = \sum_{k=1}^{K} \left| \frac{R_{j,k,\tau}^2}{R_{j,\tau}^2} - \frac{R_{j,k,\tau-1}^2}{R_{j,\tau-1}^2} \right| \qquad (9)$$

where $CFE_{i,t}$ (change in factor exposures) is the sum of the absolute change in fund *j*'s exposures to the risk factors, *k*, during the period τ, and $R_{j,k,\tau}^2$ is the relative contribution of the factor *k* to the total R^2 experienced by fund *j* during the period τ. The empirical set-up underpinning this analysis is outlined graphically in Figure 2. Analogous to the active share measure proposed by Cremers and Petajisto (2009) for changes in the weights of stocks held by funds, *CFE* measures the overall change in a fund's exposure to the risk factors, based on a comparison of the relative contributions of each factor during two consecutive and non-overlapping periods. Relative contributions are required to avoid tracking error effects in the change of the fund's exposures to the risk factors. We employ absolute values because we view both increases and decreases of the contribution of each risk factor as a change in the fund's exposure to this factor. We divide the sum of the changes in each contribution by two to ensure that a hypothetical fund changing completely its exposures to the different factors achieves a *CFE* of equal to 100%.[8]

(*INSERT FIGURE 2 AROUND HERE*)

In the next Section, we estimate for each fund the change in risk factor exposures and analyze whether this ratio is related to future fund performance.

4. Change in Factor Exposure Results

4.1. Performance of fund portfolios with different levels of CFE

In this Section, we examine the relationship between changes in funds' risk factor exposures and subsequent performance. Assuming that, for actively managed mutual funds, a change in risk factors exposures is usually motivated by the managers' expectations about the return evolution of the asset classes related to these factors, we should expect that the higher this change, the better is the subsequent performance associated with active management.

Following Amihud and Goyenko (2013), we double-sort and create twenty-five different hypothetical portfolios that invest in the funds according to their previous CFE and their past performance.[9] We sort on CFE because we aim to determine whether funds changing their exposures to a greater degree achieve better performance than funds with lower CFE. Additionally, we include the previous performance in the analysis because of earlier evidence on performance persistence (Ferreira et al., 2019; Brown and Goetzmann, 1995, among others). Specifically, we perform the following analysis. Firstly, we estimate and decompose the coefficient of determination of each fund on a monthly basis, employing daily data from the

[8] This measure is similar to the Active Share of Cremers and Petajisto (2009). However, while these authors compare the portfolio weights with those of their benchmark, we observe the differences among the contributions of the risk factors to the R^2 of a fund during two consecutive periods.

[9] Amihud and Goyenko (2013) create twenty-five fund portfolios, double-sorting first on the funds' R^2, and then on the previous funds' alpha.

previous year, using the six-factor model described in Equation (1), following the methodology of Klein and Chow (2013). The CFE is then estimated by comparing the contribution of each factor to the coefficient of determination using data from two consecutive and non-overlapping periods. Specifically, the CFE is determined by using changes in factor contributions between the current year, t, and the previous year, t-1. Subsequently, we split the sample into five quintiles according to the CFE of the fund in each month, from the lowest (P1) to the highest (P5) levels and then sorting again the funds belonging to each of these five subsamples into five quintiles, according to their previous performance, or alpha (again, from the lowest to the highest values). This alpha is also estimated over the previous 252 days, using Model (1). Hence, the funds are grouped each month into twenty-five portfolios, according to their previously experienced CFE and alpha.

We calculate the ex-post one-month returns of the twenty-five equally weighted hypothetical portfolios. These portfolios are then monthly rebalanced. Furthermore, we create additional portfolios (portfolios '*All*') that invest in our sample funds according to the level of one of these characteristics (namely, CFE or alpha). Finally, we assess the ex-post performance of these hypothetical portfolios using the six-factor model described above. Note that this analysis requires two years of data to be correctly implemented. The sample period runs from January 1992 to December 2016. Table 4 reports the alpha and significance level for each of these portfolios, as well as the differences between the portfolios investing in funds with the previously highest and lowest levels of CFE or alpha ('*P5-P1*').

(*INSERT TABLE 4 AROUND HERE*)

As shown in Table 4, the average fund experiences a significantly negative performance of 69 basis points per year. This average result, however, masks considerable heterogeneity in performance dependent upon portfolio CFE. We observe increasing performance as we move from funds with low exposure changes to those with higher changes. Specifically, this ranges from a statistically significant -132 basis points for funds with the smallest exposure changes to +66 basis points for those with the largest CFE. Funds with the largest exposure changes outperform funds with the smallest exposure changes by a statistically significant 198 basis points over the 1992-2016 period.

In Table 4, we also sort according to ex-ante portfolio alpha. Portfolios investing in the previously lowest-performing funds experience a statistically significant negative performance between -263 and -284 basis points per year. Those that invest in the previously best performing funds significantly outperform by 511 basis points those portfolios that invest each month in funds with the previously lowest performance. These findings are linked to the ongoing debate regarding the persistence in mutual fund performance (Bessler *et al*., 2018; Keswani and Stolin, 2012; Kosowski *et al*., 2006; Berk and Green, 2004).

Finally, ranking funds on CFE and past alpha reveals that those with the worst previous performance and that change their exposures least have an alpha of -264 basis points. In contrast, mutual funds with the highest previous alpha and that change their factor exposure most have a subsequent average return of 488 basis points. This results in a performance differential of 752 basis points between the two extreme portfolios. These findings indicate that fund managers with persistent performance in the past and who are willing to regularly change their risk exposures outperform in the subsequent month. We next investigate whether these findings relating to CFE hold when we control for other factors previously shown to have predictive power for fund performance.

4.2. Examining managerial skills through CFE and other measures of active management

This study proposes a novel way to measure active management in equity mutual funds, and examines its relation to fund performance. Previous studies also addressed the role that active managers play in the mutual fund industry, and concluded that more active funds and funds showing greater managerial skills subsequently achieved higher portfolio returns. Consequently, we next analyze whether the aforementioned relationship between CFE and fund performance is explained by other measures of active management that predict fund performance, such as the funds' coefficient of determination (Amihud and Goyenko, 2013), Active Share (Cremers and Petajisto, 2009) and Return Gap (Kacperczyk, *et al.*, 2008).

4.2.1. Is the evidence on the CFE driven by the funds' tracking error?

So far, we provided evidence that funds that change their risk factor exposures to a greater extent generate higher alphas than those with a lower CFE. Amihud and Goyenko (2013) previously indicated that a fund's tracking error relates to future performance. Given that our measure of factor exposure changes is calculated relative to overall R^2, we investigate whether our findings are linked with fund tracking errors.

To isolate the impact of tracking errors, we run a similar procedure to that detailed in Table 4, but this time we consider a double sort of funds on CFE and coefficient of determination. These R^2 are estimated using similar rolling windows (the previous 252 days). Funds are then grouped into twenty-five different portfolios according to their CFE and their coefficient of determination. Ex-post performance for these portfolios using Model (1) are shown in Table 5.

(*INSERT TABLE 5 AROUND HERE*)

In line with Amihud and Goyenko (2013), funds with a high R^2 experience, on average, a negative and statistically significant performance. For instance, the portfolio investing in funds with the highest previous R^2 (column *All*, row *P5*), obtain a statistically significant alpha of -1.31% per year (t-stat of -4.406). Double sorting on CFE and R^2, we note that funds with the highest R^2 but with little exposure changes have a significant alpha of -2.06% per annum. Considering only funds with the highest previous R^2, we find a statistically significant difference of 2.22% between funds with the largest and those with the smallest change in CFE. These differential results for high and low CFE funds suggest that CFE is not acting as a proxy for the coefficient of determination of a fund.

A further consideration is that funds might generate a change in their exposures due to a change in their tracking error. If a fund altering its tracking error does not have exactly the same relative contributions from each risk factor to its total R^2 at both the beginning and end of the period, it would implicitly change its overall exposures. Consequently, we address this issue by considering the change in the funds' exposures and the change in the tracking error (ΔR^2) during two consecutive periods in the double-sorting procedure. Table 6 shows the main performance results from this analysis.

(*INSERT TABLE 6 AROUND HERE*)

The evidence in Table 6 indicates that our findings are not simply a consequence of changes in tracking error. Examining tracking error first in isolation, we find no statistically significant performance for any of the tracking error portfolios (column All). Decomposing this into portfolios delineated by CFE and the change in R^2, we generally find a negative and significant performance for funds with the lowest CFE (columns P1 and P2). Contrasting those portfolios with low and high CFE for the same change in R^2, we observe a statistically significant difference in performance in three out of five cases. For the portfolios with the greatest change in R^2 there is a significant outperformance of 246 basis points between funds with the highest and lowest CFE. These findings suggest that our results are not a consequence of R^2 or changes in R^2 in the funds studied.

4.2.2. CFE and Active Share

Developed by Cremers and Petajisto (2009), the Active Share of a mutual fund is computed as the overall deviation of the fund portfolio's weights relative to its benchmark index. Active Share represents the degree to which a mutual fund differs from its benchmark, in terms of portfolio holdings (Cline and Gilstrap, 2021). Since passive strategies meant to fully-replicate stock market indices, they must present very low deviations from their benchmarks. Therefore, Active Share can be interpreted as a measure of the level of activity associated with mutual fund management.

Active Share clearly differs from the measure proposed in this study. By construction, it requires portfolio disclosed holdings to snap a picture of the fund deviation from its benchmark on an exact date, while CFE involves a completely different dataset (time-series evolution of returns) to detect any variations in the fund exposures during a period of time. Therefore, these measures capture active management in distinct ways. It is possible, however, for both measures to converge to similar conclusions in some cases. For instance, a passively-managed mutual fund that tracks a benchmark must experience low scores of Active Share and CFE. Similarly, a fund investing in a reduced number of highly-volatile stocks may reach higher levels of both measures. Nonetheless, it is important to highlight that Active Share and CFE may diverge in terms of the information captured in most situations. As Amihud and Goyenko (2013) point out, an equity fund that passively invests most of its assets in the stocks comprising a large-cap index and passively allocates the rest of its assets in the stocks of a representative small-cap index, will achieve a high Active Share, despite being passively managed. In contrast, that passive fund will be linked to a very low level of activity under the implementation of a multifactor model (both in terms of changes in R^2 and CFE).

Also, Active Share and CFE are shown to be significant predictors of future fund performance. In this sense, it becomes essential to examine whether the overall fund performance captured by higher (lower) levels of CFE is qualitatively different from that achieved by funds with higher (lower) Active Shares. To explore this issue, we first obtain data on funds' Active Share from two main sources. On the one hand, Morningstar provides these data on a monthly basis from 2002 on. Nonetheless, most of the funds in our sample report information on this variable on a quarterly frequency. On the other hand, we obtain data on funds' quarterly Active Share from 1990 to 2001 from Antti Petajisto's website.[10] We merge these two datasets using fund tickers. Given the differences in the data frequency, and in order to ensure consistency in our analyses, we assume that the monthly Active Share of each fund equals the fund's Active Share at the end of the quarter. This way, almost all the funds in our sample (2,143 funds) present monthly information on CFE and Active Share.

Next, we follow a double-sorting procedure based on these proxies of active management. Funds are then gathered into twenty-five portfolios in relation to their previous levels of CFE and Active Share. The assessment of each portfolio through the multifactor model shown in (1) yields ex-post alpha results, which are reported in Table 7 (Panel A).

(*INSERT TABLE 7 AROUND HERE*)

Panel A of Table 7 demonstrates that our findings for CFE are not a consequence of Active Share. Considering only Active Share in the analysis ('All' rows), results are linked to the conclusions reached in Cremers and Petajisto (2009). That is, and in the aggregate, mutual funds deviating more from their benchmark significantly outperform those funds with lower Active Share. This outperformance results in a difference in the annualized average alphas of 1.18% (t-stat of 2.324). In contrast, CFE is shown as a stronger predictor of future performance, given the greater differences in the risk-adjusted returns of funds exhibiting the highest and the lowest factor exposures (annualized alpha of 2.16%). Moreover, and in controlling for different levels of both variables, alpha differences between funds with high and low Active Shares (last rows) are positive, but statistically significant in only one case (column P3), while the mean alphas

[10] The authors greatly appreciate Professor Petajisto for making these data publicly available. A detailed description of the methodology and data used to estimate Active Share can be found in Petajisto (2013). For more information, please see http://www.petajisto.net/data.html

achieved by P5-P1 CFE-based portfolios (last column) are significantly positive in most of the levels of Active Share considered.

Nonetheless, this evidence appears to be a consequence of the negative risk-adjusted returns experienced by less active funds, identified through low levels of both CFE and Active Share. This underscores the importance of considering both variables to assess the degree of active management. Interestingly, this might also entail a positive correlation between Active Share and CFE as fund performance determinants, so further tests are required to examine whether the performance captured by fund CFE is explained by the dynamics of other active management proxies.

Apart from the analysis described above, we should note that any adjustments of portfolio weights may produce alterations in funds' factor exposures and in their Active Share. Accordingly, and similar to the procedure described in Table 6, we elaborate additional portfolios based on CFE and on the quarterly change in funds' Active Share. Ex-post performance of these additional portfolios are reported in Panel B of Table 7.

In line with Panel A, results in Panel B show that funds altering their deviation with respect to their benchmark the least, in terms of portfolio weights (P1 rows), experience a significantly negative alpha of -1.29% (t-stat of -2.932), in annual terms. This underperformance is mainly led by the worse returns experienced by funds that barely alter their exposures. We also find differences between the returns of low and high CFE funds ranging from 1.47% to 2.9% for portfolios sorted by the change in Active Share, with statistically significant differences observed for portfolios P2 and P3. These findings indicate that the effect of CFE on fund risk-adjusted returns is not simply due to changes in Active Share.

4.2.3. CFE and Return Gap

Return Gap refers to the difference between the net return a fund obtains during a period and the return of a hypothetical passive portfolio that mimics fund holdings at the beginning of that period. This term was firstly coined by Kacperczyk, *et al.* (2008), who defined it "as a direct measure of the value added (or subtracted) by the fund manager relative to the previously disclosed holdings" (p. 2380). In other words, managers' trading could lead to positive or negative Return Gaps (or a combination of them), while passive management must experience limited Return Gaps by construction. In their study, Kacperczyk, *et al.* (2008) observed that mutual funds reported a close-to-zero Return Gap in the aggregate. Nonetheless, some fund managers created value through their actions and, consequently, displayed better performance. Furthermore, the value added by the best and the worst fund managers seemed to persevere over time (i.e., Return Gap showed persistence), making it a forecasting tool of future fund performance. Given this evidence, we now analyze whether the CFE-performance relationship is explained by funds' Return Gap.

To construct the returns of passive portfolios investing in the previously disclosed funds' holdings, we first obtain quarterly data on mutual funds' stock holdings from the Thomson Reuters database. This dataset is linked to the main sample of this study (obtained from Morningstar) through fund tickers. Unmatched funds, and funds not reporting similar fund names and assets under management in each period are excluded. Following Hoberg, *et al.* (2018), we also delete fund observations that present excessively stale data. Specifically, and for each quarter, we restrict the analysis to funds disclosing their holdings during any day in that quarter or, if this is not available, during any day in the previous quarter. This procedure results in a sample of 1,113 different mutual funds presenting data in both databases.

Apart from stock holdings, additional data on other assets held in fund portfolios are required to construct passive portfolios mimicking funds' portfolio structure. Given that this is not available in Thomson Reuters, we retrieved from Morningstar the following items, measured as at the end of each quarter: percentage of fund's assets in stocks, in preferred stocks, in bonds, in cash and cash equivalents, and in other assets. Similar to Kacperczyk, *et al.* (2008), we use the quarterly return of the Bloomberg Barclays US Aggregate Bond Index to proxy for the behavior of bonds and preferred stocks, and the US Treasury Bill rate to capture the evolution of cash and other assets held in funds' portfolios. Accordingly, we estimate the quarterly returns of each buy-and-hold portfolio investing in the most recently disclosed fund holdings as the product of the fund weights (percentages invested in each asset class at the beginning of each quarter) times the returns of the different assets held by a fund. Return Gap for each fund is then computed as the difference between the fund's actual net return minus the net return of the corresponding buy-and-hold portfolio (i.e., in excess of fund expenses). As in Section 4.2.2, we assume that the monthly Return Gap of each fund equals the fund's Return Gap at the end of the quarter. This enables us to examine whether Return Gap drives our results on a monthly basis.

Similar to previous analyses, we develop twenty-five hypothetical portfolios that invest in the funds according to their previous levels of CFE and Return Gap, and evaluate their performance through the six-factor model described in Model (1). Ex-post alphas, as well as their significance, are shown in Table 8.

(*INSERT TABLE 8 AROUND HERE*)

Consistent with the evidence in Kacperczyk, *et al.* (2008), Table 8 shows that funds with the worst Return Gaps in previous periods (P1 and P2 rows) also experience the worst ex-post alphas in the aggregate. As a result, the differences in the performance between funds with the highest and the lowest prior Return Gaps are positive. After controlling for different levels of both variables, results indicate that this underperformance is especially relevant for those funds experiencing smaller variation in their factor exposures. For instance, high-CFE funds with the best Return Gap in the past significantly outperform their low-CFE peers (annualized alpha differences of 2.65%, t-stat of 2.111). These findings illustrate that the outperformance found for high CFE funds is not a consequence of the Return Gap.

4.3. Controlling for the effect of fund size

An alternative explanation for our results is that it stems from a fund size effect. It has been documented that larger funds (those with more assets) face more difficulties than smaller funds in altering their risk factor exposures and in generating outperformance (Bessler, Kryzanowski, Kurmann and Lückoff, 2016). Hence, larger funds should experience lower levels of CFE than smaller funds. Accordingly, Table 9 documents the performance results of twenty-five monthly-rebalanced hypothetical portfolios, double-sorting on the change in the funds' risk factor exposures and on the total net assets under management.

(*INSERT TABLE 9 AROUND HERE*)

After controlling for the effect of fund size, portfolios that invest in funds experiencing the lowest levels of CFE still obtain the lowest alphas in the sample. Conversely, portfolios that invest in previous high-CFE funds do not experience significantly negative alphas. Furthermore, we find outperformance for funds with the highest level of CFE relative to those with the lowest level of CFE. The differences in the annualized alpha are 2.32% for the smallest funds and 2.28% for the largest funds (t-statistics of 2.607 and 2.064, respectively). This highlights that our findings are not simply a consequence of small, agile funds shifting their positions on a regular basis, as the largest funds, which also actively change their factor exposures, also outperform.

4.4. CFE and fund style classification

Funds following different investment strategies tend to focus upon holdings of a particular style and have been linked with variations in performance persistence (Keswani and Stolin, 2006). In this sense, Morningstar classifies funds in several categories according to their underlying portfolio holdings over the past three years. For instance, funds investing primarily in stocks in the top 70% of the capitalization of the US market are classified as large cap funds. In contrast, small cap funds invest primarily in small stocks (stocks in the bottom 10% of the capitalization of the US market). Additionally, value funds concentrate their main investments in value stocks, that is, stocks characterized by slow growth (low growth rates for earnings, sales, book value and cash-flow) and a low valuation (low price ratios and high dividend yields). In contrast, growth funds invest primarily in growth stocks (stocks with a fast growth and a high valuation) and usually focus on companies that belong to quickly expanding industries.

Accordingly, we might expect to find differences in CFE among funds with different Morningstar Investment Style Categories. For instance, growth funds might experience, on average, greater risk factor variation in their exposures than value funds, given the uncertainty associated with growth as an investment strategy. In light of the evidence provided in previous studies (Chen *et al*., 2000; Chan *et al*., 2002; Kosowski *et al*., 2006) regarding the stronger results achieved by growth-oriented funds, the aforementioned results might be driven by behavioral differences between growth and value fund investors (Blackburn *et al*., 2014).

Therefore, we sort funds in six different classifications according to their Morningstar Category (Large-Cap, Mid-Cap, Small-Cap for funds focusing on stocks with a specific size or market capitalization; and Growth, Blend, and Value for funds investing primarily in stocks with a certain valuation or book-to-market ratios) and observe their levels of CFE. Figure 3 plots the average CFE over time for the funds in each Morningstar Category related to the stock capitalization (Figure A) and book-to-market (Figure B) classifications.

(*INSERT FIGURE 3 AROUND HERE*)

Figure 3 presents the dynamics of CFE for each fund categorization, with considerable heterogeneity evident across the categories. In Panel A, we observe that Large-Cap funds tend to have the lowest CFE, while Mid- and Small-Cap funds tend to change their exposures to a greater extent. Considering funds classified according to book-to-market, growth funds tend to have the highest overall change in their exposures to the risk factors and the greatest variation in CFE.

Similar to the previous analyses, we evaluate the performance of funds according to their CFE, conditional upon the Morningstar Category to which these funds belong. Thus, for each classification, we create five hypothetical quintile-portfolios that invest at the beginning of each period in funds with similar levels of CFE at the end of the previous period. We rebalance these portfolios again every month and assess their ex-post performance by using the six-factor model. Results are reported in Table 10.

(*INSERT TABLE 10 AROUND HERE*)

The results are in line with those documented in previous sections. That is, there is significant evidence of a superior performance for those portfolios investing in funds with the highest levels of CFE (*P5*), compared to that obtained by portfolios investing in funds with the lowest variation (*P1*). This evidence holds, in particular, for growth funds (annualized alpha for P5-P1 of 2.20%, t-statistic of 2.272), large-cap funds (annualized alpha for P5-P1 of 2.23%, t-statistic of 2.319) and small-cap funds (annualized alpha for P5-P1 of 1.98%, t-statistic of 1.900). Regarding blend funds and value funds, the differences in the alphas between *P5* and *P1* are insignificant. Funds with relatively low changes in factor exposures, on aggregate, display significant alphas, while the performance of funds with the highest variation is insignificant. An exception to this are growth funds, where those with highest CFE have a positive and significant alpha of 1.52% per annum, building on previous findings relating to timing skills for such funds (Chen *et al.*, 2013).

4.5. Luck or skill? The performance of predictive portfolios with over longer horizons

So far, we observed that funds changing their risk factor exposures to a greater extent provide investors with larger alphas than funds that have less exposure variations. One possible explanation might be that the short-term outperformance is due to luck rather than to investment skills or managers' abilities.

However, luck is a temporary phenomenon while investment skills should persist over time. Consequently, and with the aim of differentiating between luck and skill, we analyze the performance persistence for portfolios over the following *m* months. We consider twelve different out-of-sample evaluation periods with *m* ranging between 1 to 12 months. Specifically, and for each month *t*, we first sort the funds in the sample into quintiles, according to their level of CFE. Next, we examine the performance of these quintile portfolios for the following *m* months, using the ex-ante information provided by CFE at time *t*. While performance is assessed over the following 12 months, portfolios are rebalanced monthly. Figure 4 graphically illustrates how out-of-sample returns for the following 12 months are calculated.

(*INSERT FIGURE 4 AROUND HERE*)

If the evidence presented in the previous sections is due to mutual fund managers' luck, we would expect to observe attenuation in performance as we move forward in time. In the case that mutual fund managers varying their exposures to a greater degree were skilled enough to provide investors with superior alphas, then these funds should report a persistently higher performance over time. Table 11 presents the performance of each CFE portfolio in addition to the differences between portfolios investing in funds with the highest and the lowest levels of CFE for different monthly intervals post portfolio formation.

(*INSERT TABLE 11 AROUND HERE*)

Portfolios formed based upon the lowest CFE at time *t* have a significant negative alpha in every month for up to 12 months post formation. Moreover, we find a statistical outperformance of funds with the highest CFE relative to funds with the lowest CFE (*P5-P1*) for up to 11 months. These findings indicate that managers with the smallest factor exposure changes persistently underperform those who change their exposures by the most. Therefore, the outperformance of high CFE managers does not seem to be a consequence of luck as it persists for up to 11 months post portfolio formation.

4.6. CFE estimation window

In Section 3.2., *CFE* is defined as the overall change in a fund's exposure to the risk factors, based on a comparison of the relative contributions of each factor during two consecutive and non-overlapping periods. These non-overlapping periods cover a full year of daily data (i.e., 252 days) in the previous analyses. Hence, the use of a shorter window should provide more timely estimates of a change in factor exposure and capture better the interactions between the variation in the funds' exposures and subsequent performance.

Accordingly, we estimate the *CFE* during each period considering two consecutive and non-overlapping six-month periods (i.e., 126 days), instead of a whole year of data. We perform analyses analogous to those in Section 4.1 and 4.2.1 with the purpose of controlling for previous fund performance and tracking error. Specifically, we create twenty-five hypothetical portfolios that invest in funds according to their previous quintile-levels of *CFE* and alpha, both estimated using a half-year windows of daily data. These portfolios are monthly rebalanced. Panel A of Table 12 presents the performance results of this analysis. Similarly, Panel B shows the performance results of predictive portfolios generated through a double-sorting analysis that considers previous levels of CFE and coefficient of determination (also assessed during the previous six-months).

(*INSERT TABLE 12 AROUND HERE*)

Assessing performance for portfolios formed using CFE alone, we find a statistically significant difference of 315 basis points between portfolio with the highest and lowest CFE. Portfolios where the manager changes factor exposure the least lose a significant 242 basis points per annum, while those that change factor exposures the most gain 73 basis points. The increase in performance relative to the previous analysis is consequence of the timelier signal from using more recent data. Moreover, in Panel A, we investigate portfolios of funds double sorted on previous CFE and alpha. The portfolio investing in the previous best-performing funds that experience the highest CFE achieves an annualized alpha of 0.0481 (t-stat of 5.312). In contrast, the portfolio investing in the portfolio with the lowest factor change and the lowest previous alpha obtains a significantly negative alpha of -0.0327 per year (t-stat of -2.327). Furthermore, there is a statistically significant and positive difference between portfolios with the highest and lowest CFE, ranging from 202 to 647 basis points, for the four portfolios with the largest ex-ante alpha.

Our earlier findings are further corroborated in Panel B, where portfolios are double sorted on previous CFE and R^2. For all portfolios sorted by R^2, we find a positive and significant difference between portfolios with the highest and lowest CFE, ranging from 239 to 393 basis points. This further demonstrates that our findings relating to CFE are not a consequence of the funds ex-ante R^2.

4.7. Determinants of future fund performance

In this Section, we aim to investigate the effect of the CFE on future fund alphas while controlling for several fund characteristics that could act as performance determinants. To address this issue, we follow the Fama-MacBeth (1973) procedure. The dependent variable for this analysis is the ex-post performance achieved by each fund, estimated using daily data during the following month (that is, the annualized one-month alpha of each fund assessed through the six-factor model). The explanatory variables include the CFE for each fund experienced during the previous year, and some control variables, such as the funds' net expense ratio and the natural logarithms of the funds' age, size and turnover ratio (Budiono and Martens, 2010). Given the evidence in Amihud and Goyenko (2013), we also control for the funds' coefficient of determination, which is obtained from applying the six-factor model to each fund in our sample during the previous year. Additionally, we include the corresponding one-year alpha in the analysis in order to proxy for managerial abilities. Next, we estimate the time-series mean coefficients and present the main results in Table 13.

(*INSERT TABLE 13 AROUND HERE*)

As shown in Table 13, CFE presents a positive and statistically significant coefficient in the considered models. This evidence remains even after controlling for several fund characteristics that could determine fund performance. For instance, greater managerial and operating expenses and a higher coefficient of determination for a fund are related to lower subsequent performance (regarding Model 4, mean coefficients of -0.4946 and -0.0375, t-stats of -3.66 and -1.84, respectively). Also, results in Table 13 indicate that previous fund performance affects future fund alphas positively and in a statistically significant way (mean coefficient of 0.187, t-stat of 6.81), which is consistent with the evidence provided in Table 4.

4.8. Explaining CFE as a measure of funds' active management

Up to this Section, we observe that funds altering their factor exposures to a greater extent subsequently obtain higher risk-adjusted returns or multi-factor alphas than those that maintain similar exposures over time. Consequently, CFE is shown as a predictor of fund performance. This relation between CFE and future fund results prevails even after controlling for other factors that determine fund performance.

Therefore, CFE captures the degree of active portfolio management. Passive management should not lead to high exposure variations. This includes not only index-mimicking portfolios, but also other buy-and-hold strategies that deviate from a benchmark index. This does not mean that a passive portfolio must not present any changes in their exposures to common risk factors. For instance, let us assume a portfolio that currently invests in two different stocks. In a given month, portfolio weights will have simply changed if those stocks appreciate differently. This will turn into a variation in the contribution of each systematic risk factor to the explanation of portfolio returns' variability even if those stocks will not experience any individual changes in their systematic risks. In a broader sense, macroeconomic and other external factors will affect fund returns, leading to higher CFEs in some specific periods (as Figure 1 and Figure 3 suggest). In any case, a minimum variation in factor exposures will be experienced by all the funds, regardless of being actively or passively-managed. Still, and as opposed to passive strategies, active management may entail different patterns of portfolio returns over time, especially when managers assume greater factor exposures. Higher levels of mutual fund CFE (in relation to their peers) should capture higher levels of active portfolio management, therefore.

As explained in earlier Sections, previous literature proposes different proxies to quantify active management in the mutual fund industry. If these proxies are representative of the overall level of managerial activity, they may relate to CFE. Moreover, managers detecting stock market opportunities may alter fund exposures to a greater extent. If those managers are skilled enough to obtain better fund performance, then we should find a positive correlation between CFE and other measures meant to assess the value added by fund managers.

Next, we run panel regressions with two-way (time and fund) fixed effects in order to examine the relation between CFE and other measures of active management. Each model treats funds' CFE as the dependent variable. Several fund characteristics and other measures related to active management in previous studies are defined as explanatory variables. Standard errors are clustered at fund and year level. The main regression results are reported in Table 14.

(*INSERT TABLE 14 AROUND HERE*)

As Table 14 shows, several fund characteristics correlate with CFE. For instance, the slope on portfolio turnover is positive and statistically significant in all the models proposed. That is, managers altering the structure of their portfolios also occasion considerable variations in factor exposures. Consequently, and as discussed earlier, passive portfolios following buy-and-hold strategies do not experience high levels of CFE.

Other representative measures of active management or managerial abilities also show a positive and significant correlation with CFE, regardless of examining the relation individually (models from 2 to 4) or simultaneously (model 5). Specifically, the coefficient of determination has a negative effect on CFE in the second model (coefficient of -0.0898, t-stat of -4.93), implying that more active funds (identified as those with lower R^2 and higher CFE) show greater levels of tracking error in their management. Regarding the third model, and in line with the conclusions drawn from previous analyses, Active Share relates to CFE in a positive and statistically significant way (coefficient of 0.0348, t-stat of 4.42). In addition, funds experiencing greater levels of CFE also obtain higher active returns, estimated through funds' Return Gap (coefficient of 0.0555 in the fourth model). This suggests that skilled managers detecting market opportunities markedly shift funds' factor exposures over time.

Furthermore, we examine the relation between CFE and fund alphas in controlling for the aforementioned variables. As shown in the last model, we find a positive and statistically significant slope on fund performance (coefficient of 0.0547, t-stat of 4.70). This indicates that higher variations in factor exposures is associated with greater risk-adjusted returns. This relation is not driven by Active Share, Return Gap or other fund performance determinants.

These results must be interpreted with caution. It does not necessarily imply that greater exposure variations will lead to better returns in subsequent periods since stocks' behavior has an unexpected component. Nevertheless, our results highlight the potential value added by some managers that show investment skills. We should note that the performance of a fund depends, in part, on the beliefs that active managers have on the future evolution of returns. Some of them may make bad investment decisions, increasing fund CFE, but adversely affecting risk-adjusted returns. Skilled managers that aim to benefit from detected market opportunities, will be more likely to modify their factor exposures to a greater extent. Hence, and relative to other funds, high CFE levels should capture not only the degree of active management, but also predict future outperformance in the aggregate.

5. Conclusions

Recent studies have provided empirical evidence that some mutual funds are able to provide investors with greater abnormal returns, or alphas. This outperformance is often attributed to a higher degree of activity in the fund portfolio management. Nonetheless, measuring the level of active management in the mutual fund industry is not a simple issue to address, and a consensus has not yet been reached in the previous literature.

In this study, we propose a new measure to estimate the level of active management. This measure is based on the contributions of each risk factor to the explained variability in fund returns, what we define as the fund's exposures to the risk factors. Specifically, our main aim is to capture the change in these factors' contributions during two consecutive and non-overlapping periods, and to test whether mutual funds that alter their exposures to systematic factors more achieve superior performance.

For a large sample of US domestic equity mutual funds, our results suggest that funds varying their risk factor exposures to a greater extent generate higher subsequent alphas relative to those with lower change in factor exposure. Moreover, investing in funds with the best performance ex-ante, which also changed their exposures to a large degree, leads to positive and statistically significant alphas between 2.60% and 4.80%, in annualized terms. Moreover, this outperformance is not explained by other performance indicators, such as the funds' tracking error, Active Share, Return Gap, the total net assets under management, and the investment style implemented in the portfolio, since similar evidence arises after controlling for different levels of these fund characteristics.

After applying a performance persistence approach, we document that funds with the largest exposure adjustments during a period obtain up to 12 months significantly greater alphas than funds that do not experience such variation. This implies that the larger alphas obtained by funds experiencing higher variations in their exposures is attributed managerial ability to shift the risk exposure appropriately, rather than being simply attributable to luck.

In the paper, we highlight the importance of active management in the mutual fund industry. Some managers are skilled enough to detect market opportunities and trade accordingly, quickly changing the factor exposures of the portfolios they manage. Consequently, these funds are able to persistently provide investors with superior returns relative to passive funds that retain similar exposures. The evidence provided in this study, therefore, is of interest to academics, professionals and investors alike wishing to understand the behavior and performance of mutual funds over time.

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Tables

Table 1. Descriptive statistics for the sample. January 1990 – December 2016

Panel A. Characteristics of the mutual funds

	Mean	s.d.
TNA ($millions)	1,503.786	5,379.173
Expenses (%)	1.288	0.457
Turnover (%)	79.904	80.725
Net return (annualized, %)	9.506	20.589

Panel B. Annualized return of the risk factors

	Mean	s.d.
RMRF (%)	7.917	17.785
SMB (%)	1.253	9.297
HML (%)	3.297	9.531
RMW (%)	4.371	7.421
CMA (%)	2.974	6.641
UMD (%)	6.608	13.737

Panel C. Correlation between risk factors

	RMRF	SMB	HML	RMW	CMA	UMD
RMRF	1					
SMB	-0.0052	1				
	(0.6692)					
HML	-0.0683***	-0.1468***	1			
	(0.0000)	(0.0000)				
RMW	-0.3684***	-0.3525***	0.0682***	1		
	(0.0000)	(0.0000)	(0.0000)			
CMA	-0.3559***	-0.0481***	0.5060***	0.2346***	1	
	(0.0000)	(0.0001)	(0.0000)	(0.0000)		
UMD	-0.2277***	0.0845***	-0.3320***	0.1516***	0.0611***	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

This Table shows the mean and standard deviation for some characteristics of the mutual funds in the sample, and for the returns of the risk factors considered in the six-factor model. TNA refers to the monthly Total Net Assets under management, while Turnover and Expenses refer to the annual portfolio turnover and annual net expense ratios reported by the funds, respectively. The returns are annualized from a daily basis (that is, multiplied by 252). Panel C reports the correlation coefficients between the risk factors, as well as their significance (p-values, in parentheses). '***' denotes significance at the 1% level.

Table 2. Exposures of the mutual funds to the risk factors during the 1990-2016 period.

	Average coefficient	t-statistic	Contribution to Total R^2
α (annualized)	-0.011	-16.53	0
β_1 (RMRF)	0.968	428.82	0.827
β_2 (SMB)	0.341	48.24	0.044
β_3 (HML)	0.103	22.14	0.014
β_4 (RMW)	-0.314	-66.56	0.015
β_5 (CMA)	-0.170	-34.75	0.007
β_6 (UMD)	-0.143	-53.09	0.021
Number of funds	2,360		
R^2	0.928		0.928

This Table shows the average results of OLS time-series regressions where dependent variable is the daily returns of each mutual fund in the sample in excess on the return of the risk-free asset. The explanatory factors are the risk-factors considered in the five-factor model of Fama-French (2015) plus the momentum factor explained in Carhart (1997). The explanatory factors are orthogonalized using the Löwdin (1950) transformation. The performance of the mutual funds (the intercept of the model, or alpha) is annualized from a daily basis (that is, multiplied by 252). The t-statistics indicate whether the average estimates are statistically different from zero. The contribution of each orthogonalized factor to total R^2 is detailed. The number of funds considered in the analysis and the average total coefficient of determination are also reported in the last rows of the Table.

Table 3. Exposures of the mutual funds to the risk factors during recessions and expansions.

Panel A. Recession periods

	Aug. 1990 - March 1991			April 2001 - Nov. 2001			Jan. 2008 - June 2009		
	Av. Coeff.	t-stat.	Contrib. to R^2	Av. Coeff.	t-stat.	Contrib. to R^2	Av. Coeff.	t-stat.	Contrib. to R^2
α (annualized)	-0.013	-1.70	0	0.010	3.28	0	-0.026	-16.96	0
β_1 (RMRF)	0.789	56.97	0.695	0.809	146.20	0.669	0.915	411.24	0.796
β_2 (SMB)	-0.054	-2.55	0.031	0.071	6.66	0.023	0.214	26.61	0.019
β_3 (HML)	-0.529	-22.42	0.058	-0.263	-32.24	0.025	0.212	62.73	0.020
β_4 (RMW)	0.442	29.28	0.026	-0.381	-40.60	0.041	-0.188	-55.51	0.003
β_5 (CMA)	-0.487	-23.36	0.046	-0.318	-41.94	0.032	-0.47	-58.94	0.010
β_6 (UMD)	-0.219	-21.98	0.022	-0.35	-49.69	0.123	-0.386	-162.40	0.118
Number of funds	178			916			1,747		
R^2	0.877		0.877	0.913		0.913	0.967		0.967

Panel B. Expansion periods

	April 1991 - March 2000			Dec. 2001 - Dec. 2007			July 2009 - Dec. 2016		
	Av. Coeff.	t-stat.	Contrib. to R^2	Av. Coeff.	t-stat.	Contrib. to R^2	Av. Coeff.	t-stat.	Contrib. to R^2
α (annualized)	0.022	7.88	0	-0.002	-2.29	0	-0.016	-25.84	0
β_1 (RMRF)	0.816	124.75	0.635	0.972	328.09	0.832	0.996	421.27	0.838
β_2 (SMB)	0.027	2.33	0.036	0.330	38.16	0.047	0.465	66.62	0.062
β_3 (HML)	-0.345	-32.92	0.053	-0.095	-14.98	0.007	0.179	40.79	0.017
β_4 (RMW)	-0.297	-25.33	0.046	-0.261	-35.78	0.022	-0.383	-98.33	0.016
β_5 (CMA)	-0.360	-33.78	0.044	-0.051	-9.97	0.003	-0.037	-7.39	0.004
β_6 (UMD)	0.120	19.08	0.019	0.025	5.26	0.012	-0.008	-2.56	0.009
Number of funds	880			1,630			2,331		
R^2	0.833		0.833	0.922		0.922	0.946		0.946

This Table shows subperiod analysis of the average results of OLS time-series regressions where dependent variable is the daily returns of each mutual fund in the sample in excess on the return of the risk-free asset. Each fund is required to have at least thirty daily observations in order to be included in the analysis. The explanatory factors are the risk-factors considered in the five-factor model of Fama-French (2015) plus the momentum factor explained in Carhart (1997). The explanatory factors are orthogonalized using the Löwdin (1950) transformation. The performance of the mutual funds (the intercept of the model, or alpha) is annualized from a daily basis (that is, multiplied by 252). The t-statistics indicate whether the average estimates are statistically different from zero. The contribution of each orthogonalized factor to total R^2 is detailed. The number of funds considered in the analysis and the average total coefficient of determination are also reported in the last rows of the Table.

Table 4. Fund portfolio performance, double-sorting on previous funds' CFE and alpha

		CFE_t						
		P1	P2	P3	P4	P5	All	P5-P1
$alpha_{\tau}$	P1	-0.0264***	-0.0271***	-0.0275***	-0.0284***	-0.0263***	-0.0264***	0.0001
		(-3.930)	(-4.321)	(-4.283)	(-3.775)	(-2.891)	(-4.253)	(0.012)
	P2	-0.0213***	-0.0231***	-0.0212	-0.0148**	-0.0073	-0.0203***	0.0140
		(-3.421)	(-4.696)	(-4.181)	(-2.431)	(-1.007)	(-4.769)	(1.439)
	P3	-0.0157**	-0.0115**	-0.0182***	-0.0064	0.0015	-0.0103***	0.0172
		(-2.529)	(-2.526)	(-3.681)	(-1.049)	(0.203)	(-2.735)	(1.573)
	P4	-0.0108	-0.0040	-0.0003	-0.0036	0.0162**	0.0016	0.0270**
		(-1.661)	(-0.734)	(-0.065)	(-0.591)	(2.072)	(0.404)	(2.324)
	P5	0.0081	0.0084	0.0192***	0.0260***	0.0488***	0.0247***	0.0407**
		(1.164)	(1.267)	(2.890)	(3.487)	(5.223)	(4.356)	(3.233)
	All	-0.0132**	-0.0115**	-0.0096**	-0.0055	0.0066	-0.0069*	0.0198**
		(-2.252)	(-2.488)	(-2.228)	(-1.005)	(0.993)	(-1.812)	(2.032)
	P5-P1	0.0345***	0.0355***	0.0468***	0.0545***	0.0751***	0.0511***	
		(5.377)	(5.007)	(5.577)	(6.300)	(6.709)	(6.102)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar past performance (alpha) and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or alpha experienced by the funds the portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or alpha. The differences between P5 and P1 and their significance for each level of alpha (CFE) are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Fund portfolio performance, double-sorting on previous funds' CFE and R^2

		CFE$_t$						
		P1	P2	P3	P4	P5	All	P5-P1
	P1	-0.0057	-0.0010	0.0001	-0.0036	0.0024	-0.0015	0.0081
		(-0.793)	(-0.138)	(0.018)	(-0.454)	(0.301)	(-0.228)	(0.919)
	P2	-0.0051	-0.0090	-0.0060	-0.0134*	0.0110	0.0001	0.0161
		(-0.722)	(-1.393)	(-0.933)	(-1.779)	(1.345)	(0.021)	(1.534)
	P3	-0.0151**	-0.0146**	-0.0073	0.0026	0.0049	-0.0060	0.0201*
		(-2.235)	(-2.367)	(-1.297)	(0.380)	(0.573)	(-1.359)	(1.681)
R^2_τ	P4	-0.0196***	-0.0138***	-0.0156***	-0.0038	0.0128	-0.0065*	0.0324**
		(-2.999)	(-2.812)	(-2.951)	(-0.528)	(1.473)	(-1.739)	(2.540)
	P5	-0.0206***	-0.0191***	-0.0189***	-0.0095	0.0016	-0.0131***	0.0222*
		(-3.906)	(-5.303)	(-4.078)	(-1.297)	(0.188)	(-4.406)	(1.883)
	All	-0.0132**	-0.0115**	-0.0096**	-0.0055	0.0066	-0.0069*	0.0198**
		(-2.252)	(-2.488)	(-2.228)	(-1.005)	(0.993)	(-1.812)	(2.032)
	P5-P1	-0.0149**	-0.0181**	-0.0190**	-0.0060	-0.0008	(-0.0116)	
		(-2.354)	(-2.415)	(-2.131)	(-0.531)	(-0.074)	(-1.575)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar coefficients of determination (R^2) and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or R^2 experienced by the funds each portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or R^2. The differences between P5 and P1 and their significance for each level of R^2 (CFE) are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Fund portfolio performance, double-sorting on previous funds' CFE and change in R^2

		CFE$_t$						
		P1	P2	P3	P4	P5	All	P5-P1
	P1	-0.0111	-0.0105*	-0.0164**	-0.0113	0.0015	-0.0099	0.0126
		(-1.648)	(-1.716)	(-2.489)	(-1.425)	(0.198)	(-1.533)	(1.314)
	P2	-0.0120*	-0.0113**	-0.0093*	-0.0048	0.0150*	-0.0074	0.0270**
		(-1.839)	(-2.099)	(-1.846)	(-0.717)	(1.738)	(-1.586)	(2.234)
	P3	-0.0159**	-0.0131**	-0.0064	-0.0025	0.0074	-0.0061	0.0233**
		(-2.492)	(-2.430)	(-1.187)	(-0.382)	(0.905)	(-1.617)	(1.971)
ΔR^2_τ	P4	-0.0140**	-0.0112**	-0.0083	-0.0033	-0.0002	-0.0071	0.0138
		(-2.105)	(-1.961)	(-1.433)	(-0.461)	(-0.023)	(-1.464)	(1.249)
	P5	-0.0126*	-0.0097	-0.0051	-0.0038	0.0120	-0.0010	0.0246**
		(-1.911)	(-1.550)	(-0.818)	(-0.553)	(1.532)	(-0.177)	(2.362)
	All	-0.0132**	-0.0115**	-0.0096**	-0.0055	0.0066	-0.0069*	0.0198**
		(-2.252)	(-2.488)	(-2.228)	(-1.005)	(0.993)	(-1.812)	(2.032)
	P5-P1	-0.0015	0.0008	0.0113	0.0075	0.0105	0.0089	
		(-0.229)	(0.110)	(1.331)	(0.811)	(1.175)	(1.013)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar changes in their coefficients of determination (ΔR^2) and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or ΔR^2 experienced by the funds each portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or ΔR^2. The differences between P5 and P1 and their significance for each level of ΔR^2 (CFE) are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7. CFE and Active Share as predictors of fund performance

Panel A. Fund portfolio performance, double-sorting on previous funds' CFE and active share

		CFE						
		P1	P2	P3	P4	P5	All	P5-P1
AS	P1	-0.0173***	-0.0221***	-0.0193***	-0.0084	0.0018	-0.0123***	0.0191
		(-2.974)	(-5.012)	(-4.053)	(-1.349)	(0.205)	(-4.557)	(1.584)
	P2	-0.0199***	-0.0156***	-0.0190***	-0.0007	0.0053	-0.0114***	0.0253**
		(-3.105)	(-2.920)	(-3.314)	(-0.096)	(0.631)	(-3.140)	(2.156)
	P3	-0.0149**	-0.0054	-0.0123**	0.0026	0.0075	-0.0057	0.0224*
		(-2.085)	(-0.833)	(-1.991)	(0.343)	(0.810)	(-1.207)	(1.872)
	P4	-0.0074	-0.0079	0.0026	-0.0027	0.0117	-0.0004	0.0191*
		(-0.972)	(-1.083)	(0.345)	(-0.329)	(1.386)	(-0.062)	(1.690)
	P5	-0.0094	-0.0115	0.0073	-0.0025	0.0124	-0.0005	0.0218**
		(-1.222)	(-1.536)	(0.952)	(-0.326)	(1.481)	(-0.085)	(2.021)
	All	-0.0139**	-0.0127**	-0.0090**	-0.0025	0.0077	-0.0051	0.0216**
		(-2.273)	(-2.554)	(-1.954)	(-0.419)	(1.153)	(-1.394)	(2.241)
	P5-P1	0.0080	0.0106	0.0266***	0.0058	0.0107	0.0118**	
		(1.285)	(1.525)	(3.210)	(0.689)	(1.088)	(2.324)	

Panel B. Fund portfolio performance, double-sorting on previous funds' CFE and change in Active Share

		CFE						
		P1	P2	P3	P4	P5	All	P5-P1
ΔAS	P1	-0.0126*	-0.0181**	-0.0181**	-0.0034	0.0021	-0.0129***	0.0147
		(-1.702)	(-2.460)	(-2.471)	(-0.446)	(0.209)	(-2.932)	(1.073)
	P2	-0.0157**	-0.0059	-0.0124*	-0.0046	0.0126	-0.0055	0.0283**
		(-1.966)	(-0.787)	(-1.698)	(-0.554)	(1.234)	(-1.078)	(2.095)
	P3	-0.0182**	-0.0103	-0.0038	-0.0058	0.0108	-0.0006	0.0290**
		(-2.229)	(-1.478)	(-0.550)	(-0.678)	(1.166)	(-0.133)	(2.406)
	P4	-0.0098	-0.0071	0.0065	-0.0003	0.0086	-0.0032	0.0184
		(-1.250)	(-0.998)	(0.784)	(-0.041)	(0.899)	(-0.685)	(1.492)
	P5	-0.0120	-0.0123	-0.0171**	-0.0027	0.0113	-0.0062	0.0233
		(-1.455)	(-1.625)	(-2.307)	(-0.288)	(1.058)	(-1.178)	(1.654)
	All	-0.0146**	-0.0138***	-0.0077	-0.0047	0.0058	-0.0051	0.0204**
		(-2.376)	(-2.703)	(-1.549)	(-0.759)	(0.832)	(-1.394)	(2.098)
	P5-P1	0.0006	0.0058	0.0011	0.0007	0.0092	0.0067	
		(0.111)	(0.694)	(0.145)	(0.080)	(0.976)	(1.379)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar past active share (AS, in Panel A) or changes in Active Share (ΔAS, in Panel B) and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or AS/ΔAS experienced by the funds the portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or AS/ΔAS. The differences between P5 and P1 and their significance for each level of AS/ΔAS (CFE) are reported in the last column (row) of each Panel. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8. CFE and Return Gap as predictors of fund performance

		CFE						
		P1	P2	P3	P4	P5	All	P5-P1
RG	P1	-0.0139*	-0.0256***	-0.0106	-0.0094	0.0036	-0.0115	0.0175
		(-1.672)	(-3.124)	(-1.416)	(-1.002)	(0.354)	(-1.482)	(1.566)
	P2	-0.0225***	-0.0120*	-0.0175***	-0.0101	-0.0029	-0.0108*	0.0196*
		(-3.039)	(-1.904)	(-2.701)	(-1.420)	(-0.327)	(-1.902)	(1.679)
	P3	-0.0135*	-0.0134**	-0.0062	-0.0040	0.0040	-0.0030	0.0176
		(-1.846)	(-2.215)	(-1.103)	(-0.579)	(0.512)	(-0.675)	(1.499)
	P4	-0.0166**	-0.0095*	-0.0135**	-0.0035	0.0060	-0.0085**	0.0226*
		(-2.441)	(-1.712)	(-2.384)	(-0.535)	(0.637)	(-1.967)	(1.800)
	P5	-0.0113	-0.0063	-0.0021	0.0010	0.0152	-0.0003	0.0265**
		(-1.546)	(-0.968)	(-0.300)	(0.111)	(1.491)	(-0.048)	(2.111)
	All	-0.0137**	-0.0106**	-0.0123**	-0.0024	0.0062	-0.0042	0.0199**
		(-2.187)	(-2.146)	(-2.562)	(-0.413)	(0.885)	(-1.129)	(1.953)
	P5-P1	0.0026	0.0194**	0.0085	0.0103	0.0116	0.0112	
		(0.344)	(2.107)	(0.927)	(0.908)	(0.856)	(0.971)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar Return Gap (RG) and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or RG experienced by the funds each portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or RG. The differences between P5 and P1 and their significance for each level of RG (CFE) are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Fund Size Effect

		CFE$_t$						
		P1	P2	P3	P4	P5	All	P5-P1
	P1	-0.0106*	-0.0073	-0.0074	-0.0042	0.0126*	0.0007	0.0232***
		(-1.794)	(-1.327)	(-1.445)	(-0.698)	(1.849)	(0.162)	(2.607)
	P2	-0.0161**	-0.0162***	-0.0096*	-0.0098	0.0074	-0.0061	0.0235**
		(-2.569)	(-2.938)	(-1.733)	(-1.424)	(1.011)	(-1.510)	(2.268)
	P3	-0.0168***	-0.0116**	-0.0132***	-0.0074	-0.0044	-0.0096**	0.0124
		(-2.586)	(-2.098)	(-2.648)	(-1.136)	(-0.548)	(-2.219)	(1.140)
TNA$_t$	P4	-0.0076	-0.0118**	-0.0116**	-0.0037	0.0097	-0.0055	0.0172
		(-1.181)	(-2.290)	(-2.227)	(-0.599)	(1.225)	(-1.445)	(1.514)
	P5	-0.0129**	-0.0089*	-0.0058	0.0012	0.0100	-0.0033	0.0228**
		(-2.079)	(-1.941)	(-1.193)	(0.201)	(1.307)	(-0.970)	(2.064)
	All	-0.0132**	-0.0115**	-0.0096**	-0.0055	0.0066	-0.0069*	0.0198**
		(-2.252)	(-2.488)	(-2.228)	(-1.005)	(0.993)	(-1.812)	(2.032)
	P5-P1	-0.0022	-0.0015	0.0015	0.0054	-0.0026	-0.0040	
		(-0.599)	(-0.400)	(0.350)	(1.109)	(-0.400)	(-1.328)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar assets under management (TNA), and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or TNA experienced by the funds each portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or TNA. The differences between P5 and P1 and their significance for each level of TNA (CFE) are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10. The performance of quintile-portfolios in each Morningstar Category

Panel A. Growth-Value funds

	P1	P2	P3	P4	P5	All	P5-P1
Growth	-0.0068	-0.0060	0.0003	0.0060	**0.0152****	0.0032	**0.0220****
	(-1.132)	(-1.133)	(0.053)	(0.980)	**(2.023)**	(0.695)	**(2.272)**
Blend	**-0.0119****	**-0.0109****	**-0.0127*****	**-0.0113****	-0.0020	**-0.0096*****	0.0100
	(-2.331)	**(-2.522)**	**(-2.988)**	**(-2.092)**	(-0.313)	**(-2.756)**	(1.160)
Value	**-0.0187*****	**-0.0190*****	**-0.0193*****	**-0.0187*****	-0.0067	**-0.0149*****	0.0120
	(-3.209)	**(-3.937)**	**(-4.089)**	**(-3.748)**	(-0.987)	**(-3.547)**	(1.406)

Panel B. Stock-capitalization funds

	P1	P2	P3	P4	P5	All	P5-P1
Large Cap	**-0.0150*****	**-0.0133*****	**-0.0145*****	**-0.0094****	0.0073	**-0.0081*****	**0.0223****
	(-2.740)	**(-3.080)**	**(-4.043)**	**(-2.054)**	(1.149)	**(-2.636)**	**(2.319)**
Mid Cap	-0.0020	0.0001	-0.0002	0.0088	0.0085	0.0048	0.0105
	(-0.285)	(0.010)	(-0.023)	(1.216)	(0.999)	(0.861)	(1.004)
Small Cap	**-0.0157****	**-0.0148****	-0.0084	-0.0045	0.0041	-0.0062	**0.0198***
	(-2.351)	**(-2.330)**	(-1.336)	(-0.637)	(0.547)	(-1.286)	**(1.900)**

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) from each Morningstar Category (Growth, Blend, Value, Large Cap, Mid Cap, and Small Cap). Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE experienced by the funds the portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE. The differences between P5 and P1 and their significance are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Predictive portfolios' alphas, m-months horizon

Period *t+m*	P1	P2	P3	P4	P5	P5-P1
t+1	**-0.0132****	**-0.0115****	**-0.0096****	-0.0055	0.0066	**0.0198****
	(-2.252)	**(-2.488)**	**(-2.228)**	(-1.005)	(0.993)	**(2.032)**
t+2	**-0.0140****	**-0.0119*****	**-0.0090****	-0.0041	0.0063	**0.0203****
	(-2.484)	**(-2.659)**	**(-2.025)**	(-0.753)	(0.968)	**(2.184)**
t+3	**-0.0114****	**-0.0122*****	**-0.0073***	-0.0071	0.0055	**0.0169***
	(-2.121)	**(-2.821)**	**(-1.714)**	(-1.345)	(0.819)	**(1.857)**
t+4	**-0.0128****	**-0.0135*****	**-0.0082****	-0.0028	0.0058	**0.0186****
	(-2.513)	**(-3.191)**	**(-1.951)**	(-0.526)	(0.839)	**(2.049)**
t+5	**-0.0156*****	**-0.0136*****	**-0.0077***	-0.0001	0.0048	**0.0205****
	(-3.041)	**(-3.166)**	**(-1.879)**	(-0.028)	(0.663)	**(2.207)**
t+6	**-0.0165*****	**-0.0139*****	**-0.0085****	0.0006	0.0064	**0.0229****
	(-3.253)	**(-3.194)**	**(-2.130)**	(0.123)	(0.878)	**(2.476)**
t+7	**-0.0170*****	**-0.0133*****	**-0.0077***	0.0013	0.0051	**0.0221****
	(-3.356)	**(-3.175)**	**(-1.905)**	(0.251)	(0.687)	**(2.386)**
t+8	**-0.0189*****	**-0.0124*****	**-0.0071***	0.0023	0.0045	**0.0233****
	(-3.702)	**(-2.948)**	**(-1.787)**	(0.459)	(0.585)	**(2.506)**
t+9	**-0.0168*****	**-0.0121*****	-0.0066	-0.0002	0.0042	**0.0209****
	(-3.348)	**(-2.922)**	(-1.611)	(-0.044)	(0.549)	**(2.300)**
t+10	**-0.0146*****	**-0.0109*****	-0.0048	-0.0031	0.0016	**0.0162***
	(-3.006)	**(-2.708)**	(-1.209)	(-0.592)	(0.212)	**(1.884)**
t+11	**-0.0148*****	**-0.0117*****	-0.0064	-0.0014	0.0008	**0.0155***
	(-3.128)	**(-2.944)**	(-1.626)	(-0.283)	(0.101)	**(1.815)**
t+12	**-0.0110****	**-0.0091****	**-0.0081****	-0.0045	-0.0007	0.0104
	(-2.419)	**(-2.284)**	**(-2.059)**	(-0.854)	(-0.092)	(1.231)

This Table reports the portfolio alpha for months t+m, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed at time t using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE). Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE experienced by the funds the portfolio invests in at time t. The differences between P5 and P1 and their significance are reported in the last column (rows) of the Table. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 12. Variation in the funds' exposures during a six-month period

Panel A. Fund portfolio performance, double-sorting on previous funds' CFE and performance

		CFE_t						
		P1	P2	P3	P4	P5	All	P5-P1
$alpha_\tau$	P1	-0.0327***	-0.0277***	-0.0250***	-0.0175**	-0.0222**	-0.0239***	0.0105
		(-5.113)	(-4.458)	(-3.984)	(-2.441)	(-2.310)	(-3.978)	(1.020)
	P2	-0.0248***	-0.0203***	-0.0072	-0.0083	-0.0046	-0.0142***	0.0202**
		(-4.407)	(-4.277)	(-1.511)	(-1.340)	(-0.571)	(-3.362)	(2.085)
	P3	-0.0225***	-0.0126***	-0.0083*	0.0061	-0.0030	-0.0097***	0.0194**
		(-4.261)	(-2.766)	(-1.768)	(1.035)	(-0.421)	(-2.609)	(2.121)
	P4	-0.0252***	-0.0083*	0.0016	0.0039	0.0195***	-0.0027	0.0448***
		(-4.305)	(-1.766)	(0.297)	(0.674)	(2.910)	(-0.694)	(4.552)
	P5	-0.0167**	0.0014	0.0217***	0.0350***	0.0481***	0.0233***	0.0647***
		(-2.327)	(0.223)	(3.219)	(4.393)	(5.312)	(4.218)	(5.245)
	All	-0.0242***	-0.0138***	-0.0028	0.0041	0.0073	-0.0069*	0.0315***
		(-4.494)	(-3.210)	(-0.649)	(0.839)	(1.161)	(-1.812)	(3.651)
	P5-P1	0.0161**	0.0291***	0.0467***	0.0525***	0.0703***	0.0472***	
		(2.558)	(4.083)	(6.013)	(4.966)	(5.508)	(5.924)	

Panel B. Fund portfolio performance, double-sorting on previous funds' CFE and R^2

		CFE_t						
		P1	P2	P3	P4	P5	All	P5-P1
R^2_τ	P1	-0.0150**	-0.0087	-0.0012	-0.0049	0.0110	-0.0012	0.0260***
		(-2.063)	(-1.149)	(-0.163)	(-0.685)	(1.389)	(-0.187)	(3.128)
	P2	-0.0272***	-0.0156**	-0.0028	0.0045	0.0122	-0.0018	0.0393***
		(-4.070)	(-2.541)	(-0.444)	(0.669)	(1.375)	(-0.313)	(3.979)
	P3	-0.0244***	-0.0143***	0.0015	0.0092	0.0039	-0.0029	0.0283**
		(-3.865)	(-2.689)	(0.260)	(1.335)	(0.442)	(-0.645)	(2.549)
	P4	-0.0300***	-0.0108***	-0.0044	0.0110*	0.0108	-0.0086**	0.0408***
		(-5.283)	(-2.589)	(-0.916)	(1.766)	(1.351)	(-2.395)	(3.682)
	P5	-0.0252***	-0.0189***	-0.0114***	-0.0007	-0.0013	-0.0132***	0.0239**
		(-5.395)	(-5.853)	(-2.691)	(-0.106)	(-0.171)	(-4.363)	(2.330)
	All	-0.0242***	-0.0138***	-0.0028	0.0041	0.0073	-0.0069*	0.0315***
		(-4.494)	(-3.210)	(-0.649)	(0.839)	(1.161)	(-1.812)	(3.651)
	P5-P1	-0.0102	-0.0102	-0.0102	0.0042	-0.0123	-0.0119	
		(-1.477)	(-1.355)	(-1.239)	(0.416)	(-1.179)	(-1.557)	

This Table reports the portfolio alpha, annualized, using returns over the period 1992-2016. Equally weighted portfolios are formed using funds with similar relative levels of previous variation in their exposures to the risk factors (CFE) and similar past alpha (Panel A) or R^2 (Panel B) and are monthly rebalanced. Specifically, *P1* (*P5*) is related to the lowest (highest) level of CFE or alpha/R^2 experienced by the funds the portfolio invests in at the beginning of each month. *All* refers to all the funds in the sample, without taking into account the specific level of CFE or alpha/R^2. The differences between P5 and P1 and their significance for each level of alpha/R^2 (CFE) are reported in the last column (rows) of each Panel. The dependent variable is the daily return of each portfolio. The alpha is calculated as the annualized intercept in a model containing the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

Table 13. Cross-sectional regressions of future fund performance

	Model 1		Model 2		Model 3		Model 4	
	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
CFE	0.0760***	(3.177)	0.0745***	(3.014)	0.0611**	(2.461)	0.0464**	(2.031)
LogAge			-0.1259*	(-1.731)	-0.1204	(-1.560)	-0.0324	(-0.444)
Expenses			-0.5025***	(-3.516)	-0.5432***	(-3.719)	-0.4946***	(-3.655)
LogTNA			-0.0008	(-0.024)	0.0126	(0.362)	-0.0259	(-0.732)
LogTurnover			-0.1769**	(-1.953)	-0.1556*	(-1.669)	-0.1051	(-1.167)
OneYearR^2					-0.0414*	(-1.945)	-0.0375*	(-1.839)
OneYearAlpha							0.1866***	(6.812)
Constant	-1.4569***	(-5.014)	0.2960	(0.358)	4.1359*	(1.826)	4.4202**	(2.059)
Adjusted R^2	0.0219		0.0301		0.0424		0.0564	

This Table reports the results of Fama-MacBeth regressions to understand the relationship between performance and a series of fund-specific characteristics. The dependent variable is the annualized alpha of the funds obtained from applying the six-factor model during the following month. The explanatory variables include the variation in the fund exposures to the risk factors (*CFE*), the natural logarithm of the number of months since the fund inception (*LogAge*), net expense ratio (*Expenses*), natural logarithms of the funds' Total Net Assets (*LogTNA*) and turnover ratio (*LogTurnover*), and the funds' previous coefficient of determination and performance (*OneYear*R^2 and *OneYearAlpha*, respectively), both measures estimated during the previous year. T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively. The adjusted coefficient of determination is also reported.

Table 14. Determinants of Change in Factor Exposures of mutual funds

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
LogAge	-0.0066***	(-3.01)	-0.0057***	(-2.67)	-0.0033	(-1.32)	-0.0060*	(-1.72)	-0.0005	(-0.13)	0.0000	(0.01)
Expenses	0.6683*	(1.92)	0.6428*	(1.96)	0.4397	(1.48)	0.5733	(1.26)	0.2434	(0.67)	0.3047	(0.83)
LogTNA	0.0019***	(2.76)	0.0024***	(3.38)	0.0017**	(2.48)	0.0020**	(2.41)	0.0022***	(2.68)	0.0024***	(2.91)
LogTurnover	0.0038***	(4.70)	0.0037***	(4.74)	0.0044***	(5.51)	0.0040***	(4.09)	0.0045***	(4.75)	0.0046***	(4.90)
OneYearR^2			-0.0898***	(-4.93)					-0.0473**	(-2.51)	-0.0444**	(-2.38)
ActiveShare					0.0348***	(4.42)			0.0319***	(3.44)	0.0308***	(3.36)
ReturnGap							0.0555***	(2.81)	0.0585***	(2.69)	0.0494**	(2.39)
OneYearAlpha											0.0547***	(4.70)
Constant	0.0841***	(4.99)	0.1543***	(6.84)	0.0417**	(2.16)	0.0816***	(3.64)	0.0692**	(2.27)	0.0605**	(1.99)
Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Time Effects	Yes		Yes		Yes		Yes		Yes		Yes	
# funds	2,199		2,199		2,111		1,108		1,094		1,094	
Adjusted R^2	0.4819		0.4854		0.4943		0.4822		0.4943		0.4960	

This Table reports the results of panel regressions with the variation in the fund exposures to the risk factors (CFE) as dependent variable. The explanatory variables include the natural logarithm of the number of months since the fund inception (*LogAge*), net expense ratio (*Expenses*), natural logarithms of the funds' Total Net Assets (*LogTNA*) and turnover ratio (*LogTurnover*), the percentage of shares in the portfolio that differ from the benchmark holdings (*ActiveShare*), the difference between fund returns and the returns of a passive portfolio investing in the previously disclosed fund holdings (*ReturnGap*), as well as funds' previous coefficient of determination and performance (*OneYear*R^2 and *OneYearAlpha*, respectively), both measures estimated during the previous year. T-stats (in parentheses) are from standard errors two-way clustered at fund and year level. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively. The adjusted coefficient of determination is also reported.

Figure 1. Factors' contributions to the explanation of the variability of the overall mutual fund returns

Figure 1A. The decomposition of the coefficient of determination into contributions from the risk-factors over time.

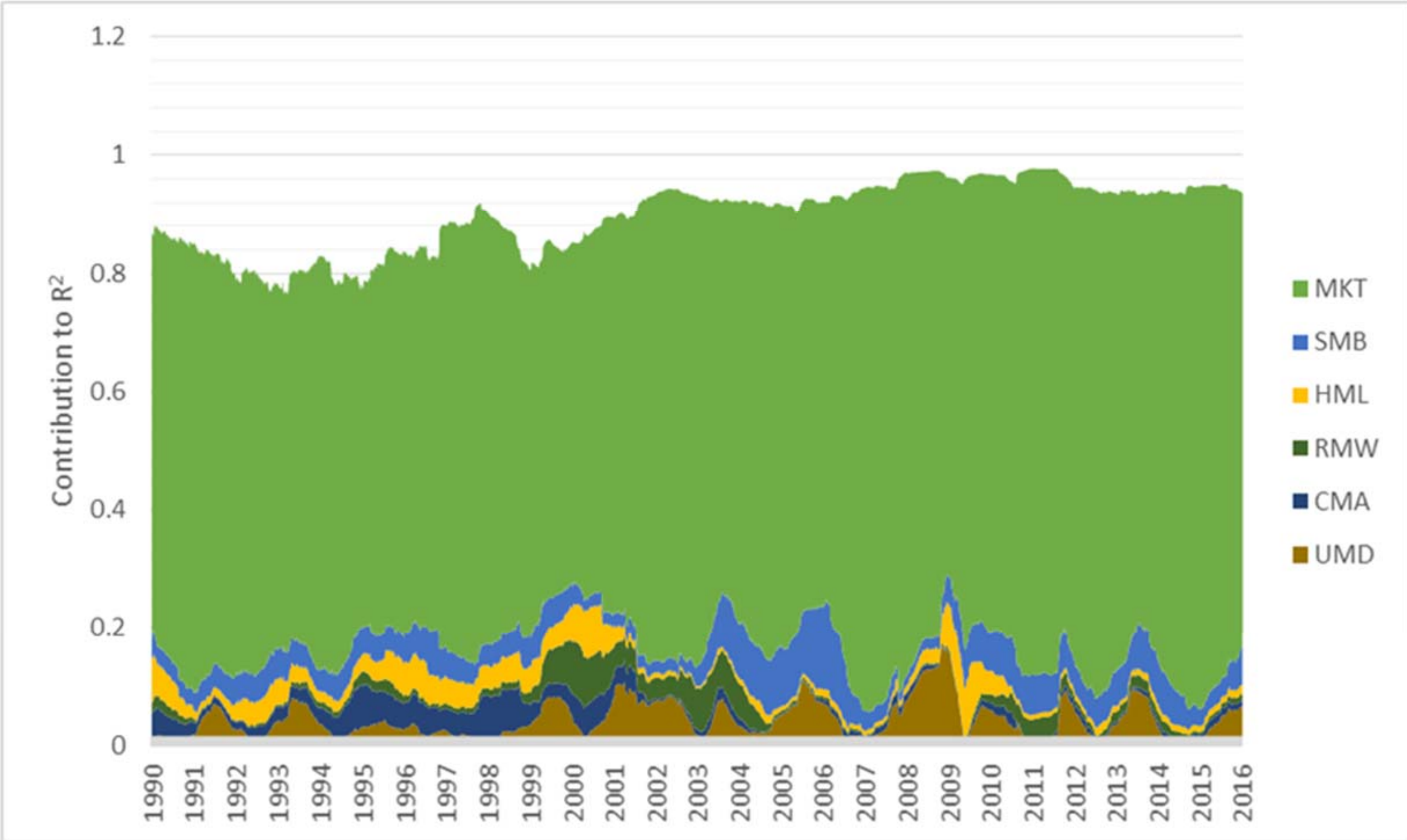


Figure 1B. The average contributions of the SMB, HML, RMW, CMA, and UMD factors to the variation in fund returns over time.

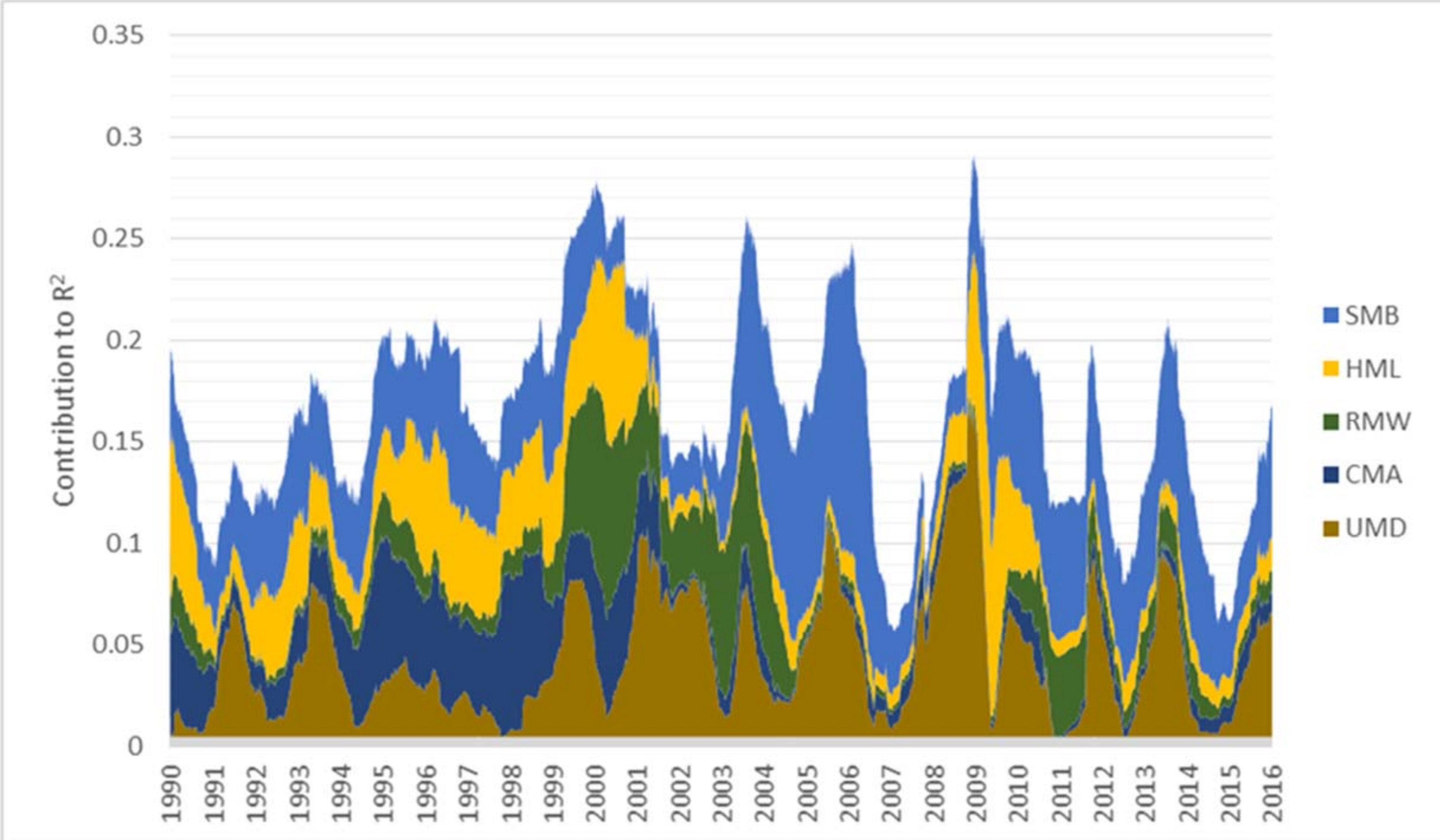


Figure 2. Estimation timeline for (i) CFE and (ii) Alpha and R^2.

This figure illustrates how the CFE, Alpha and R^2 are estimated in-sample, while performance is evaluated out-of-sample.

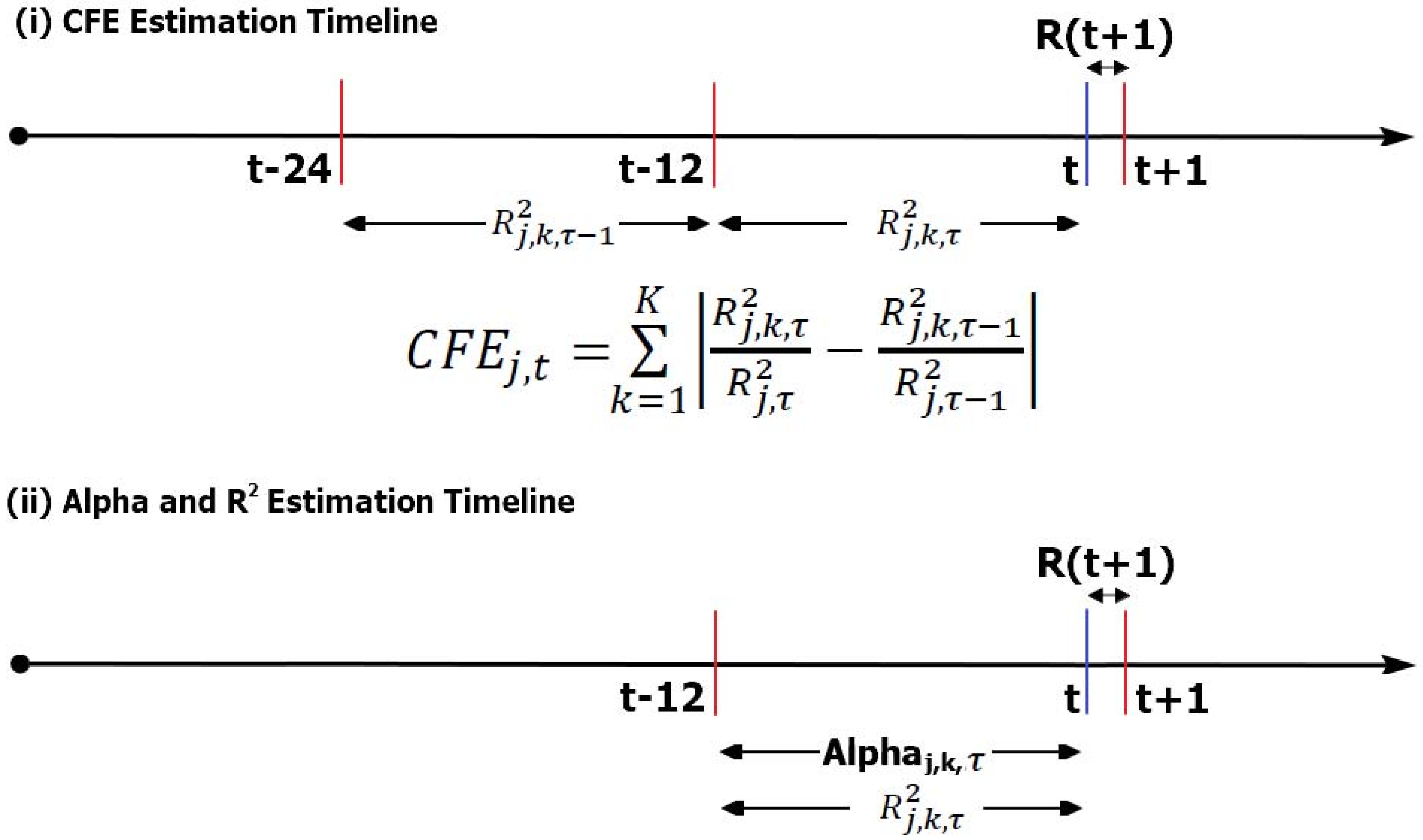


Figure3. Regarding CFE according to mutual fund investment style

Figure 3A. The average CFE estimated for Large-Cap, Mid-Cap and Small-Cap funds over time.

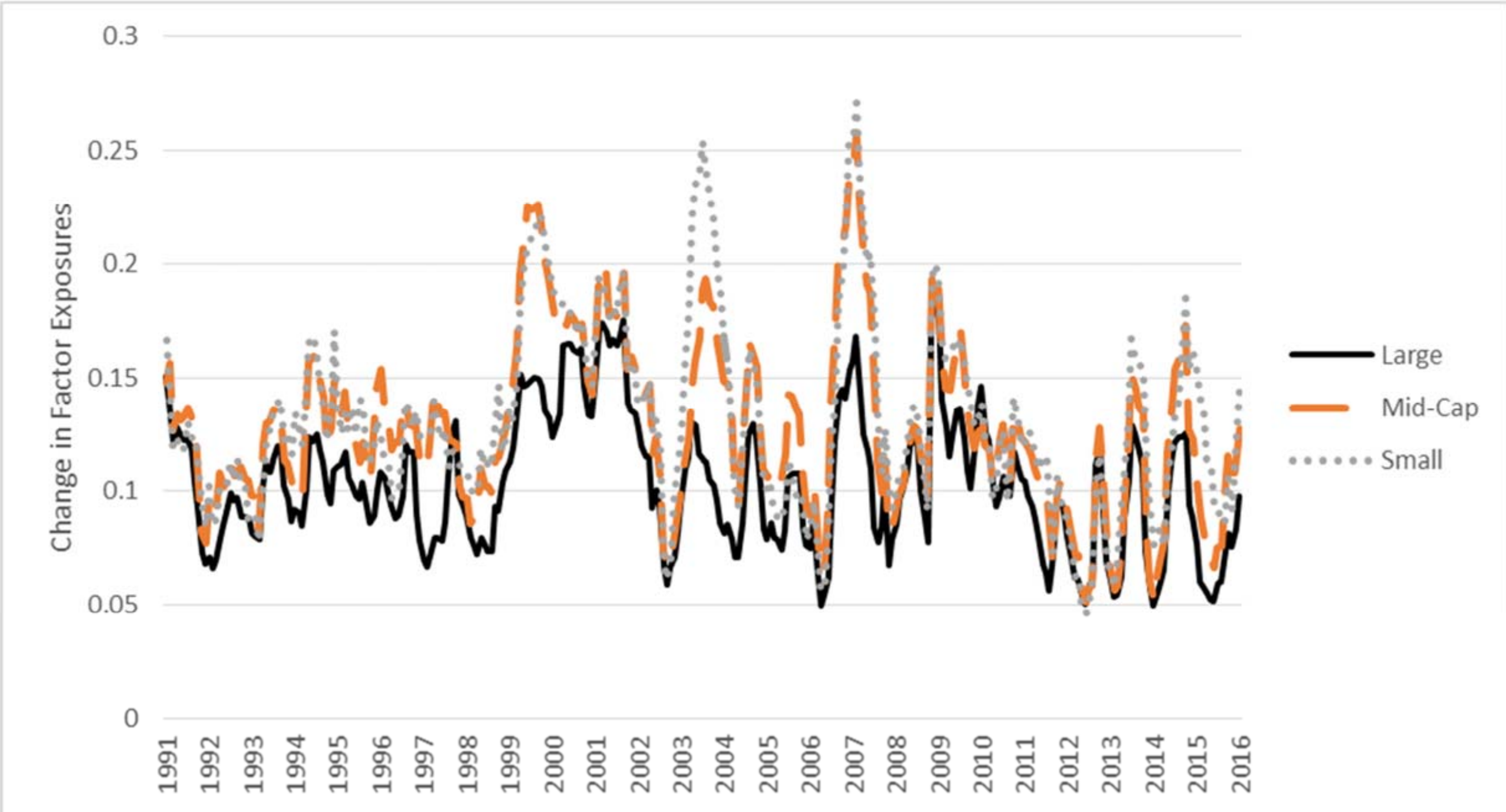


Figure 3B. The average CFE estimated for Growth, Blend and Value funds over time.

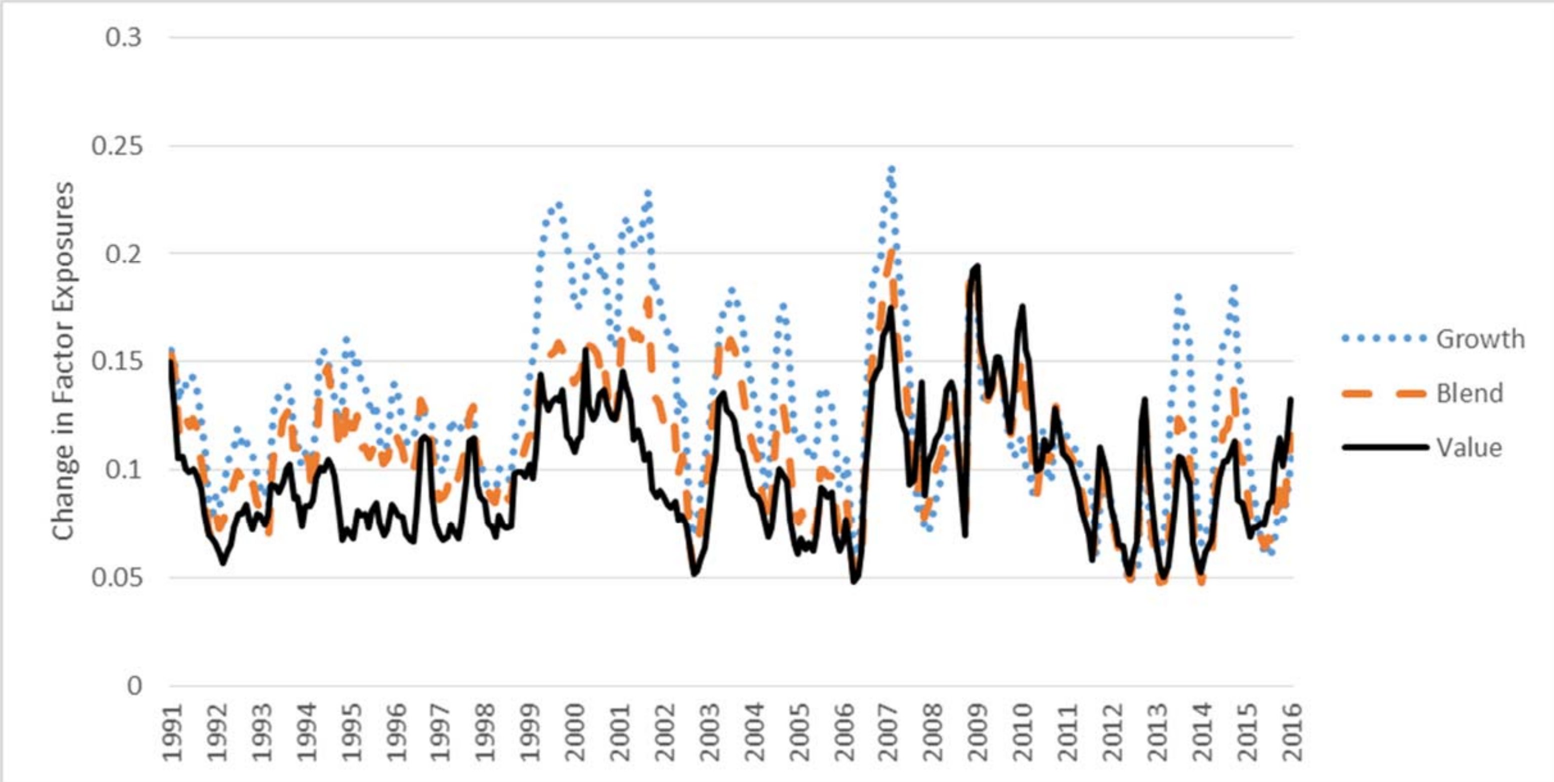
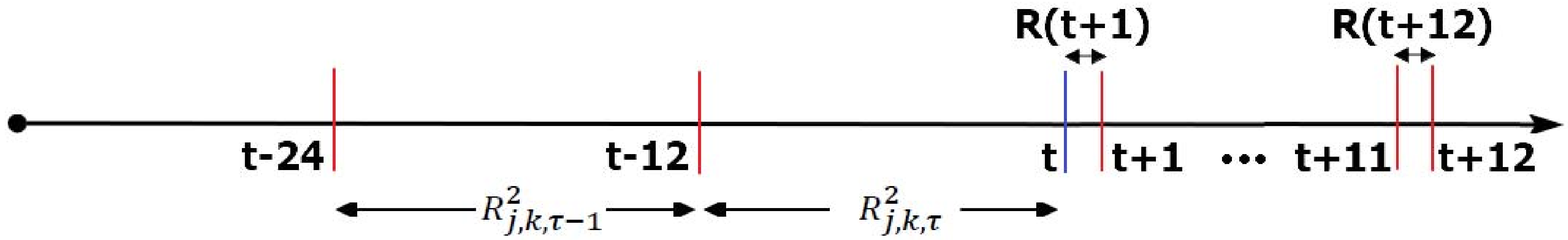


Figure 4. Performance persistence calculations.

This plot illustrates how CFE is calculated in-sample and performance is measured out-of-sample for the following 12 months.



$$CFE_{j,t} = \sum_{k=1}^{K} \left| \frac{R^2_{j,k,\tau}}{R^2_{j,\tau}} - \frac{R^2_{j,k,\tau-1}}{R^2_{j,\tau-1}} \right|$$