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DEMAND AND MANAGEMENT OF MUTUAL FUNDS

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CHAPTER 1: MOTIVATION OF THIS THESIS

MOTIVATION OF THIS THESIS

1.1. Introduction

Mutual funds are investment vehicles gathering in their portfolios a huge amount of money collected from several shareholders. These investors purchase funds' shares with the aim of obtaining potential capital gains and other incomes from their investments. To achieve this goal, mutual funds usually invest in a pool of securities including stocks, bonds, treasury bills, cash, money market instruments or other assets.

There are many reasons explaining why investors decide to invest in mutual funds rather than investing on their own, such as their low transaction costs, their broad diversified portfolios, the customer services offered by fund companies such as moving the invested money around among funds, and the professional management that some funds (i.e., actively-managed or *active* funds) experience in their portfolios (Gruber, 1996). In addition, the tax benefits related to regulated funds (e.g., 401(k) plans) and the increase in the variety of funds with specific investment objectives also meet the investors' demand in satisfying their needs.

Accordingly, the fund industry worldwide experienced a huge growth over the previous decades. As shown in the last version of the Investment Company Fact Book[1], the total net assets of worldwide regulated open-end funds exceeded 49 trillion dollars at the end of 2017. The United States is the largest fund industry in the world since US

[1] For more information, see the 2018 Investment Company Fact Book published by the Investment Company Institute (http://www.icifactbook.org).

funds run more than 22 trillion dollars at the end of the same year[2], most of them being specifically managed by open-end mutual funds.

Regarding the evolution of this type of investment vehicle, Figure 1.1 shows the increase of the total net assets (or *TNA*) managed by open-end funds (*mutual funds*, from now on) during the last twenty years. These data were collected manually from the aforementioned report of the Investment Company Institute. For comparative purposes, the total net assets run by other US-registered companies over time are also included.

As shown in Figure 1.1, mutual funds raised their dollars under management from 5.5 trillion in 1998 to 18.7 trillion in 2017. This constitutes an increase of more than three times their managed assets during the last two decades. Moreover, a continuous growth is observed since the end of the recent financial crisis (June 2009, according to the National Bureau of Economics Research[3]). Other US-registered investment companies also experienced a considerable growth during the last years, especially, exchange-traded funds or *ETFs*, which managed a total of 3 trillion dollars at the end of 2017. This evidence implies that mutual funds were and remain by far the largest investment vehicle in the United States.[4]

[2] Funds from other regions, such as European and Asia-Pacific regions, managed 17.7 and 6.5 trillion dollars, respectively.
[3] See http://www.nber.org/cycles/cyclesmain.html for more information about the different US Business Cycles.
[4] Open-end mutual funds differ in two main characteristics from other types of funds (e.g., closed-end funds and exchange-traded funds: firstly, they can be bought or sold anytime during a trading day, but at the price determined at the end of the trading day; secondly, one of the sides of a transaction of fund shares is the fund itself.

Figure 1.1. Evolution of the assets in US-registered investment companies during the last two decades.

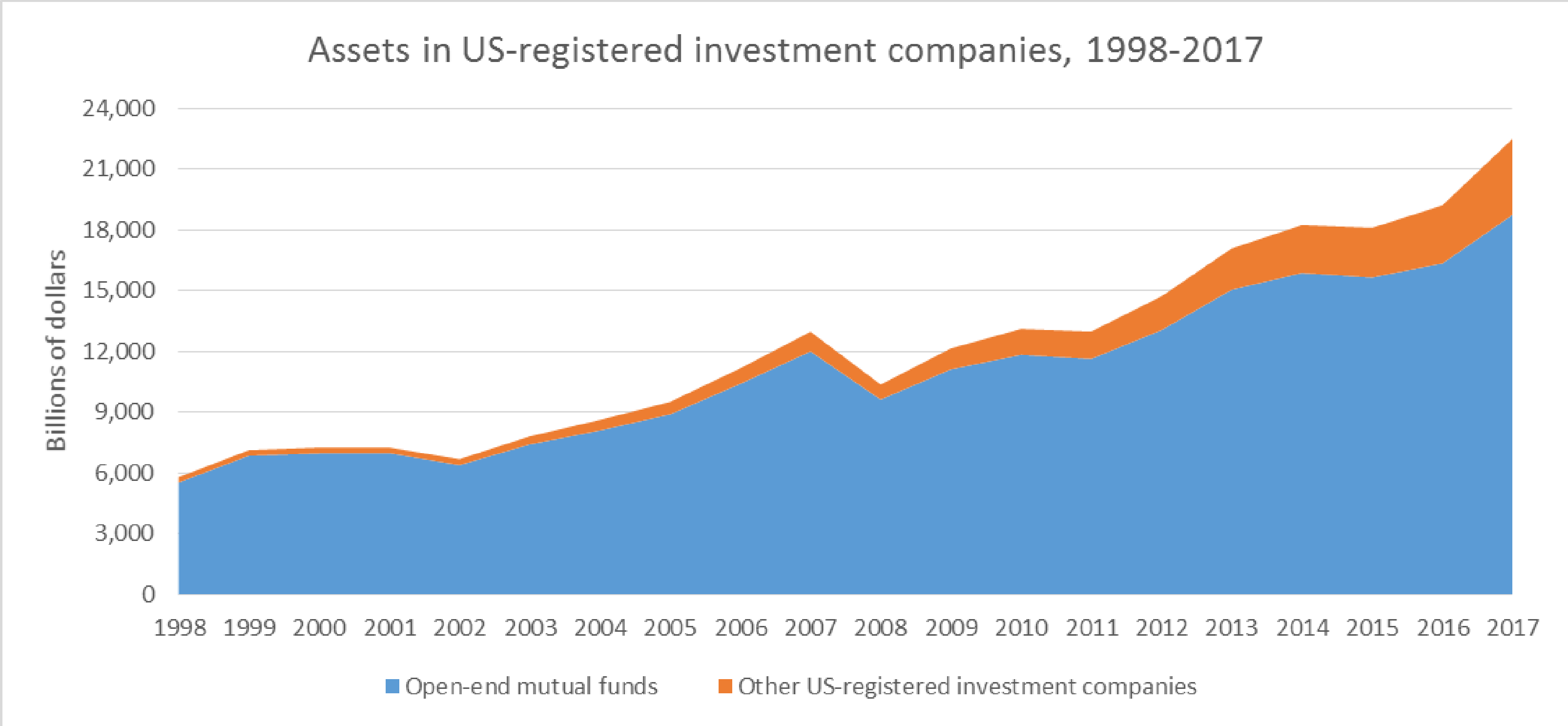

Figure 1.1. This figure shows the evolution of the assets under US-registered investment companies' management during the period 1998-2017. The yearly net assets for open-end mutual funds are shown in blue, while the sum of the net assets per annum for other US-registered investment companies (i.e., closed-end funds, exchange-traded funds and unit investment trusts) is shown in orange. All the information refers to year-end data.

This significant growth of the mutual fund industry attracted the attention of academics, who aim to understand the behaviour of mutual funds over time. Several interesting reviews about mutual funds and their performance can be found in Ferson (2010), Elton and Gruber (2013), and Cuthbertson, Nitzsche and O'Sullivan (2016).

Given the evidence provided in Figure 1.1, it is very important to understand the factors driving the demand for mutual funds, as well as the behaviour of these investment vehicles. In this sense, and although the returns of the fund are not the only reason determining the investors' decision, they are a key variable in attracting net cash flows to the fund portfolio. Mutual fund results directly depend on the evolution of the assets held in the fund portfolio. For instance, Sharpe (1992) shows that the returns of a mutual fund are linked (or exposed) to the asset classes this fund usually invests in, in accordance with the fund's investment objectives.

Regarding the previous literature about fund performance, several articles proposed different measures to capture fund performance more than fifty years ago (Treynor, 1965; Sharpe, 1966; Jensen, 1968). Nonetheless, and since the contributions of Sharpe (1992), Fama and French (1993), and Gruber (1996), the use of multifactor models is widely accepted in assessing mutual fund performance[5]. These models extend the widely-known Capital Asset Pricing Model by adjusting the funds' returns to several benchmarks or additional risk factors (Carhart, 1997; Busse, Goyal and Wahal, 2010; Cortez, Silva and Areal, 2012; and Fama and French, 2015; among others). In any case, the overall abnormal return that a mutual fund provides to its investors is measured through the intercept of the model applied; in other words, the average return that a

[5] The estimation of the risk-adjusted returns achieved by a fund could potentially be biased if relevant benchmarks or factors are omitted in the specification of the model, as pointed out by Pástor and Stambaugh (2002) and Matallín-Sáez (2006).

fund experiences during a period in excess of the returns obtained by a passive portfolio that mimics the funds' exposures to the considered benchmarks or factors. Because of that, this return is also named as the risk-adjusted return or the *alpha* of a fund (from the nomenclature commonly employed in these models).

Besides the influence of the fund results, other factors should also have a significant impact on the investors' demand. For example, other performance determinants that can potentially alter subsequent net cash flows, such as the size of the fund's complex and the costs related to the search of information (Sirri and Tufano, 1998), the type of expenses borne in the fund portfolio (Barber, Odean and Zheng, 2005; Houge and Wellman, 2007) or the manager replacement (Andreu, Sarto and Serrano, 2015). Fund managers' also play a key role in the attraction of money from investors, since they can potentially enhance mutual fund performance. Hence, if managers, through an active management, are able to add some value to the fund results, they could greatly influence the demand of the fund, especially in case of investors detecting their managerial abilities.

Despite the evidence on the overall underperformance of active mutual funds (Carhart, 1997; Berk and Green, 2004; and Fama and French, 2010; among others), some recent studies (e.g., Cremers and Petajisto, 2009; Amihud and Goyenko, 2013) observe that some funds provide significantly greater alphas than others in differing to a greater extent from their benchmarks or risk factors, attributing this better performance to a higher degree of activity in the portfolio management (as a consequence of managerial skills, therefore). In contrast, other studies point out that funds taking higher risk positions experience worst risk-adjusted returns (Huang, Sialm and Zhang, 2011).

Thus, there is some controversy in the evidence reported the previous studies, and it seems to mainly depend on the measures employed in the analyses related to the investors' demand, the fund performance and the active management of the portfolio. In other words, these variables are barely quantifiable, and a consensus on their measurement has not yet been reached in the literature.

In this context, the studies included in this thesis aim to shed some light on these issues. Firstly, two measures capturing the fund demand (i.e., implied flows and current net cash flows) are compared, identifying the conditions where a higher error is generated in the estimation of both the investors' flows and the effect of their determinants. Secondly, and given that the fund performance is one of the main drivers in the investment decisions, we observe the interactions among the risk-adjusted returns and the trading activity measured through the information available to investors (i.e., the information reflected in the fund prospectus). Finally, we propose a new measure to capture managerial skills in the mutual fund industry that is based on the alteration of the exposures to several risk factors (Change in Factors Exposures), and assess its relationship with future performance.

Therefore, this thesis proposes the evaluation of different aspects related to the efficiency and analysis of the behaviour of mutual funds and their demand. The US mutual fund industry is analysed due to its representativeness, since it is the largest fund industry worldwide. Our sample focuses on more than 17,000 share-classes related to 5,255 US open-end funds that invest mainly in equities of the same market. Additionally, several economic cycles and other characteristics are taken into account to avoid any potential bias.

In sum, this thesis contributes to the extant literature on estimating properly the mutual fund demand and the effect of its determinants, as well as on assessing both the behaviour and the performance of the funds in relation to their level of management activity. The implications of these studies are of interest for investors and managers (in optimizing the financial results of their investments), and for regulators and other stakeholders (in order to conduct the necessary actions to facilitate and improve the publicly available information on equity mutual funds).

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CHAPTER 2: INVESTING IN MUTUAL FUNDS: THE DETERMINANTS OF IMPLIED AND ACTUAL NET CASH FLOWS

INVESTING IN MUTUAL FUNDS: THE DETERMINANTS OF IMPLIED AND ACTUAL NET CASH FLOWS

2.1. Introduction

Understanding mutual fund investors' behaviour has attracted much attention from both professionals and researchers. Many authors have studied the effect of characteristics such as performance or expenses on the demand for mutual funds. And measuring the flows into and out of the funds is a reasonable way to estimate this demand.

In this context, the standard definition of net cash flows or "new money" in a fund during a given period is equal to the fund size in the same period minus the appreciation of the fund size in the previous period; that is, the growth of the fund with respect to the growth that would have happened with no flows, and with all the dividends reinvested in the fund. This rough definition has been used in several studies (e.g., Barber *et al.*, 2005; Cooper *et al.*, 2005; Gruber, 1996; Guercio and Reuter, 2014; Huang *et al.*, 2007; Jayaraman *et al.*, 2002; Zhao, 2005), mainly due to the lack of more specific data.

However, it is worth noting that this estimate of net cash flow entails certain implicit assumptions. For example, net cash flows occur in the last moment of each period, so they incur neither return nor related costs during that period. Aware of this fact, some authors have also considered that such flows occur at the beginning of the period, and conclude that using one or the other method does not lead to significant differences in their results (Bhattacharya *et al.*, 2013; Feng *et al.*, 2014; Friesen and Sapp, 2007; Sirri and Tufano, 1998; Zheng, 1999). Nevertheless, this is also a rough definition for estimating mutual fund flows, and does not provide the precise amount of investors' flows going into and out of the fund.

Other authors, however, have emphasised the importance of defining mutual funds' net cash flows using specific information on inflows and outflows (Andreu and Sarto, 2016; Christoffersen *et al*., 2013; Ivković and Weisbenner, 2009; Keswani and Stolin, 2008). That is, the amount of net cash flows experienced by the fund during a period is equal to the total inflows minus the total outflows generated in that period. Thus, this method estimates net cash flows accurately, while previous methods provide an approximate picture of the real flows into and out of a mutual fund. Despite this, the fund data required to estimate fund flows precisely are not always available for some countries and databases.

Accordingly, an error may be introduced by using a rough method as the definition of mutual fund flows, which would lead to differences in the results of the determinants of net flows, or even in their persistence. To our knowledge, only Keswani and Stolin (2008) make a brief comparison between rough and accurate methods for a sample of UK mutual funds, comparing the regressions of these measures on some variables, such as the lagged flow or the performance experienced by the fund. They attribute the differences in the slopes of each regression to the inherent noise created when estimating implied flows.

Then, the main interest of this chapter is to analyse the effect of the determinants of the mutual fund demand, showing that the use of a rough measure can lead to a noise in the estimate of the flows experienced by the fund. For this purpose, we analyse a large sample of US equity mutual funds. Our results indicate that depending on the methodology applied, there are important differences in the net cash flow estimates. These differences are higher for smaller funds, funds with higher inflows and outflows, and funds experiencing higher returns in absolute terms. Furthermore, the use of the implied flows in the regressions causes an error in estimating the effect of determinants that explain the variability of mutual fund flows, especially during bullish periods. This lack of precision is higher particularly when fund flows are estimated for longer periods.

The rest of this chapter is structured as follows. The next section describes the data and the applied methodology. Section 3 reports the results. Finally, the main conclusions are presented.

2.2. Data and methodology

The period analysed runs from December 1999 to July 2015. The sample initially comprises 17,773 US domestic equity share-class funds. We aggregate multiple share classes of the same fund, a common practice in the literature. We then remove all the funds from the sample with no available data for size, return, sales and redemptions. This information is required to construct both measures of fund flows. Our sample finally consists of 2,985 US domestic equity mutual funds. There is no survivorship bias since the sample includes both disappeared and new funds during the sample period.

For each fund we obtain from Morningstar the fund's name, fund Id, inception date, and fund objective. Since we want to estimate different net cash flows and to show their relation to other variables, we also download monthly information on total net asset (TNA), return, sales, and redemptions. Finally, we also obtain information on the annual expense ratio of each fund.

As commented above, in some previous studies, net cash flows have been indirectly estimated, as shown in equation (1).

$$Implied\ Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}} \tag{1}$$

Where *Implied Flow*$_{i,t}$ is the estimated monthly net cash flow in relative terms that fund i experiences during period t. $R_{i,t}$ is the monthly return of that fund during period t, and $TNA_{i,t}$ refers to the total net assets of the same fund during period t. Two important assumptions are made in this method: the generated dividends are entirely reinvested in the fund, and cash flows occur in the last moment of the period.

We now calculate net cash flows directly. Thus, as shown in (2), we define the fund net cash flow as the total inflows minus the total outflows that occur in a mutual fund in the same period.

$$Net\ Cash\ Flow_{i,t} = \frac{Sales_{i,t} - Red_{i,t}}{TNA_{i,t-1}} \tag{2}$$

Where *Net Cash Flow*$_{i,t}$ is the monthly net cash flow in relative terms that fund i experiences during period t, $Sales_{i,t}$ is the total inflows made by investors of fund i during period t, and $Red_{i,t}$ refers to the total redemptions made by investors of fund i during period t.

Following Cashman *et al*. (2012), we eliminate from the sample observations that appear to contain data errors. Specifically, we remove observations in which the net flow, sales or redemptions exceed 70% of the size of the fund in the previous period. Additionally, in order to ensure a consistent comparison, we require the funds to present information on both fund flows' measures during each period.

Table 2.1 reports the descriptive statistics for the sample. The average fund experiences similar amounts of sales (334.93 millions of dollars) and redemptions (334.53

millions of dollars), but net flows seem to differ according to the methodology applied. Net cash flows estimated by equation (1) are greater (31.74 million dollars) than the funds' actual net cash flows (1.62 million dollars). In relative terms, these differences in the net flows also hold (8.66% for implied flows, and 2.99% for net cash flows). This information reveals important differences between the indirect and the direct estimate of net cash flows. Consequently, the results of the analysis of the determinants of investors' demand for funds could differ when using different cash flows measures.

Table 2.1. Characteristics of the mutual fund sample

	Mean	Standard deviation
TNA ($millions)	754.78	3,178.88
Sales ($millions)	334.93	353.81
Redemptions ($millions)	334.53	359.64
Net Cash Flow ($millions)	1.62	154.29
Implied Flow ($millions)	31.74	79.33
Net Cash Flow (%)	2.99%	12.61%
Implied Flow (%)	8.66%	6.90%
Annualised Return %	6.11%	1.62%
Net Expense Ratio (%)	1.32%	0.72%

This table shows some descriptive statistics of our sample of 2,985 US equity mutual funds for the period December 1999-July 2015. *TNA* represents the assets of the fund under management and *Annualised Return* is the annualised monthly return of the fund. *Net Expense Ratio* is the annual net expense ratio borne by the fund. *Sales* and *Redemptions* describe the flows going into and out of the fund, respectively. *Net Cash Flow* and *Implied Flow* are the accurate and approximate net fund flow measures, respectively. The units of these characteristics are in parentheses.

2.3. Results

2.3.1. Differences between net and implicit cash flow

In this section, we analyse whether there are significant differences between the two flow measures during the sample period. For robustness purposes, the same analysis is also run for four sub-periods related to different market conditions: two bear regimes (from December 1999 to December 2003, and from January 2008 to December 2009) and two bull regimes (from January 2004 to December 2007, and from 2010 to the end of the sample period).

We apply ordinary least squares to the time-series regressions for each fund in the sample. Previous studies (Edelen, 1999; Peng *et al*., 2011; among others) also employ this approach. The advantage of using this methodology is that the estimates of the regressions are allowed to differ across funds, so we allow flows in each fund to respond differently to the explanatory variables. If the coefficients from the regressions were mainly negative (or positive) in most of the regressions, then the mean of these coefficients would be negative (or positive) and significantly different from zero.

Accordingly, we regress the estimated flows (*Implied Flow*$_{i,t}$) on the actual net cash flows (*Net Cash Flow*$_{i,t}$) as follows:

$$Implied\ Flow_{i,t} = \beta_{i,0} + \beta_{i,1} Net\ Cash\ Flow_{i,t} + \varepsilon_{i,t} \qquad (3)$$

If there are no significant differences, we should obtain a close to zero intercept, a slope close to unity, and a very high coefficient of determination. However, if these are not the cases, results would show that there are important differences estimating fund flows, and a noise would be considered when calculating implied flows. Table 2.2 presents the results of this analysis.

Table 2.2. Regression of Implied Flow on Net Cash Flow

	December 1999-July 2015		December 1999-December 2003		January 2004-December 2007		January 2008-December 2009		January 2010-July 2015	
	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	0.055	(0.000)	0.174	(0.000)	0.023	(0.261)	-0.002	(0.939)	0.037	(0.070)
Net Cash Flow	0.847	(0.000)	0.812	(0.000)	0.845	(0.000)	0.890	(0.000)	0.875	(0.000)
Number of funds	2,985		1,644		2,153		1,536		2,023	
Adjusted R^2	0.737		0.693		0.743		0.831		0.801	

This table reports the average of the coefficient estimates across the OLS time-series regressions for each fund in the sample. The dependent variable is the *Implied Flow* of the fund, defined as the estimated monthly net cash flow in relative terms. The explanatory variable is *Net Cash Flow*, measured as the net percentage fund flow using flows into and out of the fund in the same period. Results are reported for the whole period and the sub-periods considered. P-values (in parentheses), the number of funds and the average adjusted R^2 for each period are also reported.

Results show significant differences between the two measures of estimated cash flows. Regarding the main period, the adjusted R^2 is quite high (0.737), which suggests that implied flows are a good estimate of net cash flows. In contrast, the mean coefficient on the net cash flows (0.847) is positive but significantly lower than the unity, which is in line with the lower variability of implied flows observed in Table 2.1. The evidence is very similar for all of the sub-periods considered. In short, implied flows seem to be a good estimate of actual cash flows into and out of the fund, but also entail an implicit error in their calculation.

We next analyse the variables that can potentially create these differences. That is, the components that lead to an increase in the deviation of the two flow measures. Specifically, the variables that are involved in both fund flows methodologies: return, size, sales, and redemptions.

To find out how the different characteristics of a fund affect these differences in net cash flow estimates, we create a new variable, *Implied Excess Flow*, which we define as the absolute value of the difference between the implied flows and the actual net cash flows. Consequently, the higher the value of this variable, the higher the deviation generated through equation (1). In other words, the higher the error assumed when using implied flows.

Therefore, we regress the *Implied Excess Flow* of each fund on the aforementioned variables, as described in Equation (4):

$$Implied\ Excess\ Flow_{i,t} = \beta_0 + \beta_1 R_{i,t} + \beta_2 R_{i,t}^2 + \beta_3 LogTNA_{i,t} + \beta_4 Sales_{i,t} + \beta_5 Red_{i,t} + \varepsilon_{i,t} \qquad (4)$$

Where $LogTNA_{i,t}$ refers to the size of fund i during period t, measured as the logarithm of the total net assets under the fund management.

On the one hand, we hypothesise that higher returns, in absolute terms, should increase the deviation between the two flow measures. Because of that, we also consider the square of the return as an explanatory variable. Thus, we expect β_1 not to be statistically significant (the greater effect of a positive return on the estimated flows would be diminished by the higher effect of a negative return). Nonetheless, β_2 may be positive and significantly different from zero. On the other hand, fund size should negatively affect the *Implied Excess Flows*, because, given a certain level of net cash flow, the more assets the fund manages, the lower this level of relative cash flows will be. Finally, sales (redemptions) may positively affect the differences in estimates of cash flows since the appreciation experienced (not experienced) during the period will be considered as an inflow (outflow) when using implied flows.

Table 2.3 reports the results of this analysis. As we expected, results show that the coefficient on fund return is not significant (p-value of 0.235), so it seems that it does not contribute to the deviation in the two net cash flow estimates. However, both high positive and negative returns generate larger differences in the flow measures since β_2 is positive and statistically significant. Regarding the effect of the fund size on the *Implied Excess Flows*, results show that the coefficient of this variable is negative (-0.238) and statistically significant. It means that given a certain level of cash flow, the deviation among both measures is smaller when considering funds managing more assets, and so lower differences are generated. Finally, coefficients on the fund sales (0.060) and fund redemptions (0.101) are also significant, implying that greater levels of these variables lead to larger differences in the two fund flow estimates.

Table 2.3. Explaining the Implied Excess Flow

	Mean	p-value
Intercept	2.184	(0.001)
Return	0.002	(0.235)
$Return^2$	0.001	(0.005)
Logarithm TNA	-0.238	(0.005)
Sales	0.060	(0.000)
Redemptions	0.101	(0.000)
Number of funds	2,909	
Adjusted R^2	0.269	

This table reports the results of the coefficient estimates across the OLS time-series regressions for each fund in the sample. The dependent variable is the *Implied Excess Flow*, measured as the absolute value of the difference between the implied flows and the actual net cash flows. The table includes the mean and p-value (in parentheses) of the coefficients of the explanatory variables, namely, the return and the square of the return experienced by the fund in the period, the log of the total assets under management, and the sales and redemptions going into and out of the fund in the same period. The number of funds and the average adjusted R^2 are also reported.

In short, results in Table 2.3 reflect that implied flows defined in (1) does not accurately estimate the real net flows experienced by a fund during a period, and it generates an error which is greater in smaller funds, and in the presence of higher levels of sales, redemptions, or return achieved by the fund.

2.3.2. Analysis of the determinants of fund cash flow

Consequently, and in view of the results of the previous section, the lack of precision in the calculation of net cash flows may also create an error in estimating the determinants of investors' fund flows. Therefore, we regress both flow measures on the variables that can affect the fund investors' demand, according to the previous literature: the return experienced by the fund during the previous period (*Return*), the risk borne by the fund portfolio (*Risk*), and the growth rate of net flow for all funds in the same objective as the fund in the previous period (*Lagged Objective Flow*). We also consider the *Lagged Cash Flows* in the analysis, in order to observe the persistence of this variable over time. Finally, we also consider some control variables, such as the fund size (*Log Lagged TNA*), the level of expenses (*Expense Ratio*), and the age of the fund since inception (*Age*).

On the one hand, we expect that the return and the lagged flows positively affect the net flows, since the return and the previous investments made by other investors can influence the fund investor's choices. On the other hand, we suppose that the risk borne by the portfolio negatively affects the net flows since we assume investors to be risk averse. We also hypothesise that the effect of the independent variables on the fund flows could be distorted when considering implied flows, due to the inherent error that this measure implies.

Table 2.4 reports the results of this analysis, showing the average coefficients (and their significance) estimated through the regressions for each fund in the sample, as well as the mean differences between the two models. The number of funds and the adjusted coefficient of determination are also reported.

Table 2.4. Regression of the monthly fund flows on fund characteristics

Independent Variables	Implied Flows Mean	Implied Flows p-value	Net Cash Flows Mean	Net Cash Flows p-value	Mean Differences Mean	Mean Differences p-value
Intercept	68.163	(0.000)	57.823	(0.000)	10.340	(0.060)
Log Lagged TNA	-8.482	(0.000)	-7.269	(0.000)	-1.214	(0.016)
Expense Ratio	1.809	(0.310)	1.287	(0.472)	0.522	(0.838)
Age	-0.019	(0.000)	-0.012	(0.016)	-0.008	(0.283)
Return	0.067	(0.000)	0.066	(0.000)	0.001	(0.810)
Risk	-0.268	(0.000)	-0.177	(0.000)	-0.092	(0.044)
Lagged Objective Flow	0.107	(0.000)	0.117	(0.000)	-0.010	(0.775)
Lagged Cash Flow	0.159	(0.000)	0.196	(0.000)	-0.037	(0.000)
Number of funds	2,881		2,881			
Adjusted R^2	0.259		0.291		-0.032	(0.000)

This table shows the average results and their significance (in parentheses) of the coefficient estimates across the OLS time-series regressions for each fund in the sample. The first and second columns report the results of the regression of the *Implied Flows*, defined as the estimated monthly net cash flow in relative terms. The third and fourth columns show the results of the regression of the *Net Cash Flows*, measured as the net percentage fund flow using flows into and out of the fund in the same period. The fifth and sixth columns report the results of the mean differences of each coefficient and their statistical significance. The explanatory variables are the log of the funds under management in the previous period (*Log Lagged TNA*), the net expense ratio borne by the fund during the previous year (*Expense Ratio*), the age of the fund since inception, in months (*Age*), the monthly return of the fund in the previous period (*Return*), the risk of the fund measured as the standard deviation of the last 12 monthly returns (*Risk*), the growth rate of net flow for all funds in the same objective as the fund in the previous period (*Lagged Objective Flow*), and the growth rate of net flow for the fund in the previous period (*Lagged Cash Flow*), measured in the same terms as the dependent variable. The number of funds and the average adjusted R^2 are also reported.

Results are consistent with our expectations. On the one hand, previous returns, past flows related to the fund's objective and those experienced in the portfolio have positive and significant effects on the level of net flows experienced by the fund during the following period, regardless of the net cash flow estimate. In addition, the risk borne by the fund's portfolio impacts negatively on both implied flows (coefficient of -0.268) and net cash flows (-0.177).

On the other hand, the comparison of the mean coefficients of the two models shows that some of the results differ when implied flows (as in (1)) are used. Firstly, there are statistically significant differences in the adjusted coefficient of determination: the adjusted R^2 for the net cash flows (0.291) is significantly higher than the adjusted R^2 for the implied flows (0.259). This implies that the model of actual fund flows is a better fit than the model that considers the approximate flows as the dependent variable. Moreover, there are differences regarding the coefficient of the explanatory variables. Firstly, the coefficient of lagged flows is significantly lower in the model of implied flows (0.159) than in the model of the net cash flows (0.196). This result indicates that implied flows underestimate the effect of the persistence of the fund flows. In addition, the effect of the fund size and the effect of the risk assumed by the portfolio on the fund flows are greater when considering implied flows.

Next, we wonder if this evidence is robust when we use data with a different frequency. If implied flows entailed an inherent error, we could expect this lack of precision to be higher when using two-quarterly information, for example. We therefore consider different windows to analyse the effect of the previous variables on the cash flows.

Table 2.5 presents the results for the mean coefficients of the explanatory variables and their significance when using quarterly (Panel A), two-quarterly (Panel B) and annual data (Panel C). The number of funds and the average adjusted coefficient of determination are also reported.

Table 2.5. The determinants of quarterly, two-quarterly and annual fund flows

Panel A: Quarterly flows

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	126.057	(0.000)	111.710	(0.000)	14.347	(0.108)
Log lag TNA	-15.823	(0.000)	-14.088	(0.000)	-1.735	(0.028)
Expense Ratio	6.402	(0.128)	5.899	(0.123)	0.503	(0.929)
Age	-0.004	(0.526)	-0.004	(0.608)	-0.001	(0.937)
Return	0.060	(0.000)	0.050	(0.000)	0.010	(0.156)
Risk	-0.293	(0.000)	-0.224	(0.000)	-0.068	(0.239)
Lagged Objective Flow	0.033	(0.540)	-0.011	(0.841)	0.044	(0.566)
Lagged Cash Flow	0.171	(0.000)	0.200	(0.000)	-0.030	(0.001)
Number of funds	2,213		2,213			
Adjusted R^2	0.330		0.349		-0.019	(0.015)

Panel B: Two-quarterly flows

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	492.488	(0.000)	157.479	(0.000)	335.009	(0.000)
Log lag TNA	-61.183	(0.000)	-19.043	(0.000)	-42.140	(0.000)
Expense Ratio	22.797	(0.001)	4.795	(0.260)	18.002	(0.023)
Age	0.112	(0.000)	0.014	(0.064)	0.098	(0.000)
Return	-0.150	(0.000)	0.016	(0.042)	-0.165	(0.000)
Risk	-0.829	(0.000)	-0.376	(0.000)	-0.454	(0.000)
Lagged Objective Flow	1.163	(0.000)	0.312	(0.002)	0.851	(0.000)
Lagged Cash Flow	0.190	(0.000)	0.206	(0.000)	-0.016	(0.232)
Number of funds	903		903			
Adjusted R^2	0.305		0.335		-0.030	(0.010)

Table 2.5. (*Continued*)

Panel C: Annual flows

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	-1,565.324	(0.000)	-370.469	(0.000)	-1,194.855	(0.000)
Log lag TNA	164.365	(0.000)	39.826	(0.000)	124.539	(0.000)
Expense Ratio	95.254	(0.005)	21.136	(0.160)	74.118	(0.046)
Age	0.143	(0.012)	-0.023	(0.362)	0.166	(0.008)
Return	-0.001	(0.986)	0.052	(0.024)	-0.053	(0.451)
Risk	3.291	(0.000)	0.784	(0.065)	2.507	(0.001)
Lagged Objective Flow	-1.043	(0.115)	-0.885	(0.011)	-0.158	(0.832)
Lagged Cash Flow	-0.381	(0.000)	-0.024	(0.525)	-0.358	(0.000)
Number of funds	139		139			
Adjusted R^2	0.595		0.391		0.204	(0.000)

This table shows the average results and the significance (in parentheses) of the coefficient estimates across the OLS time-series regressions for each fund in the sample. Panel A, Panel B and Panel C refer to fund flows estimated in a quarterly, two-quarterly and annual basis, respectively. The first and second columns report the results of the regression of the *Implied Flows*, defined as the estimated net cash flow in relative terms. The third and fourth columns show the results of the regression of the *Net Cash Flows*, measured as the net percentage fund flow using flows into and out of the fund in the same period. The fifth and sixth columns report the results of the mean differences of each coefficient and their statistical significance. The explanatory variables are the log of the funds under management in the previous period (*Log Lagged TNA*), the net expense ratio borne by the fund during the previous year (*Expense Ratio*), the age of the fund since inception, in months (*Age*), the return of the fund in the previous period (*Return*), the risk of the fund measured as the standard deviation of the last 12 monthly returns (*Risk*), the previous growth rate of net flow for all funds in the same objective as the fund (*Lagged Objective Flow*), and the growth rate of net flow for the fund in the previous period (*Lagged Cash Flow*), measured in the same terms as the dependent variable. The number of funds and the average adjusted R^2 are also reported.

The evidence in Panel A is very similar to that in Table 2.4. On the one hand, previous returns and previous fund flows have positive and statistically significant effects on the fund flows during the following period, while the effect of the portfolio's risk is significantly negative. On the other hand, there are significant differences in the mean coefficients of some explanatory variables. For instance, the effects of fund size and of previous fund flows are significantly lower in the model in which the dependent variable is the implied flows (coefficients of -1.735 and -0.03, respectively).

Turning to Panel B, we have some very interesting results. Firstly, previous returns have a positive and statistically significant effect (coefficient of 0.014) on the actual net cash flows (as in (2)). Nevertheless, they seem to have a negative (coefficient of -0.150) effect on the implied flows, estimated as in (1). Moreover, the effect of the net expense ratio on the implied flows seems to be significantly positive (coefficient of 22.797), but it is non-significant (p-value of 0.260) when a more accurate measure of net cash flows is considered. Also, most of the differences in the mean coefficients from both models are statistically significant. The same evidence is found for the annual-based analysis. In other words, the distortion generated by implied flows is higher when longer windows are used in their estimation.

Overall, the evidence related to analyses for different windows indicates that the use of implied flows, despite being a good approximation of the actual net cash flows experienced by the fund, could lead to wrong conclusions on the determinants of the investors' flows, especially if they are estimated during longer periods (e.g., two-quarterly or annually).

2.3.3. Does the effect of the determinants of fund cash flow change during bullish and bearish periods?

To observe whether there are any differences in the estimates among different sub-periods, we distinguish between bearish and bullish periods, and study the effect of the determinants of investors' flows. Only monthly flows are studied due to the lack of sufficient information for a consistent analysis on a quarterly or annual basis.[6]

Table 2.6 shows the results of these analyses. Specifically, Panel A and Panel C report the results for two bearish periods (2000-2003 and 2008-2009), while Panel B and Panel D present the results for two bullish periods (from 2004 to 2007, and from 2010 to the end of the sample period).

Results for the bullish periods are in line with those in Table 2.4. For instance, the higher the fund's previous returns, the higher the level of net flows attracted (the mean coefficients range from 0.061 to 0.108). Previous flows also have positive and statistically significant effects, and the risk borne by the fund's portfolio impacts negatively on both net cash flow measures. Moreover, the inherent error assumed by implied flows generates significant differences in the effect of some explanatory variables, such as previous fund size and previous fund flows.

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[6] For instance, the 2008-2009 period only covers eight quarterly observations.

Table 2.6. The determinants of fund flows during bullish and bearish periods

Panel A: Bearish period. January 2000–December 2003

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	132.497	(0.000)	77.203	(0.009)	55.294	(0.150)
Log lag TNA	-17.515	(0.000)	-13.699	(0.000)	-3.816	(0.093)
Expense Ratio	10.386	(0.475)	22.043	(0.219)	-11.657	(0.613)
Age	0.037	(0.061)	0.053	(0.008)	-0.016	(0.577)
Return	0.048	(0.000)	0.059	(0.000)	-0.010	(0.404)
Risk	-0.120	(0.175)	-0.004	(0.957)	-0.115	(0.345)
Lagged Objective Flow	0.396	(0.000)	0.270	(0.000)	0.126	(0.072)
Lagged Cash Flow	0.004	(0.731)	0.030	(0.001)	-0.026	(0.060)
Number of funds	1,278		1,278			
Adjusted R^2	0.258		0.270		-0.011	(0.261)

Panel B: Bullish period. January 2004–December 2007

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	180.238	(0.000)	138.747	(0.000)	41.491	(0.010)
Log lag TNA	-21.553	(0.000)	-17.032	(0.000)	-4.521	(0.001)
Expense Ratio	-5.479	(0.411)	-3.422	(0.593)	-2.057	(0.824)
Age	0.081	(0.000)	0.074	(0.000)	0.008	(0.738)
Return	0.108	(0.000)	0.087	(0.000)	0.021	(0.097)
Risk	-0.386	(0.000)	-0.183	(0.090)	-0.203	(0.165)
Lagged Objective Flow	0.207	(0.000)	0.208	(0.000)	-0.001	(0.980)
Lagged Cash Flow	0.097	(0.000)	0.127	(0.000)	-0.030	(0.003)
Number of funds	1,886		1,886			
Adjusted R^2	0.283		0.301		-0.018	(0.033)

Table 2.6. (*Continued*)

Panel C: Bearish period. January 2008– December 2009

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	52.936	(0.044)	42.962	(0.112)	9.974	(0.791)
Log lag TNA	-10.351	(0.000)	-10.828	(0.000)	0.477	(0.714)
Expense Ratio	17.491	(0.414)	30.633	(0.166)	-13.142	(0.669)
Age	0.038	(0.048)	0.022	(0.250)	0.015	(0.573)
Return	0.089	(0.000)	0.101	(0.000)	-0.013	(0.130)
Risk	0.023	(0.649)	0.032	(0.521)	-0.009	(0.894)
Lagged Objective Flow	0.043	(0.118)	0.029	(0.299)	0.014	(0.710)
Lagged Cash Flow	-0.080	(0.000)	-0.071	(0.000)	-0.009	(0.444)
Number of funds	1,170		1,170			
Adjusted R^2	0.225		0.231		-0.006	(0.565)

Panel D: Bullish period. January 2010– July 2015

	Implied Flows		Net Cash Flows		Mean Differences	
Independent Variables	Mean	p-value	Mean	p-value	Mean	p-value
Intercept	99.440	(0.000)	82.797	(0.000)	16.643	(0.069)
Log lag TNA	-12.324	(0.000)	-10.321	(0.000)	-2.004	(0.009)
Expense Ratio	-1.240	(0.741)	-1.054	(0.788)	-0.186	(0.973)
Age	0.019	(0.024)	0.021	(0.011)	-0.002	(0.848)
Return	0.061	(0.000)	0.064	(0.000)	-0.003	(0.707)
Risk	-0.121	(0.004)	-0.105	(0.017)	-0.016	(0.790)
Lagged Objective Flow	0.106	(0.010)	0.098	(0.038)	0.008	(0.898)
Lagged Cash Flow	0.105	(0.000)	0.121	(0.000)	-0.017	(0.047)
Number of funds	1,898		1,898			
Adjusted R^2	0.184		0.196		-0.012	(0.067)

This table shows the average results and the significance (in parentheses) of the coefficient estimates across the OLS time-series regressions for each fund in the sample. Results are presented for each sub-period. The first and second columns report the results of the regression of the *Implied Flows*. The third and fourth columns show the results of the regression of the *Net Cash Flows*. Both measures of flows are defined as in Table 2.2. The fifth and sixth columns report the mean differences of each coefficient and their statistical significance. The explanatory variables are the log of the funds under management in the previous period (*Log Lagged TNA*), the fund's net expense ratio during the previous year (*Expense Ratio*), the fund age since inception, in months (*Age*), the monthly return of the fund in the previous period (*Return*), the risk of the fund measured as the standard deviation of the last 12 monthly returns (*Risk*), the growth rate of net flow for all funds in the same objective as the fund in the previous period (*Lagged Objective Flow*), and the growth rate of net flow for the fund in the previous period (*Lagged Cash Flow*), measured in the same terms as the dependent variable. The number of funds and the average adjusted R^2 are also reported.

Regarding bearish periods (Panel A and Panel C), we also find similar evidence for the effect of previous returns on the fund flows (their coefficient is significantly positive). In contrast, it seems that the risk borne by the portfolio has no significant effect on the fund flows during these sub-periods. Also, the differences in the mean coefficients of both models are not significant at the 5% level.

In sum, implied flows, that is, flows indirectly estimated using data on fund size and return, seem to be a good measure of the actual net cash flows experienced by the fund. However, this measure implicitly assumes an error in its calculation. And this error can lead to differences in the estimate of the fund investors' response to some related variables, especially during bullish periods.

2.4. Conclusion

Explaining the variability in the cash flows of a mutual fund has attracted much attention from both professionals and academics. Accordingly, estimating the effect of some determinants on the fund investors' demand plays an important role in the mutual fund management. For instance, mutual fund returns in the portfolio attract investors' flows. In addition, previous cash flows into the fund also have positive and significant effects on investment decisions. In contrast, the effect of the risk borne in the portfolio is significantly negative, at least during bullish periods. Nevertheless, the effect of these determinants can change depending on which measure of net cash flows is used.

Many authors, because of the unavailability of the data for inflows and outflows in some countries, estimate net cash flows that occurred during a period using fund size and returns information. According to them, these implied flows correspond to the cash flows that are not due to dividends and capital gains. Notwithstanding, this measure implicitly assumes that all the flows occur at the end of the period, and that all dividends are reinvested in the fund. This is an approximation of the actual cash flows into and out of the mutual funds and, therefore, causes an inherent noise in their calculation.

This study shows that, although this method seems to be a good measure, there is indeed a deviation in this rough estimate of cash flows in relation to the actual fund flows. The higher the fund return (in absolute terms), the greater the differences generated, presumably due to the no appreciation of the flows experienced by the fund. Moreover, smaller funds and funds experiencing higher levels of inflows and outflows are also proportional to this error in the flows estimate.

Accordingly, this rough measure causes an error when estimating the effect of the explanatory determinants of the fund flows, such as the return or the flows experienced by the fund. This inaccuracy is more important during bullish periods, especially when longer time horizons are considered in estimating the fund flows.

In conclusion, implied flows are a good approximation to the actual cash flows experienced by the fund during a period, especially when there is no information related to the fund inflows and outflows. Nevertheless, we have to consider that their calculation is not always accurate. And this lack of precision can lead to distorted results of the analysis where implied flows are considered.

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CHAPTER 3: INSTITUTIONAL INVESTMENT MANAGEMENT: AN INVESTOR'S PERSPECTIVE ON THE RELATION BETWEEN TURNOVER AND PERFORMANCE

INSTITUTIONAL INVESTMENT MANAGEMENT: AN INVESTOR'S PERSPECTIVE ON THE RELATION BETWEEN TURNOVER AND PERFORMANCE

3.1. Introduction

The considerable growth of the mutual fund industry has led to a significant number of studies on mutual fund performance. Elton and Gruber (2013) and Ferson (2010) provide a review of this literature. The overall evidence is that, in aggregate, active management of mutual funds does not offer investors any added value, compared to the net return obtained by following a passive strategy.

In this context, some recent studies have developed different active management measures, and explore their relation with funds' results. For instance, Kacperczyk *et al.* (2005) demonstrate that better performing mutual fund managers are those who decide to deviate from their benchmarks and concentrate their investments in a few industries where they can obtain informational advantages. Cremers and Petajisto (2009) suggest that funds outperform their benchmarks when they differ from their portfolios' holdings. In the same vein, Amihud and Goyenko (2013) find that funds with lower coefficients of determination perform better. In contrast, Huang *et al.* (2011) show how funds that increase their specific risk can lead to worse performances than funds that maintain stable risk levels over time.

Notwithstanding, fund investors face some difficulties in constructing these measures, and can fail to accurately determine the level of active management in the fund portfolio. They can, however, easily observe the turnover ratio, as reported in the fund's prospectus, and interpret it as a simple measure of the fund's trading activity, assuming that the higher this ratio, the higher the level of transactions reached by fund managers will be.

In the previous literature on institutional investment management some controversy surrounds the relation between turnover and performance. Some studies do not support a high turnover ratio in mutual fund management, since a higher level has no significant effect on fund performance (Golec, 1996; Gottesman and Morey, 2007; Ippolito, 1989), or may even be negative (Chow *et al.* 2011; Elton *et al.*, 1993). In addition, Carhart (1997) considers turnover ratio as a proxy of trading costs, and observes that fund performance is reduced in every buy-and-sell transaction. In contrast, other authors (Dahlquist *et al.*, 2000; Wermers, 2000) conclude that high-turnover funds are able to obtain better results and they are equally or more attractive to risk-averse investors (Taylor and Yoder, 1994). Moreover, using gross returns, Pástor *et al.* (2017) show that the turnover in active funds is positively related to their benchmark-adjusted returns, suggesting that fund managers identify time-varying profit opportunities and trade accordingly.

Therefore, portfolio turnover must be a concern for fund investors aiming to enhance their investment returns. However, they do not know *a priori* the level of turnover assumed in the fund portfolio during a specific period; rather, the fund's prospectus reports the turnover ratio reached during the previous year. Thus, if mutual funds generally reach similar levels of this ratio over two consecutive years, then fund investors could interpret this information as a proxy of the potential turnover the fund will have in the near future.

In this context, the objective of this chapter is to delve into the relationship between the turnover reported in the fund prospectus and the performance experienced by fund investors. For a sample of US equity mutual funds during the period 1999–2014, we analyse the persistence in the relative level of this characteristic on a year-to-year basis[7]. We find that a fund reaching a specific level of turnover relative to the rest of funds during one year is more than likely to reach a similar level during the following year.

Given this evidence, fund investors could take advantage of the turnover information previously reported in the fund prospectus, and invest accordingly. Hence, we examine the performance of different investment strategies based on the level of lagged-fund turnover. To address this issue, we use a similar procedure to the methodology of Amihud and Goyenko (2013), and create 25 hypothetical portfolios that invest in funds with different levels of lagged turnover and past performance. Results show that investing in funds with a previous low turnover ratio can lead to better performances than investing in previously high-turnover funds.

Despite this evidence, we need to take into account that other variables related to the fund can play an important role in driving the analysis results. As Gallagher *et al.* (2006) and Lavin and Magner (2014) noted, the turnover ratio reached by mutual funds can be influenced by other variables. The managers' remuneration should also be related to both turnover ratio and mutual fund performance. After controlling for factors related to agency problems, efficiency, and behavioural bias, we observe that portfolio turnover still impacts negatively on the risk-adjusted net returns that fund investors obtain.

[7] Lavin and Magner (2014) prove that turnover ratio measured on a monthly basis is persistent up to three months.

In addition, we apply a vector autoregressive (VAR) model in order to understand the interactions between the turnover, the managers' remuneration and the mutual fund performance. Results show that a one positive shock in the standard deviation of the portfolio turnover implies a negative response in the mutual fund performance over time.

In short, this chapter contributes to the previous literature in several ways. Firstly, our results show that high-turnover funds have not provided investors with greater risk-adjusted returns than low-turnover funds in recent years. In fact, they performed significantly worse after the onset of the recent financial crisis. Secondly, we also show that investing in previously low-turnover funds can lead to higher risk-adjusted returns than investing in previously high-turnover funds. Finally, we show that the evidence on the relation of fund investors' risk-adjusted returns and portfolio turnover is not driven by other variables, and a positive one standard deviation shock in the turnover deteriorates the performance of the fund over time.

The rest of the chapter is organised as follows. Section 2 describes the data and the methodology used in the study. Section 3 presents the main results. Section 4 concludes with the main findings.

3.2. Performance methodology and data

As we are interested in measuring performance as experienced by fund investors, we first compute the daily fund net return using the daily return index. The daily return index is defined as the daily account balance experienced by an investor who invested in one share on the inception date. It reflects any uninvested cash accrued to the account (future distributions and daily dividends). This data is from the Morningstar database.

Then we use the Carhart (1997) four-factor model[8] to calculate the mutual fund performance, as described in Equation (1). This model has been widely applied in the literature to assess portfolio management (Ammann *et al.*, 2012; Bessler *et al.*, 2016; Chen and Chen, 2017; Kacperczyk *et al.*, 2014; Karoui and Meier, 2009).

$$R_{p,t} = \alpha_p + \beta_{1,p} R_{MKT,t} + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + \varepsilon_{p,t} \quad (1)$$

where $R_{p,t}$ is the excess risk-free daily mutual fund return during the period t; $R_{MKT,t}$ is the excess risk-free daily return of the market factor; and SMB_t, HML_t and UMD_t are the daily returns on the size (*Small-Minus-Big*), value (*High-Minus-Low*), and momentum (*Up-Minus-Down*) factor mimicking portfolios, respectively. The data of the daily factors are from Professor Kenneth R. French's website.

According to the SEC, the turnover ratio is defined as the minimum of purchases and sales experienced by a mutual fund during a year, divided by the average of total net assets (TNA) managed by the mutual fund during the same year. This measure has relative advantages. Firstly, by using the minimum of purchases or sales, investors' flows do not affect the turnover ratio. That is, when a fund has positive (negative)

[8] We also ran the Fama-French (1993) three-factor model, which leads us to similar conclusions. Results are therefore not reported for the sake of brevity.

investor flows, purchases (sales) are usually involved, but if they are not also accompanied by sales (purchases), they are not considered when measuring the portfolio turnover (Lavin and Magner, 2014). Moreover, as it is reported in the prospectus, the turnover is directly reviewed by investors, and thus affects their mutual fund decisions. However, this ratio also presents some problems. For instance, we are not able to construct this ratio without data on funds' purchases and sales, which prevents us from replicating this measure to observe whether the portfolio turnover reported in the prospectus is estimated accurately. Being a declared variable, it is not clear whether funds tend to show a turnover close to the industrial average in their prospectus. In addition, because it is reported annually, we are unable to perform a consistent comparison between portfolio turnover and mutual fund performance on a different basis (e.g., monthly). Despite these problems, Morningstar indicates that a low turnover (20-30%) could be interpreted as a buy-and-hold strategy in mutual fund management, while a ratio higher than 100% is related to an investment strategy with considerable buying and selling of securities.

In order to control for the effect of some fund characteristics on the turnover, we also obtain data on the net expense ratio, the total net assets, tracking error and information ratio compared to the fund's benchmark, managers' remuneration, liquidity, number of stocks held in the portfolio, and number of years since the inception date of each mutual fund.

The mutual fund data are from Morningstar for the period January 1999–December 2014. We split the main period into two sub-periods in order to observe any differences in the results of the analysis. The first sub-period covers the years before the recent financial crisis, and runs from January 1999 to December 2007. The second sub-period covers the following crisis years from January 2008 to December 2014.

Our sample consists of 17,773 US domestic equity share-class funds. However, as the turnover ratio refers to the fund as a whole, we grouped the different share classes belonging to the same fund. Our final sample comprises 4,058 mutual funds[9]. There is no survivorship bias in our sample, since we include all the funds in existence during this period, whether or not they disappeared.

Panel A and B of Table 3.1 show the main descriptive statistics for some fund characteristics during the whole sample period and both sub-periods, as well as for the Carhart (1997) factors. Because the aim of this chapter is to compare the fund risk-adjusted net returns among different levels of portfolio turnover, we order the sample according to the fund turnover in year *t*, and we split the sample into quintiles. We repeat this process for each year until the end of the sample period. The first quintile comprises the lowest-turnover funds, and the fifth quintile contains the highest-turnover funds. Panel C of Table 3.1 shows the average turnover ratio of the funds in each quintile, as well as their annual return and risk.

Panel A and Panel B reveal differences in the data when considering the two sub-periods, which can lead to different results. Firstly, the first (second) sub-period is characterised by its lower (higher) return and lower (higher) risk. Thus, as the first row of Panel B shows, the return of the market factor is 5.98% (10.12%), and the risk is 18.03% (23.06%) for the first (second) sub-period. The second sub-period is therefore more volatile. For mutual funds, as the second row of Panel A shows, these values are, respectively, 7.74% (9.27%) in return and 17.45% (23.61%) in risk.

[9] Since turnover is calculated yearly, and since the level of portfolio turnover is not the same during a whole year as during a month, each year we remove all the observations that are susceptible to data error. Specifically, for each year we remove funds that do not have at least 230 daily data on return, or that do not present data on the fund characteristics, due to the impossibility of consistent analysis.

Table 3.1. Descriptive statistics of the sample

Panel A. Characteristics of mutual funds

	January 1999–December 2014		January 1999–December 2007		January 2008–December 2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
TNA (millions)	1,597.16	7,098.06	1,584.30	6,196.40	1,604.41	7,559.20
Annualised Return (%)	8.41	20.38	7.74	17.45	9.27	23.61
Turnover (%)	85.06	121.07	90.68	137.91	79.31	100.69
Net Expense Ratio (%)	1.24	0.49	1.30	0.51	1.20	0.47

Panel B. Annualised factors returns

	January 1999–December 2014		January 1999–December 2007		January 2008–December 2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Market (%)	7.80	20.39	5.98	18.03	10.12	23.06
SMB (%)	4.41	10.20	5.40	10.23	3.14	10.16
HML (%)	3.51	10.71	5.98	10.62	0.33	10.81
UMD (%)	4.53	16.34	10.38	14.62	-2.97	18.31

Table 3.1. (*Continued*)

Panel C. Annualised portfolio return and risk, quintiles sorted on turnover

	January 1999–December 2014			January 1999–December 2007			January 2008–December 2014		
	Turnover (%)	Return (%)	Risk (%)	Turnover (%)	Return (%)	Risk (%)	Turnover (%)	Return (%)	Risk (%)
Quintile 1 (low)	14.04	8.07	19.64	14.80	6.85	16.46	13.25	9.63	23.09
Quintile 2	36.79	8.35	19.75	39.60	7.43	16.44	33.91	9.53	23.33
Quintile 3	61.18	8.22	20.08	65.67	7.22	16.88	56.60	9.50	23.57
Quintile 4	95.10	8.79	20.91	101.64	8.35	17.99	88.43	9.35	24.14
Quintile 5 (high)	218.39	8.62	21.45	231.93	8.84	19.32	204.56	8.34	23.90

This table shows the mean and standard deviation for the following mutual fund characteristics (Panel A): total net assets (TNA), annualised return, turnover and net expense ratios. Panel B shows the same descriptive statistics for the returns of the factors considered in the Carhart (1997) four-factor model. Panel C reports the average turnover ratio, the annualised return, and the standard deviation of the returns (Risk) for the mutual funds belonging to each quintile (sorting on turnover ratio).

Panel C also shows that mutual funds with different levels of portfolio turnover experience different returns and risks. First of all, high-turnover funds bear higher volatility (21.45%) than low-turnover funds during the whole period (19.64%). These differences remain in both sub-periods. Regarding the fund return, high-turnover funds (quintiles 4 and 5) achieve better returns during the first sub-period than low-turnover funds, but the opposite is found for the second sub-period, where quintile 1 obtains better returns (9.63%).

In summary, Table 3.1 shows that there are differences in the mean return and risk of mutual funds with different levels of portfolio turnover. Consequently, in the next section we explore in greater depth the dynamics of the level of portfolio turnover and its interaction with fund performance in order to analyse whether mutual funds assuming higher levels of portfolio turnover provide investors with any added value in terms of risk-adjusted return.

3.3. Results

3.3.1. Mutual fund performance and portfolio turnover

Given the evidence in Table 3.1 for the differences in terms of return and risk among funds with different levels of portfolio turnover, we now analyse whether these funds differ significantly in terms of performance.

To address this issue, we form quintile-portfolios, a usual approach in the previous literature (Vargas *et al*., 2014; among others). Specifically, for each year t, we calculate the average daily returns of five equally-weighted portfolios which invest yearly in mutual funds with similar levels of turnover. Thus, portfolio-quintile 'Low' includes funds with the lowest portfolio turnover, while portfolio-quintile 'High' comprises the highest-turnover funds. Then, to estimate the portfolio performance, we regress each portfolio daily return according to the Carhart (1997) four-factor model.

Table 3.2. Performance results, based on sorting on fund turnover rate

Panel A: January 1999–December 2014

	Low	2	3	4	High	All	Low-High
α_p (annualised)	-0.001	-0.001	-0.005	-0.004	-0.009	-0.004	0.008
	(-0.17)	(-0.25)	(-0.95)	(-0.72)	(-1.27)	(-0.83)	(1.16)
Adj. R^2	0.994	0.992	0.991	0.988	0.982	0.992	

Panel B: January 1999–December 2007

	Low	2	3	4	High	All	Low-High
α_p (annualised)	0.001	0.001	-0.005	0.001	0.001	-0.000	-0.000
	(0.16)	(0.11)	(-0.77)	(0.15)	(0.10)	(-0.04)	(-0.02)
Adj. R^2	0.993	0.990	0.988	0.981	0.973	0.989	

Panel C: January 2008–December 2014

	Low	2	3	4	High	All	Low-High
α_p (annualised)	-0.007**	-0.011**	-0.013**	-0.018***	-0.027***	-0.015***	0.020***
	(-2.07)	(-2.25)	(-2.34)	(-2.75)	(-3.24)	(-2.85)	(2.83)
Adj. R^2	0.998	0.997	0.996	0.995	0.991	0.997	

This table reports the performance quintile-portfolios that invest in funds according to their turnover. The performance is measured as the intercept (*a*) of the four-factor model. The performance difference between the portfolios investing in funds with the lowest and the highest portfolio turnover (*Low-High*) are also reported. '*', '**', and '***' denote significance at 10%, 5%, and 1% levels, respectively. T-statistics (in parentheses) are from Newey-West's (1987) heteroscedasticity and autocorrelation consistent covariance estimator.

Table 3.2 shows the results of the regressions for the whole period (Panel A) and both sub-periods (Panel B and Panel C). As we aim to compare the performances of the lowest and the highest quintile to verify whether mutual funds assuming high turnover ratios provide investors with any added value in relation to low-turnover funds, we also include the results of their performance differences in the last column.

3.3.2. Turnover persistence

In this section, we focus on the evolution of the turnover for a mutual fund in order to predict the future behaviour of this fund characteristic. In other words, we wonder if, given a specific level of fund turnover during a year, mutual funds reach a similar level during the following year.

To address this question, we form contingency tables, which have been previously used in the literature to demonstrate if fund performance is persistent over time (Brown and Goetzmann, 1995; Malkiel, 1995). This methodology is suitable to observe the association among several variables, in this case, the annual turnover reached by a fund during two consecutive years. Thus, for each fund in quintile p in year t, we identify the quintile it will belong to during the following year $t+1$, or if it disappears (*Gone*).

If there is no persistence in the level of turnover reached by a fund, we could assume that the probability of staying in the same turnover-sorted quintile is 20% (otherwise, 80%). Assuming, therefore, that the sample is binomially distributed, and having a reasonably large data set (more than 30 observations), we can infer a good approximation considering that the sample is normally distributed. Results are shown in Table 3.3.

Table 3.3. Turnover persistence

		Fund-year observations into each quintile in year *t+1*, sorted on turnover rate						Surviving funds			
		Low	2	3	4	High	Gone	Repeat	Don't repeat	All	Z-Test
Fund-year observations into each quintile in year *t*, sorted on turnover rate	Low	3,801	1,068	246	133	70	827	3,801	1,517	5,318	93.84
	2	1,054	2,632	1,170	350	126	804	2,632	2,700	5,332	53.60
	3	219	1,178	2,365	1,214	311	852	2,365	2,922	5,287	44.96
	4	83	312	1,228	2,576	1,058	879	2,576	2,681	5,257	52.57
	High	53	115	306	1,053	3,640	965	3,640	1,527	5,167	90.66
	All funds	5,210	5,305	5,315	5,326	5,205	4,327	15,014	11,347	26,361	150.00

This table presents the number of funds that belong to two specific quintiles of ranked fund turnover ratios over a one-year interval. The number of funds that exist for one year but disappear during the following year (*Gone*), the number of funds repeating in the same quintile over two consecutive years (*Repeat*), and the number of funds belonging to different quintiles over two consecutive periods (*Don't Repeat*) are also reported. The Malkiel (1995) Z-test is presented in the last column of the table.

Results in Table 3.3 clearly show a persistence in the level of turnover of the mutual funds (Z-test: 150). Concretely, about 57% of the sample (15.014 of 26.361 fund-year observations) repeats in the same quintile over two consecutive years. Moreover, if we interpret the contiguous quintiles as levels of turnover close to the level reached in the previous year, 91% of the sample has an equal or similar turnover to that achieved during the previous year, relative to the turnover ratio of the other funds of the sample.

Therefore, Table 3.3 shows that there is evidence that a fund will continue to experience the same or similar turnover level as it reached previously. So in the next section we are interested in analysing whether fund investors can benefit from turnover persistence to improve their performance.

3.3.3. Performance of investment strategies based on previous portfolio turnover

Analysis of the evolution of mutual funds' turnover shows it to persist over time. Thus, we could consider the turnover reported in the fund's prospectus in a given year as a proxy of the level of turnover assumed in the fund portfolio during the following year. In this section we ask whether investors can make fund investment decisions that lead to better risk-adjusted returns, taking past level of turnover as a reference. That is, we analyse whether investors who invest in funds with past low turnover ratios can obtain greater performances than investing in past high-turnover funds.

Following Amihud and Goyenko (2013), we now evaluate an investment strategy based on the past level of fund turnover and past fund performance[10]. For each year *t*,

[10] Amihud and Goyenko (2013) sort their portfolios on funds' lagged R^2, and on lagged alpha.

we split the sample into quintiles, sorting on fund past turnover ratio. Then, for each quintile we reorder the subsample into quintiles, now sorting on their past performance. Thus, for each quintile based on fund turnover, the subsample is divided into five quintiles based on fund performance. Therefore, the sample is grouped into 25 different subgroups. Then we compute the daily returns of each equally-weighted portfolio formed by the funds in each subgroup over the year. We repeat this process for each successive year until the end of the period considered. Hence, the 25 portfolios represent investment strategies based on past performance and past turnover and they are formed by time series of returns from 2000 to 2014. From these returns, finally we estimate the fund performance using the four-factor model. The performance results of these portfolios are reported in Table 3.4.

Results in Panel A of Table 3.4 show that almost none of these strategies have a performance significantly different from zero during the whole period 2000–2014. Only the portfolio that invests in funds with past high turnover ratios and low lagged-performance underperforms by 220 basis points per year (t-statistic: -2.05). In addition, this portfolio significantly underperforms the portfolio that invests in funds with low lagged-turnover ratio and low past performance in 170 basis points per year (t-statistic: 2.04).

However, results vary when we consider different sub-periods. On the one hand the last row of Panel B shows evidence of the persistence in the performance of mutual funds during the first sub-period. For all the mutual funds in the sample ('*All*' column), a statistically significant difference of 4% annualised (t-statistic: 2.27) is reported between the best-performing funds and the worst-performing funds during the previous year. Regarding the level of fund turnover, we do not find statistically significant differences among the performance of funds with high and low past turnover. However, as columns

'*4*' and '*High*' show, it should be considered that only portfolios with a negative and statistically significant alpha (from -1.7% to -3.5% per year) are those that invest in funds with high levels of past turnover and low past performance, while the only portfolios with a positive and statistically significant alpha (between +1.7% and +2.2% per year) are those that invest in funds with a relatively low level of past turnover and high past performance, as shown in row '*High*' and columns '*2*' and '*3*'. In short, Panel B shows that portfolios investing in funds with relatively low (high) past turnover and high (low) past performance obtain a significantly positive (negative) performance during the first sub-period.

On the other hand, Panel C shows that the evidence of persistence in the mutual fund performance disappears during the second sub-period, a result consistent with the findings in Matallín-Sáez *et al*. (2016). In any event, all the portfolios that invest in funds based on their previous turnover, but not considering their past performance ('*All*' row), obtain negative and statistically significant alphas. In addition, it is worth noting that this underperformance worsens as the considered level of past turnover increases.

In fact, as shown in the '*High*' column, portfolios that invest in funds with the highest turnover levels have a statistically significant alpha between -2% and -3.1% annualised, depending on the level of past fund performance. Consequently, these portfolios experience the lowest performances shown in Panel C. Indeed, the difference in performance between portfolios that invest in funds with the lowest and the highest level of past turnover and without considering past fund performance (last row of column '*Low-High*') is positive (1.6% per year), and statistically significant (t-statistic: 2.28).

Table 3.4. Fund portfolio *alpha*, based on sorting on lagged annual turnover rate and alpha

Panel A: January 2000–December 2014

	$Turnover_{t-1}$						
$Alpha_{t-1}$	Low	2	3	4	High	All	Low-High
Low	-0.005	-0.004	-0.002	-0.012	-0.022**	-0.009	0.017**
	(-0.60)	(-0.56)	(-0.26)	(-1.22)	(-2.05)	(-1.08)	(2.04)
2	0.000	-0.004	-0.006	-0.010	-0.015*	-0.007	0.015**
	(0.03)	(-0.63)	(-0.93)	(-1.40)	(-1.71)	(-1.12)	(2.09)
3	-0.003	-0.002	-0.003	-0.006	-0.007	-0.004	0.004
	(-0.68)	(-0.43)	(-0.50)	(-0.91)	(-0.95)	(-0.88)	(0.45)
4	-0.002	0.003	0.007	-0.004	-0.008	-0.001	0.006
	(-0.39)	(0.45)	(0.74)	(-0.68)	(-0.91)	(-0.15)	(0.54)
High	0.002	0.004	0.001	-0.006	-0.007	-0.001	0.009
	(0.28)	(0.64)	(0.21)	(-0.65)	(-0.56)	(-0.14)	(0.77)
All	-0.002	-0.001	-0.001	-0.007	-0.012	-0.004	0.010
	(-0.33)	(-0.12)	(-0.11)	(-1.31)	(-1.62)	(-0.88)	(1.32)
High-Low	0.007	0.009	0.004	0.007	0.015	0.008	
	(0.68)	(0.87)	(0.37)	(0.49)	(0.93)	(0.75)	

Panel B: January 2000–December 2007

	$Turnover_{t-1}$						
$Alpha_{t-1}$	Low	2	3	4	High	All	Low-High
Low	-0.015	-0.013	-0.012	-0.028*	-0.035**	-0.021	0.020
	(-1.32)	(-1.15)	(-0.92)	(-1.89)	(-2.00)	(-1.64)	(1.61)
2	-0.007	-0.012	-0.011	-0.017*	-0.024*	-0.014*	0.016
	(-0.96)	(-1.50)	(-1.46)	(-1.76)	(-1.77)	(-1.72)	(1.46)
3	-0.010	-0.006	-0.006	-0.008	0.004	-0.005	-0.013
	(-1.52)	(-0.78)	(-0.79)	(-0.92)	(0.34)	(-0.80)	(-0.99)
4	-0.004	0.010	0.015	0.004	0.010	0.007	-0.014
	(-0.51)	(1.19)	(1.00)	(0.53)	(0.69)	(0.94)	(-0.81)
High	0.015	0.022**	0.017*	0.016	0.025	0.019*	-0.010
	(1.63)	(2.01)	(1.80)	(1.10)	(1.30)	(1.70)	(-0.60)
All	-0.004	0.000	0.000	-0.006	-0.004	-0.003	0.000
	(-0.66)	(0.03)	(0.06)	(-0.82)	(-0.35)	(-0.40)	(0.00)
High-Low	0.030**	0.035**	0.029*	0.044**	0.060**	0.040**	
	(2.01)	(2.18)	(1.86)	(2.03)	(2.33)	(2.27)	

Table 3.4. (*Continued*)

Panel C: January 2008–December 2014

	Turnover$_{t-1}$						
Alpha$_{t-1}$	Low	2	3	4	High	All	Low-High
Low	-0.011*	-0.010	-0.011	-0.016	-0.023**	-0.014*	0.011
	(-1.71)	(-1.23)	(-1.32)	(-1.64)	(-2.12)	(-1.89)	(1.12)
2	-0.002	-0.011**	-0.014**	-0.015**	-0.023***	-0.013**	0.021***
	(-0.37)	(-1.98)	(-2.04)	(-2.20)	(-2.75)	(-2.33)	(2.66)
3	-0.004	-0.009*	-0.011*	-0.015**	-0.020***	-0.012**	0.017**
	(-1.25)	(-1.90)	(-1.86)	(-2.29)	(-2.60)	(-2.46)	(2.16)
4	-0.010**	-0.014**	-0.014**	-0.021***	-0.025***	-0.017***	0.015**
	(-2.29)	(-2.16)	(-2.20)	(-3.16)	(-3.06)	(-2.96)	(2.10)
High	-0.015	-0.013*	-0.023**	-0.023***	-0.031**	-0.021**	0.016*
	(-1.60)	(-1.66)	(-2.53)	(-2.65)	(-2.53)	(-2.42)	(1.77)
All	-0.008**	-0.011**	-0.015**	-0.018***	-0.024***	-0.015***	0.016**
	(-2.36)	(-2.41)	(-2.51)	(-2.72)	(-2.93)	(-2.84)	(2.28)
High-Low	-0.004	-0.003	-0.012	-0.007	-0.009	-0.007	
	(-0.30)	(-0.31)	(-1.07)	(-0.73)	(-0.74)	(-0.72)	

This table shows the performance of hypothetical portfolios that invest yearly in mutual funds according to their previous level of portfolio turnover and previous performance. Mutual funds are sorted first on quintiles (from *Low* to *High*) according to their turnover ratio and then on quintiles according to their previous performance. Portfolios that invest in mutual funds without sorting on at least one of these characteristics are denoted by *All*. The performance is measured as the intercept (a) of the four-factor model. The performance differences between *Low* and *High* are also reported. '*', '**', and '***' denote significance at 10%, 5%, and 1% levels, respectively. T-statistics (in parentheses) are from Newey-West's (1987) heteroscedasticity and autocorrelation consistent covariance estimator.

Summing up, results in Table 3.4 show that since the recent financial crisis portfolios which invest in funds with the lowest levels of past turnover perform better than those investing in funds with the highest past turnover ratios. For the sub-period 2000–2007, these differences are not statistically significant, but we observe that the only portfolios with negative (positive) and statistically significant performances are those that invest in high (low) past turnover funds and have low (high) past performance.

3.3.4. Do other variables drive the effect of turnover on fund performance?

In this section, we analyse the impact of the fund's turnover ratio on fund performance, but controlling for the effect of other variables. To address this issue, we employ panel data regressions under the following assumptions: firstly, the individual (or specific) effects are uncorrelated with the independent variables (random effects); secondly, there is a correlation between them, so the individual effects can change across funds (fixed effects).

The dependent variable is the yearly alpha of each fund, estimated as the intercept of model (1). The portfolio *Turnover*, as reported in the prospectus of the fund, is considered as an explanatory variable. Additionally, *Remuneration*, measured as the natural logarithm of the annual amount managers receive, is included in the model due to its relevance to the fund investors and because it should influence both turnover ratio and fund performance. We expect that turnover ratio and the managers' remuneration will negatively affect mutual fund performance, since both variables increase the costs the portfolio has to bear.

As documented in Lavin and Magner (2014), three main dimensions could influence funds' turnover ratio. The first dimension is related to the efficiency of the fund, that is, decisions that aim to reduce the transaction and operating costs in the portfolio. The second one refers to the agency problems in mutual fund management. Finally, behavioural biases, such as managers' overconfidence, also play an important role in the level of portfolio turnover. As we are interested in analysing the impact of the turnover on fund performance, we should control for the effect of some variables that could significantly influence portfolio turnover.

Therefore, in the regressions we include variables related to efficiency (the liquidity of the fund measured as the percentage of the average cash the fund holds, or *Liquidity*; and the natural logarithm of the number of stocks held in the portfolio, or *Stocks*), behavioural biases (the previous alpha as a measure of the managers' overconfidence, or *LagAlpha*) and agency problems (the natural logarithm of the years since inception, or *Age*; the volatility of the fund returns over a year, or *Risk*; the tracking error, or *TrackError*; and the fund's information ratio, or *InfRatio*). The natural logarithm of the total assets managed by the fund (*Size*) and the net expense ratio (*Expenses*) are considered as control variables. Results are shown in Table 3.5.

In line with our expectations, the turnover ratio and the managers' remuneration are negatively related to the risk-adjusted net returns perceived by fund investors during the same year in any of the considered models. Specifically, a 100% increase in the portfolio turnover implies a drop in the annualised performance of between 0.4% and 0.7% per year. Managers' remuneration also has a negative and statistically significant effect on mutual fund performance (coefficients between -0.348 and -0.394).

In Panel B, we consider the fund performance as a linear function of the past turnover ratio, or *LagTurnover*. Results are very similar to those in Panel A. That is, after removing the impact of some variables on the turnover ratio, previous portfolio turnover and managers' remuneration still have a negative and statistically significant effect on the annualised risk-adjusted net returns obtained by fund investors.

Table 3.5. Fund performance as a function of turnover ratio

Panel A. The effect of turnover ratio on fund performance

	Model 1		Model 2		Model 3	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Turnover	-0.007	(0.000)	-0.006	(0.000)	-0.004	(0.007)
Remuneration	-0.023	(0.623)	-0.348	(0.001)	-0.394	(0.001)
Liquidity	-0.017	(0.030)	0.005	(0.474)	0.002	(0.740)
Stocks	-0.075	(0.237)	0.283	(0.174)	0.378	(0.056)
Risk	0.013	(0.078)	0.023	(0.049)	0.134	(0.004)
TrackError	0.018	(0.793)	-0.102	(0.225)	-0.020	(0.758)
InfRatio	-0.038	(0.140)	-0.385	(0.000)	-0.305	(0.000)
Age	-0.605	(0.000)	-3.292	(0.000)	-2.025	(0.019)
LagAlpha	-0.071	(0.000)	-0.242	(0.000)	-0.211	(0.000)
Size	0.273	(0.000)	0.663	(0.000)	0.240	(0.171)
Expenses	-0.360	(0.085)	0.206	(0.865)	0.932	(0.409)
Intercept	-3.581	(0.000)	-2.078	(0.576)	4.825	(0.349)
Random effects	Yes		No		No	
Fixed effects	No		Yes		Yes	
Time dummies	No		No		Yes	
F-test			50.40	(0.000)	40.38	(0.000)
Hausman Test	2,518.77	(0.000)				
R^2	0.048		0.074		0.138	

Table 3.5. (*Continued*)

Panel B. Does portfolio turnover predict fund performance?

	Model 1		Model 2		Model 3	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
LagTurnover	-0.006	(0.000)	-0.004	(0.049)	-0.003	(0.061)
Remuneration	-0.026	(0.579)	-0.352	(0.001)	-0.398	(0.001)
Liquidity	-0.016	(0.036)	0.003	(0.677)	0.001	(0.880)
Stocks	-0.076	(0.227)	0.263	(0.205)	0.368	(0.062)
Risk	0.010	(0.169)	0.021	(0.073)	0.131	(0.006)
TrackError	0.010	(0.888)	-0.109	(0.196)	-0.023	(0.724)
InfRatio	-0.032	(0.193)	-0.378	(0.000)	-0.298	(0.000)
Age	-0.610	(0.000)	-3.256	(0.000)	-2.030	(0.019)
LagAlpha	-0.072	(0.000)	-0.243	(0.000)	-0.212	(0.000)
Size	0.280	(0.000)	0.683	(0.000)	0.256	(0.146)
Expenses	-0.358	(0.081)	0.260	(0.834)	0.959	(0.405)
Intercept	-3.633	(0.000)	-2.595	(0.498)	4.564	(0.380)
Random effects	Yes		No		No	
Fixed effects	No		Yes		Yes	
Time dummies	No		No		Yes	
F-test			48.63	(0.000)	39.88	(0.000)
Hausman Test	2,546.62	(0.000)				
R^2	0.047		0.073		0.138	

This table shows the results of panel data regressions. Random effects and fund fixed effects are considered. The dependent variable is the annual performance of the funds, measured as the intercept (a) of the four-factor model. The independent variables are the turnover ratio of the fund (*Turnover*), the natural logarithm of the annual remuneration of the fund managers (*Remuneration*), the average liquidity of the fund (*Liquidity*), the natural logarithm of the number of stocks held in the portfolio (*Stocks*), the volatility of the returns (*Risk*), the tracking error (*TrackError*) and the information ratio (*InfRatio*) of the funds compared to their benchmark, the natural logarithm of the years of the fund since inception (*Age*), the previous annual fund performance (*LagAlpha*), the natural logarithm of the total net assets managed by the fund (*Size*), and the annual net expense ratio (*Expenses*). Time dummies are considered in the last model. P-values (in parentheses) are from standard errors grouped by funds, and they are robust to heteroscedasticity, autocorrelation and temporal correlation.

3.3.5. Addressing the interdependence of the endogenous variables: a VAR approach.

In this section, we apply a vector autoregressive (VAR) model to establish the causality between the portfolio turnover, managers' remuneration and mutual fund performance. These variables are assumed to affect each other, and the VAR model allows us to document the interdependence among them. Therefore, they are considered as endogenous variables, while the age and size of the funds are included as exogenous variables in the following model:

$$Y_t = a_0 + \sum_{j=1}^{J} A_j Y_{t-j} + BX_t + u_t \tag{2}$$

where Y_t is a vector that includes the endogenous variables in the period t; X_t is a vector containing the exogenous variables in the same period; and u_t is the residual vector of the model. As indicated by the lag selection criteria, four lags are considered for the endogenous variables.

Table 3.6. Vector autoregressive (VAR) model

	Turnover	Remuneration	Alpha
Lag1Turnover	0.6219***	-0.0004***	-0.0078***
	(70.07)	(-3.67)	(-7.06)
Lag2Turnover	0.0951***	0.0005***	0.0043***
	(9.31)	(4.03)	(3.36)
Lag3Turnover	0.0272***	0.0000	-0.0013
	(2.71)	(-0.42)	(-1.08)
Lag4Turnover	0.0897***	0.0003***	-0.0007
	(11.13)	(2.98)	(-0.70)
Lag1Remuneration	-0.9274	0.6471***	-0.4510***
	(-1.37)	(82.07)	(-5.35)
Lag2Remuneration	1.1571*	0.0753***	-0.3830***
	(1.82)	(10.22)	(-4.86)
Lag3Remuneration	1.1635**	0.0271***	0.0021
	(2.26)	(4.53)	(0.03)
Lag4Remuneration	-0.1909	-0.0008	0.1408***
	(-0.46)	(-0.18)	(2.76)
Lag1Alpha	-0.0199	0.0099***	-0.1032***
	(-0.28)	(11.80)	(-11.54)
Lag2Alpha	-0.0292	0.0054***	-0.1033***
	(-0.44)	(6.96)	(-12.56)
Lag3Alpha	0.0875	0.0066***	0.0667***
	(1.34)	(8.78)	(8.26)
Lag4Alpha	-0.0235	0.0016**	-0.0157**
	(-0.39)	(2.30)	(-2.07)
Size	-2.0477***	0.2392***	0.8543***
	(-4.86)	(48.91)	(16.34)
Age	-0.2653	-0.2372***	-0.9515***
	(-0.26)	(-20.03)	(-7.52)
Constant	31.7920***	-0.3884***	-5.1959***
	(6.49)	(-6.83)	(-8.55)
R^2	0.739	0.919	0.066

This table shows the coefficients of a vector autoregressive model with four lags on the endogenous variables. *Turnover* (turnover ratio), *Remuneration* (natural logarithm of the managers' annual remuneration) and *Alpha* (performance of the mutual funds, measured as the intercept of the four-factor model) are considered as endogenous variables. *Size* (natural logarithm of the total net assets) and *Age* (natural logarithm of the years of the fund since inception) are considered as exogenous variables. T-statistics are shown in parentheses. '*', '**', and '***' denote significance at 10%, 5%, and 1% levels, respectively.

Results are shown in Table 3.6. The main coefficients and the t-statistic for each endogenous variable are reported. On the one hand, the evidence in Table 3.6 is in line with the aforementioned results. Firstly, the turnover ratio is highly autocorrelated. As shown in the table, the first-lag turnover has a statistically significant coefficient of 0.6219. Moreover, the fund performance is affected negatively by the previous turnover ratio (coefficient of -0.0078 for the first lag) and by managers' remuneration (coefficient of -0.4510 for the first lag), both of which are statistically significant (t-statistics of -7.06 and -5.35, respectively). On the other hand, the coefficients of the previous performance on managers' remuneration are positive and statistically significant. This implies that their remuneration directly depends on the results achieved in the portfolio, which allows the interests of managers and investors to be aligned, reducing the potential agency problems that arise in mutual fund management.

Finally, the impulse response function (IRF) related to this model indicates the impact of a positive change (or shock) in the explanatory variable (impulse variable) on the dependent variable (response variable) over the following periods. Figure 3.1 plots the results for the responses (Figure 3.1.a) and the cumulative responses (Figure 3.1.b) of the mutual fund performance when a positive one standard deviation shock is generated in the variables that are considered endogenous in the model.

Figure 3.1 shows that the effect of one-unit positive shock in the turnover leads to a drop in the mutual fund performance, accumulating -1.10% after ten years (Figure 3.1.b). This effect is more relevant during the first two periods, when the alpha responds with a decrease of -0.33% and -0.29%, respectively (Figure 3.1.a). Similarly, the negative response of the performance due to a shock of the same magnitude in the managers' remuneration is more pronounced over the second and third sub-periods (responses of -0.30% and -0.38%), and decreases after the fourth year.

Figure 3.1. Impulse response function.

Figure 3.1.a. Response to Cholesky One S.D. Innovations ± 2 S.E.

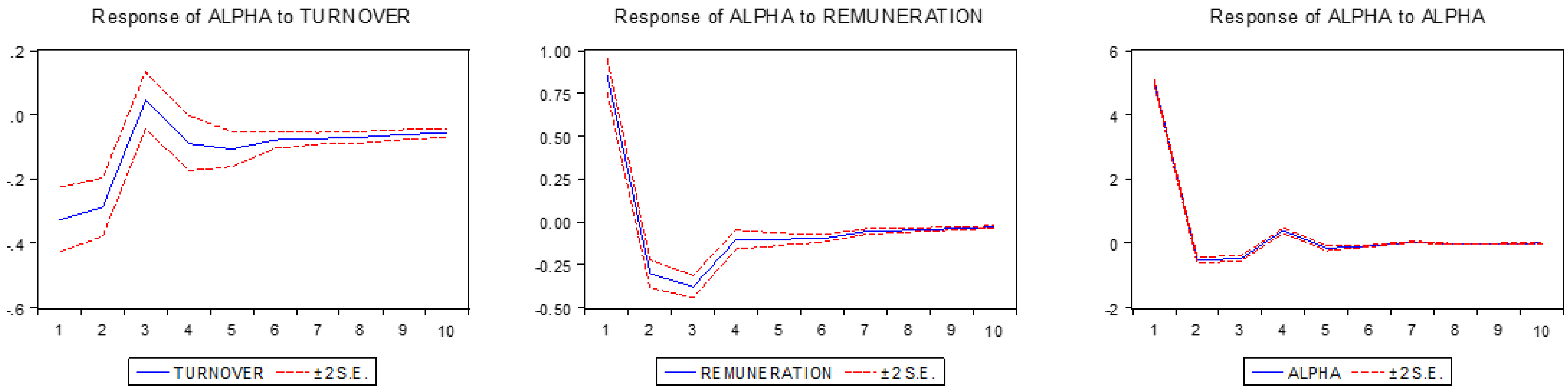

Figure 3.1.a. This figure shows the response over time periods of the mutual fund performance (Alpha), measured as the intercept of the four-factor model, to shocks in Turnover (turnover ratio), Remuneration (natural logarithm of the managers' remuneration) and Alpha. Size and Expenses are considered as exogenous variables.

Figure 3.1. (*Continued*)

Figure 3.1.b. Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.

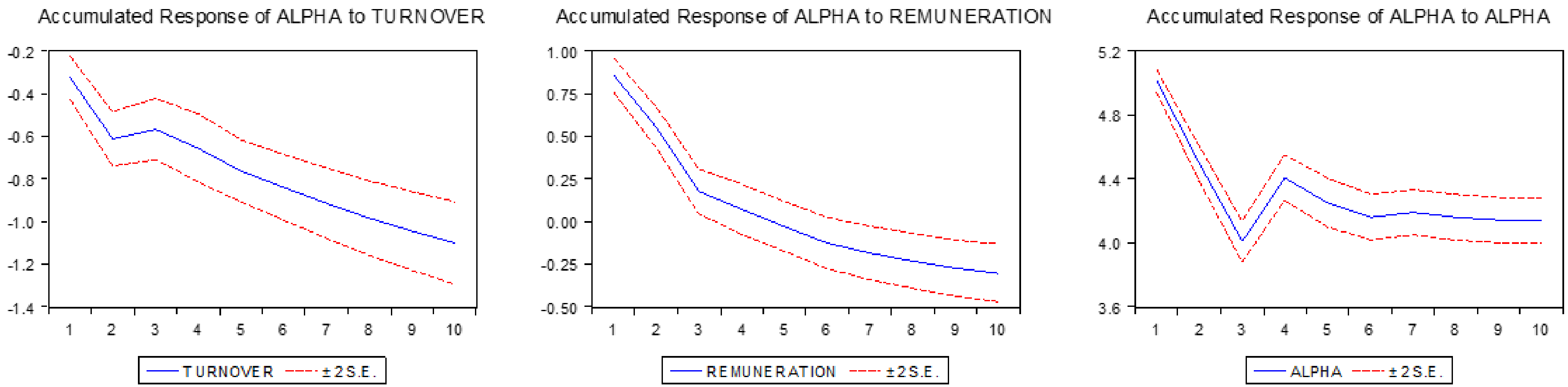

Figure 3.1.b. This figure shows the accumulated response over time periods of the mutual fund performance (Alpha), measured as the intercept of the four-factor model, to shocks in Turnover (turnover ratio), Remuneration (natural logarithm of the managers' remuneration) and Alpha. Size and Expenses are considered as exogenous variables.

3.4. Conclusions

In this chapter, we consider the fund turnover ratio as a good proxy to observe trading activity in mutual fund management, assuming that a higher level of this characteristic implies that fund managers reach higher levels of purchases and sales. A high turnover ratio can be motivated by managers' efforts to increase their added value to the fund portfolio, but involving high trading costs at the same time. As the information on this ratio is reported in the fund prospectus, it is reviewed by investors, and thus directly affects their investment decisions. Then, analysing the relationship between turnover and performance may be of interest to evaluate whether a strategy based on this ratio leads to better net results for investors.

In contrast to the previous literature, this chapter aims to analyse this relationship from the investor's perspective. Investors do not know *a priori* the specific portfolio turnover ratio reached in the mutual fund management. In light of the evidence from this chapter, they can use the information reported in the prospectus as a proxy of the level of portfolio turnover during the following year.

Our results suggest that a strategy based on investing in high-turnover funds does not provide investors with better risk-adjusted returns than investing in funds with low levels of portfolio turnover. Therefore, rational investors aiming to enhance their results should pay attention to this characteristic when selecting funds to invest in, otherwise their risk-adjusted net returns could deteriorate.

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CHAPTER 4: MUTUAL FUND PERFORMANCE AND CHANGES IN FACTORS EXPOSURES

MUTUAL FUND PERFORMANCE AND CHANGES IN FACTORS EXPOSURES

4.1. Introduction

Superior mutual fund performance mainly depends on optimal asset-allocation decisions, which requires correctly setting ex-ante the perfect fund exposure to those risk factors delivering the highest abnormal risk premium during the next period. Hence, a portfolio manager reveals skill and not luck if the ex-post realised return of the portfolio holdings are persistently higher than that of a passively managed or randomly selected portfolio investing in the same asset universe. However, persistently outperforming an appropriate benchmark is a difficult endeavour as most evidence from the asset management industry and asset management 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), respectively. 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 persistence resulting from active management (Cremers and Petajisto, 2009). While acknowledging that profit opportunities often vanish when strategies become publicly available (McLean and Pontiff, 2016), we consider a new perspective on active fund management, by asking whether funds which regularly alter their exposures to systematic factors achieve better performance.

The literature on measuring mutual fund performance has focused on many different approaches, which we group according to two main methodologies: the characteristic-based and the return-based approaches. The characteristic-based performance analysis employs data on several characteristics or portfolio holdings to analyse returns. For instance, Daniel *et al*. (1997) observe the return of each stock held by a fund in excess of the return of the average stock with similar characteristics and develop several ratios to measure the stock picking and timing abilities of mutual fund managers. Kackperczyk *et al*. (2005) use portfolio weights to estimate an industry concentration index which 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 analyses how much funds differ from their benchmark in terms of their portfolio holdings, and conclude that funds differing widely from their benchmark obtain greater alphas.

The characteristic-based methodologies, however, have an important disadvantage as they largely depend on having access to exact portfolio holding information. Instead of requiring such a huge information set and data, the return-based analysis requires and focuses only on portfolio returns to evaluate mutual fund performance. Sharpe (1992) for instance, estimates the coefficients of a twelve-asset class model and shows that portfolio returns are exposed to the asset classes funds usually invest in. In this context, some studies (Grinblatt and Titman, 1992; Malkiel, 1995; among others) analyse 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, multifactorial models that extend the classic Capital Asset Pricing Model (CAPM) by including characteristic-based risk factors as explanatory variables in the regression 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 similar passively managed portfolio.

In this chapter, we follow a return-based approach, deriving and proposing a new measure for active management of equity mutual funds. This measure is the change in the funds' exposures to common risk factors from one period to the next period. The exposures of a fund to the different asset classes or risk factors is 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). This is the main advantage relative to the aforementioned characteristic-based methodologies applied in measuring the performance of actively managed funds.

To address this issue, we first 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 analysing 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 risk factor included in the model explains. Hence, our focus is on the contribution of each risk factor to the fund's total coefficient of determination. Our motivation for measuring these contributions as the funds' actual exposures resides on a simple fact: Two different risk factors can have a similar and statistically significant sensitivity effect (beta) on fund returns, but one of them can better explain the variation of these returns. Thus, the size of the beta explains the sensitivity but does not explain the importance of this risk factor with respect to portfolio risk contribution.

In the empirical analysis, we apply the democratic decomposition of the coefficient of determination (R^2) introduced by Klein and Chow (2013). This methodology is suitable to decompose the R^2 into the contributions of each risk factor. As shown in the literature, this orthogonalisation method is preferable to other techniques such as sequential orthogonalisation or Principal Component Analysis due to its higher resemblance 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).

For a large sample of actively managed US mutual funds for the period from 1990 to 2016, we observe, that in aggregate, most of the variation of fund returns is explained by the market factor. This is not surprising and the result is consistent with the values of R^2 reported in previous studies that employ the CAPM. However, other factors also contribute to the total coefficient of determination in a relevant way, especially the size and momentum factors. In addition, our results strongly support the idea that funds' exposures to the different risk factors are evidently time varying.

After decomposing the coefficient of determination of two consecutive and non-overlapping periods (e.g., t_0 and t_1), we introduce a method to estimate the overall change in fund's exposures by simply comparing the 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 analyse whether active funds changing their risk factor exposures to a greater degree, i.e., highly active-managed funds, outperform funds that hardly adjust their exposures over time. The reason behind this hypothesis is simple: fund managers that are skilled and better than the average manager in forecasting the evolution of a risk factor, will adjust their portfolio holdings accordingly, leading to an overall change in the risk exposures of the fund.

The empirical evidence provided in this chapter strongly supports our argument in that funds presenting the greatest change in exposure from one period to the next subsequently outperform, on average, by 198 basis points per year, those mutual funds that reveal the smallest variation in exposure. Building on these initial findings, we also investigate the performance of a strategy, which invests in the previously best performing funds (highest alpha) that also had changed their exposures from the last to the previous period by a large degree. This strategy resulted in annualised alphas between 2.60% and 4.80%.

Because of the evidence provided in Amihud and Goyenko (2013), Chen *et al.* (2004), and Chan *et al.* (2002), we additionally analyse whether the funds' tracking error, fund size and the manager's investment style, respectively, significantly affect fund performance. Even after controlling for each of these performance-related characteristics suggested in the literature, funds that adjust their exposures to a larger degree still experience higher alphas than funds that do not alter their exposures to the different risk factors. Finally, we document that a hypothetical portfolio investing in funds with the largest preceding adjustments in their exposures obtains a superior performance relative to a hypothetical portfolio that invests in funds with little exposure changes for periods of up to 12 months. This implies that the larger alphas obtained by funds experiencing higher variations in their exposures is attributed to the abilities of their managers to shift the risk exposure appropriately, rather than being a matter of luck.

This chapter contributes to the literature in several ways. First, we propose a new ratio for measuring the level of activity displayed by mutual fund managers by comparing the variation of the fund exposures during two consecutive periods. This measure is based on a return analysis of the risk factors of actively managed US mutual funds. Therefore, it does not require portfolio level data for implementation. This is an advantage over other measures of active management requiring detailed information on portfolio holdings. Also, and in contrast with previous studies addressing fund exposures, we do not focus on the slope estimates, or betas, given that two risk factors with significantly different contributions to the explanation of the variability in the portfolio returns can present similar beta coefficients in estimating the regressions. Thus, it is not risk factor sensitivity that matters, but the size of the exposure to the risk factors. Hence, we employ orthogonalised risk factors in our model, which allows us to estimate the fund exposures as the contribution of each risk factor to the total coefficient of determination. Furthermore, we form predictive quintile-portfolios that invest in funds according to their variation (high or low) in the fund exposures between two consecutive periods. This analysis provides additional evidence that investing in funds that vary the overall exposures to a larger degree generate larger alphas than investing in funds that have the lowest variation in their risk exposures. Finally, we show that the relation between the change in the funds' exposures and the subsequent performance is unrelated to other characteristics, such as the portfolio's tracking error, funds size, or the investment style followed by the fund.

The rest of the chapter proceeds as follows. Section 2 describes our sample of US equity mutual funds 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.

4.2. Performance methodology and data

4.2.1. Performance methodology

We implement a six-factor model to measure the mutual fund performance[11]. Given the evidence in Matallín-Sáez (2006) about the omission of relevant benchmarks, we apply the standard performance measurement model used in the literature in that we extend the Fama and French (2015) five-factor model by including 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 the average returns amongst 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 Jenson's alpha (a_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.[12]

[11] 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.

[12] 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

4.2.2. 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. We obtain different fund characteristics such as the fund identifier, the fund's 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 of each fund, monthly total net assets under management (TNA), the annual net expense ratio, and the 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, reducing the sample to 3,990 actively managed US equity mutual funds. We also exclude all funds with less than $15 million in assets under management. The usual explanation in the literature for excluding this group of funds is that their reported returns might be upward biased (Elton, Gruber, and Blake, 1996; Elton, Gruber, and Blake, 2001; Chen *et al*., 2004; and Amihud and Goyenko, 2013; among others).

We require further that the 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-subsidised by their fund families (Evans, 2010; Gaspar, Massa, and Matos, 2006; and 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 in 2,360 actively managed US equity mutual funds. Some descriptive statistics for this sample are reported in Panel A of Table 4.1. Some descriptive statistics for the returns on the factors in Equation (1) are presented in Table 4.1 (Panel B), and the correlations between the risk factors are reported in Table 4.1 (Panel C). To no surprise, almost all risk factors are significantly correlated with each other. For instance, the SMB and the RMW factors are negatively correlated (-0.3525), while the correlation between the HML and the CMA factors is significantly positive (0.5060) for the entire period.

Table 4.1. 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 (annualised, %)	9.506	20.589

Panel B. Annualised 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

Table 4.1. (*Continued*)

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 annualised 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.

4.3. Funds' exposure to the risk factors

4.3.1. Democratic decomposition of R^2

In this section, we analyse the exposure of the mutual funds to the risk factors in Equation (1). That is, we want to assess how much the individual mutual fund returns depend on the 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) implements, in his classic study, a model with twelve asset-classes with some restrictions[13] and considers the beta of each explanatory variable as the proportion of the portfolio invested in the related asset class. In addition, other studies (Bollen and Busse, 2001; Chen, Adams, and Taffler, 2013; Andreu, Matallín-Sáez, and Sarto, 2018; among others) analyse the timing abilities of the mutual fund managers by employing the models of 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 prior to positive or negative behaviour of this factor, respectively. These exposures are again measured through the beta estimates.

In this chapter, we are interested in examining the contribution of each risk factor to mutual fund return variability. Thus, we do not focus on the slope estimates. The reason is as follows: We know that the risk factors described are likely to have a significant impact on the returns of a mutual fund. Some factors, however, will contribute relatively more than others in explaining the variation in returns. To observe a more accurate mutual funds exposure to the different risk factors, we decompose the

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

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. With this aim, we apply the democratic decomposition of the R^2 shown in Klein and Chow (2013). This methodology employs orthogonalised risk factors, which allows us to explain the individual contribution of each factor to the total R^2 of the model. The variances of the orthogonalised factors are identical to the original factors, but they are uncorrelated with each other (in contrast with the non-orthogonalised risk factors, as shown in Panel C of Table 4.1). Hence, the contribution of each orthogonalised factor is not related to (or distorted by) other specific factors included in the model.

This methodology does not require the choice of an initial factor in the orthogonalisation sequence, and does not modify the volatility or variance of the factors' returns. Moreover, the intercept and the error terms of the regression model remain unchanged after the orthogonalisation process[14], implying that the performance estimation results are not affected by using non-orthogonalised or orthogonalised risk factors.

The orthogonalisation procedure is structured as follows. Let us consider F_{TxK} as the matrix containing the returns of the K factor-mimicking portfolios during each period from 1 to T. That is:

$$F_{TxK} = \left[f_t^k\right]_{t=1,\ldots,T}^{k=1,\ldots,K} = \begin{bmatrix} f_1^1 & f_1^2 & \cdots & f_1^K \\ f_2^1 & f_2^2 & \cdots & f_2^K \\ \vdots & \vdots & \ddots & \vdots \\ f_T^1 & f_T^2 & \cdots & f_T^K \end{bmatrix} \tag{2}$$

The K factor-mimicking portfolios are assumed to be uncorrelated with the error term of Model (1), $\varepsilon_{i,t}$, but not among each other. In order to apply the democratic

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

decomposition shown in Klein and Chow (2013), we first need to apply a symmetric orthogonalisation to the risk-factors. In other words, we need to create a linear transformation, S_{KxK}, that allows us to generate the orthogonalised factors, $F^{\perp}_{TxK}$, from the previously matrix F_{TxK}:

$$F^{\perp}_{TxK} = F_{TxK} S_{KxK} \tag{3}$$

Firstly, we estimate the demeaned matrix of F_{TxK}, $\tilde{F}_{TxK}$, which is required to obtain uncorrelated and orthogonal factors:

$$\tilde{F}_{TxK} = \left[\tilde{f}_t^k\right]_{t=1,\dots,T}^{k=1,\dots,K} = \begin{bmatrix} f_1^1 - \overline{f^1} & f_1^2 - \overline{f^2} & \cdots & f_1^K - \overline{f^K} \\ f_2^1 - \overline{f^1} & f_2^2 - \overline{f^2} & \cdots & f_2^K - \overline{f^K} \\ \vdots & \vdots & \ddots & \vdots \\ f_T^1 - \overline{f^1} & f_T^2 - \overline{f^2} & \cdots & f_T^K - \overline{f^K} \end{bmatrix} \tag{4}$$

Next, we estimate M_{KxK} by multiplying *T-1* times the variance-covariance matrix associated to the aforementioned factors' returns, V_{KxK}. Mathematically:

$$M_{KxK} = (T-1)V_{KxK} = (T-1)\begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & \cdots & \sigma_{1,K} \\ \sigma_{2,1} & \sigma_2^2 & \cdots & \sigma_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{K,1} & \sigma_{K,2} & \cdots & \sigma_K^2 \end{bmatrix} = \tilde{F}'_{TxK}\tilde{F}_{TxK} \tag{5}$$

In these lines, we should note that the matrix $\tilde{F}^{\perp}_{TxK}$ would be orthonormal if:

$$\left(\tilde{F}^{\perp}_{TxK}\right)'\tilde{F}^{\perp}_{TxK} = \left(\tilde{F}_{TxK}S_{KxK}\right)'\left(\tilde{F}_{TxK}S_{KxK}\right) = S'_{KxK}\left(\tilde{F}'_{TxK}\tilde{F}_{TxK}\right)S_{KxK} = S'_{KxK}M_{KxK}S_{KxK} = I_{KxK} \tag{6}$$

Implying the following equivalence:

$$S_{KxK}S'_{KxK} = M^{-1}_{KxK} \tag{7}$$

The orthogonalisation procedure is then considered symmetric when:

$$S_{KxK} = M^{-1/2}_{KxK} \tag{8}$$

Given that real symmetric matrices (such as M_{KxK}) are diagonalizable by orthogonal matrices, we can find the corresponding diagonal matrix, D_{KxK}, by applying:

$$M_{KxK} = O_{KxK} D_{KxK} O'_{KxK} \tag{9}$$

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:

$$S_{KxK} = M_{KxK}^{-1/2} = O_{KxK} D_{KxK}^{-1/2} O'_{KxK} \tag{10}$$

The following step is to rescale the factors to their original variances:

$$S_{KxK} \longmapsto S_{KxK}\sqrt{T-1}\begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_K \end{bmatrix} \tag{11}$$

where σ_k refers to the standard deviation of factor k.

Having estimated the square matrix containing the linear transformation, S_{KxK}, the orthogonalised factors, $F_{TxK}^{\perp}$, are obtained by applying Equation (3). These orthogonalised factors can be used as the explanatory variables in Equation (1) to generate beta estimates related to these factors, which are employed to decompose democratically the coefficient of determination, as follows:

$$R_j^2 = \sum_{k=1}^{K} R_{j,k}^2 = \sum_{k=1}^{K} \left(\hat{\beta}_{k_j}^{\perp} \frac{\sigma_k}{\sigma_j}\right)^2 \tag{12}$$

where R^2_j is the coefficient of determination estimated using the orthogonalised-factor model for fund j. $R^2_{j,k}$ is the contribution of each orthogonalised factor k to the total R^2 of the estimated model. $\hat{\beta}_{k_j}^{\perp}$ is the estimated coefficient on the orthogonalised factor k

in the fund j's regression, and σ_j is the standard deviation of the returns of the same fund, respectively.

We next apply the democratic decomposition of the coefficient of determination to the entire sample period. We run ordinary least squares (OLS) time-series regressions for each fund in the sample. This methodology allows 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 4.2 along with the factor contribution to the total R^2. The R^2 and the number of funds used in the analysis are reported as well.

In line with the previous literature, the average fund generates a significantly negative performance of 110 basis points per year. In addition, the slope on the market factor is very close to one, as the sample consists of equity mutual funds that invest primarily in US stocks and reflect, on average, the market index. Unsurprisingly, this factor also explains most of the total variability (82.7%) of the 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 is significantly negative (coefficient of -0.170), but its contribution to the total R^2 is very low (contribution of 0.7%).

Table 4.2. Exposures of the mutual funds to the risk factors during the 1990-2016 period

	Average coefficient	t-statistic	Contribution to Total R^2
α (annualised)	-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 the OLS time-series regressions whose dependent variables are the daily returns of each mutual fund in the sample in excess on the return of the risk-free asset. The dependent variables are the risk-factors considered in the five-factor model of Fama-French (2015) plus the momentum factor explained in Carhart (1997). These six risk-factors are orthogonalised to avoid any correlation between them. The performance of the mutual funds (the intercept of the model, or alpha) is annualised from a daily basis (that is, multiplied by 252). The t-statistics show if the average estimates are significantly different from zero. The contribution of each factor is estimated using the democratic decomposition of the R^2 shown in Klein and Chow (2013). The number of funds considered in the analysis and the total coefficient of determination are also reported in the last rows of the Table.

As all funds included in the sample are actively managed, and given the evidence shown in previous studies (e.g., Kosowski, 2011; Matallín-Sáez, Soler-Domínguez and Tortosa-Ausina, 2016), we next analyse whether their exposure to the different risk factors changes depending on the business cycle. According to the National Bureau of

Economic Research (NBER), six different sub-periods are present in our sample period[15]. These sub-periods are classified as recessions (from August 1990 to March 1991, from April 2001 to November 2001, and from January 2008 to June2009) or expansions (from April 1991 to March 2001, from December 2001 to December 2007, and from July 2009 to December 2016). Similar to Table 4.2, Table 4.3 reports the results of the aforementioned analysis for the funds that existed in each of the NBER sub-periods. Recessions and expansions sub-periods are shown in Panel A and Panel B, respectively.

Table 4.3. 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 (annualised)	-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

[15] 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

Table 4.3. (*Continued*)

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 (annualised)	0.022	7.88	0	-0.002	-2.29	0	-0.016	-25.84	0
β1 (RMRF)	0.816	124.75	0.635	0.972	328.09	0.832	0.996	421.27	0.838
β2 (SMB)	0.027	2.33	0.036	0.330	38.16	0.047	0.465	66.62	0.062
β3 (HML)	-0.345	-32.92	0.053	-0.095	-14.98	0.007	0.179	40.79	0.017
β4 (RMW)	-0.297	-25.33	0.046	-0.261	-35.78	0.022	-0.383	-98.33	0.016
β5 (CMA)	-0.360	-33.78	0.044	-0.051	-9.97	0.003	-0.037	-7.39	0.004
β6 (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 the average results of the OLS time-series regressions whose dependent variables are the daily returns of each fund in the sample in excess of the return of the risk-free asset. Each fund is required to present at least thirty observations on daily returns in order to be included in the analysis. The dependent variables are the risk-factors considered in the five-factor model of Fama-French (2015) plus the momentum factor explained in Carhart (1997). These six risk-factors are orthogonalised to avoid any correlation between them. The performance of the mutual funds (the intercept of the model, or alpha) is annualised from a daily basis (that is, multiplied by 252). The t-statistics show if the average estimates are significantly different from zero. The contribution of each factor is estimated using the democratic decomposition of the R^2 shown in Klein and Chow (2013). The number of funds considered in the analysis and the total coefficient of determination are also reported in the last rows of each Panel.

As expected, the average fund's exposures to the different risk factors is time varying. On the one hand, the market factor provides the highest contribution in explaining the variability of the mutual funds' returns during the sub-periods. Its contribution, however, varies between 63.5% during the first expansion 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 financial crisis). These findings provide initial evidence that mutual fund managers alter their risk factor exposures over time, perhaps a consequence of active fund management.

As the NBER sub-periods have different lengths, and with the aim of observing accurately the 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 4.1 shows the plot of the overall results of this analysis[16]. Figure 4.1.a presents the contribution of all the risk factors in the model, while Figure 4.1.b omits the contribution of the market factor to better visualise the exposure changes for the remaining factors.

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

Figure 4.1. Factors' contributions to the explanation of the variability of the overall mutual fund returns.

Figure 4.1.a. The decomposition of the coefficient of determination into the contributions of the risk-factors over time

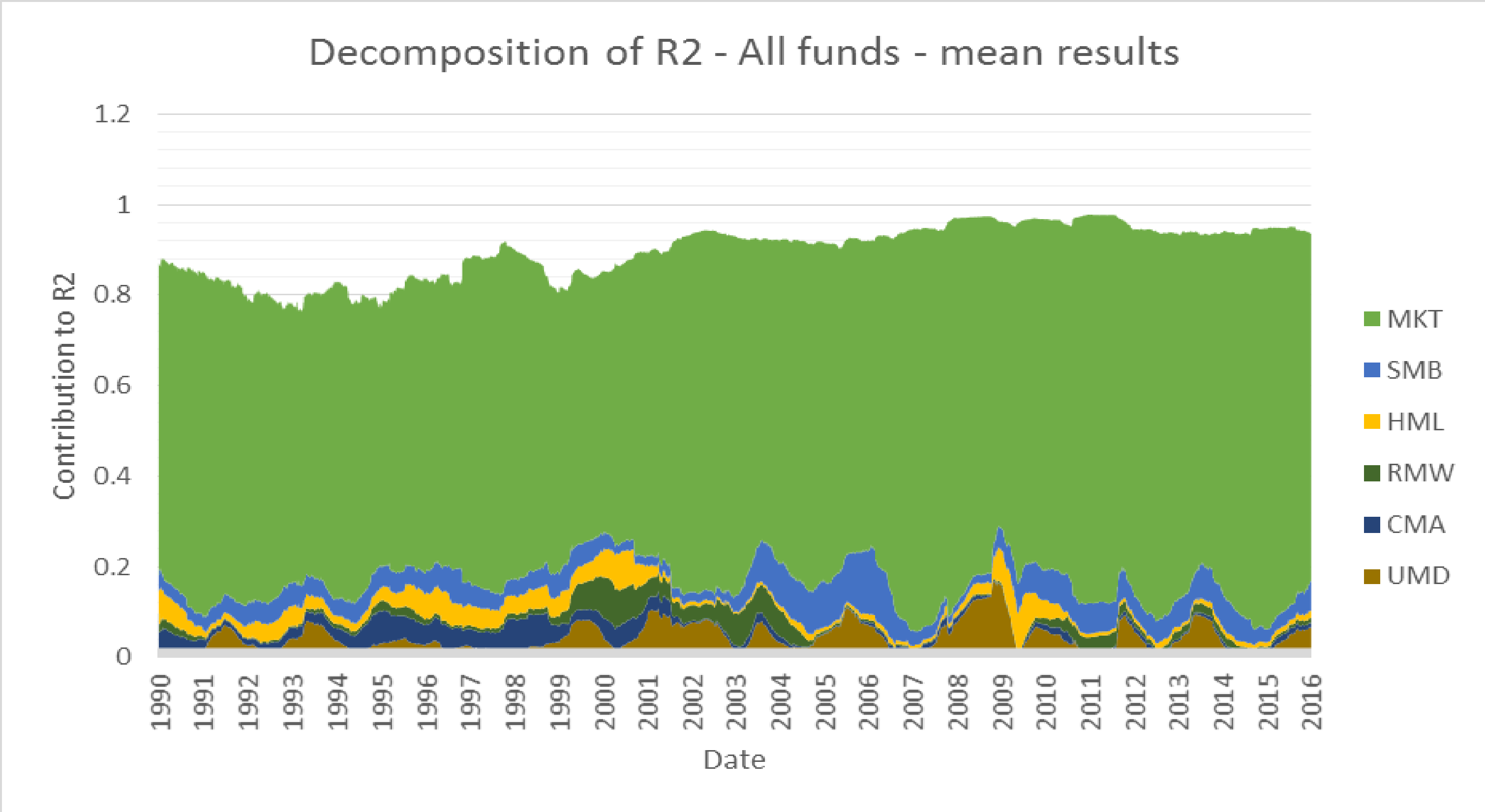
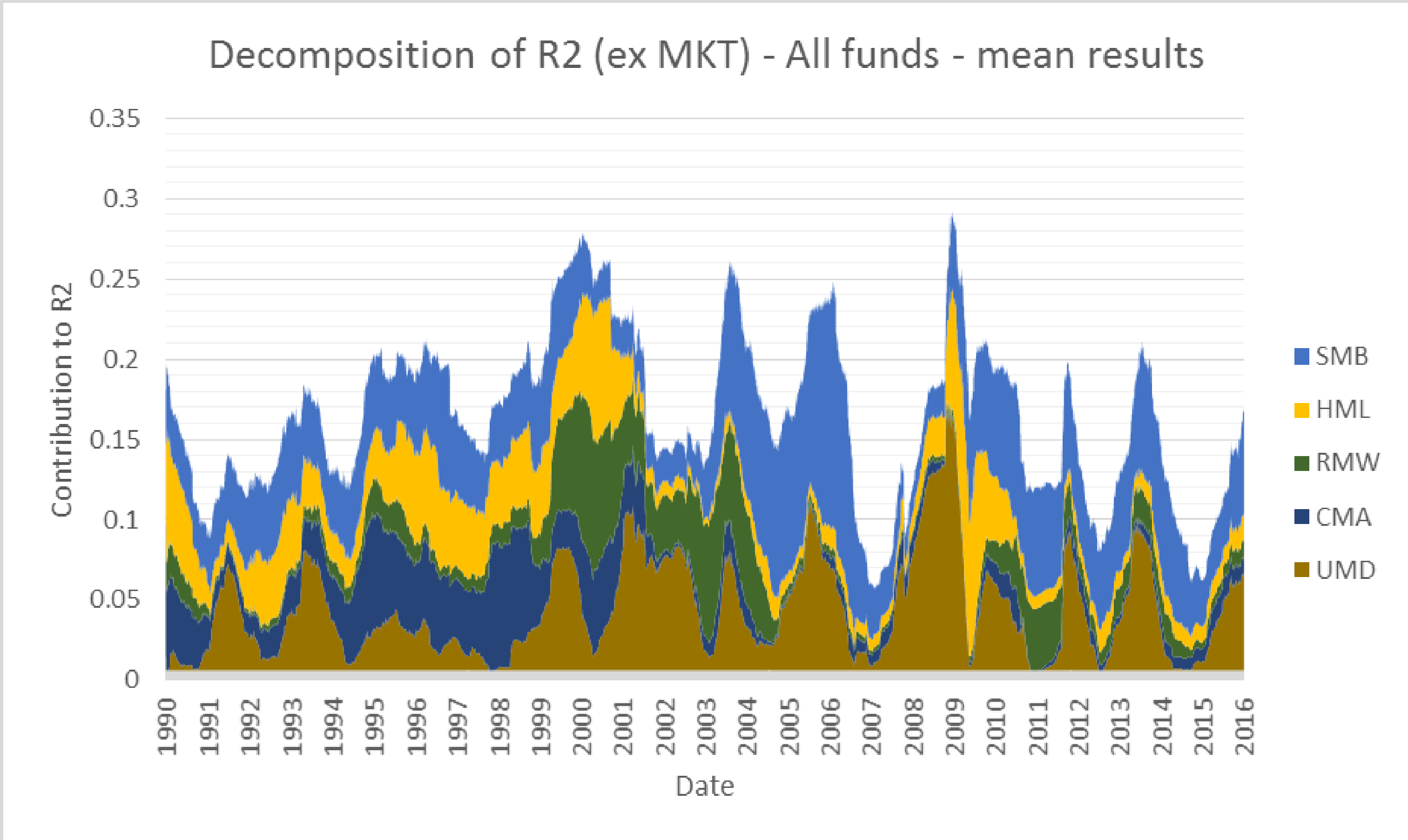


Figure 4.1. (*Continued*)

Figure 4.1.b. The contributions of the SMB, HML, RMW, CMA, and UMD factors to the variability of the fund returns over time



In line with the results in Table 4.2 and Table 4.3, most of the variability in mutual fund returns is attributed to the market factor. Other factors (e.g., SMB, UMD), however, also play an important, but dynamic, role in explaining mutual fund returns. Nevertheless, some risk factors (e.g., CMA), despite being statistically significant, do not contribute much to explaining the variability in mutual fund returns since 2001.

In sum, we clearly find 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 for this change and study its impact on mutual fund performance.

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

Given the evidence 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:

$$CFE_{j,t} = \frac{1}{2}\sum_{k=1}^{K}\left|\frac{R^2_{j,k,t}}{R^2_{j,t}} - \frac{R^2_{j,k,t-1}}{R^2_{j,t-1}}\right| \quad (13)$$

where $CFE_{i,t}$ (change in exposures) is the sum of the absolute change in fund *j*'s exposures to the risk factors, *K*, during the period *t*, and $R^2_{j,k,t}$ is the relative contribution of the factor k to the total R^2 experienced by fund j during the period t. CFE then 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 the 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%.[17]

For illustration purposes, let us assume that a fund's performance is affected by only two factors (A and B) during two periods. The contributions of A and B to the R^2 experienced by the fund during the first period are 0.3 and 0.6, respectively. Then, the total R^2 equals 0.9. Now, imagine that A contributes in a very similar level (0.33) to the explanation of the variability of the fund returns during the second period. Assuming that the fund does not vary its tracking error (R^2 remains unchanged), a decrease in the contribution of B (from 0.6 to 0.57) must result. The reader should note that the fund's exposures during the second period are very similar to those experienced in the first period. After all, the change in the exposures to the risk factors that this fund experiences during these periods equals 3.33%. But, in the hypothetical case that the factor variation had altered significantly more during the second period (for instance, 0.75 on A and 0.15 on B), then the fund would have achieved a higher CFE during this period (50% for the previous example).

In the next Section, we estimate for each fund the change in risk factor exposures and analyse whether this ratio can predict future fund performance.

[17] 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.

4.4. Results

4.4.1. Performance of fund portfolios with different levels of CFE

In this Section, we examine the relationship between changes in the funds' risk factor exposure and their subsequent performance. Assuming that for actively managed mutual funds a change in the exposures to the risk factors 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 of these funds.

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[18]. We sort on CFE because we aim to observe whether funds changing their exposures to a greater degree achieve better performances than funds experiencing lower CFE. Additionally, we include previous performance in the analysis because of earlier evidence on performance persistence (Brown and Goetzmann, 1995; Cortez, Paxson and Armada, 1999; among others). Specifically, we perform the following analysis. Firstly, we estimate and decompose the coefficient of determination of each fund in each month using the six-factor model described in Equation (1), following the methodology of Klein and Chow (2013). As we use a 252-day rolling window in the regressions, our analysis is based on a one-year time span of daily data. Next, we compare in each month, and for each fund, the contribution of each factor to the coefficient of determination using two consecutive and non-overlapping periods (that is, using two years of daily data), and estimate the CFE related to this fund. Subsequently,

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

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 subsequent one-month returns of the twenty-five equally weighted hypothetical portfolios that invest in the funds that belong to each level in each month. 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 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 4.4 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').

Table 4.4. Fund portfolio performance, double-sorting on previous funds' CFE and performance

		CFE$_{t-1}$						
		P1	P2	P3	P4	P5	All	P5-P1
alpha$_{t-1}$	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 performance of different hypothetical portfolios during the 1992-2016 period. These portfolios invest equally-weighted in 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 of these portfolios. The independent variables are the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). The performance of each portfolio is then estimated as the intercept of the model, and it is annualised form a daily basis (that is, multiplied by 252). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

As shown in Table 4.4, the average fund experiences a significantly negative performance of 69 basis points per year. However, this is an average result since some portfolios investing in some funds achieve much lower performance and some a much higher performance. For instance, the portfolios investing in the previous lowest-performing funds experience a statistically significant negative performance between -263 and -284 basis points per year. Portfolios that monthly invest in the previously best performing funds significantly outperform portfolios that invest each month in funds with the previously lowest performance (an overall alpha of 5.11%). Thus, we observe some positive and negative performance persistence in the short run, which is in contrast to the arguments by Berk and Green (2004) and the empirical evidence in Bessler *et al*. (2018). It is, however, consistent with other portfolio optimization strategies that consistently are able to outperform the benchmark (Bessler and Wolff, 2015; Bessler, Opfer and Wolff, 2017; Bessler and Wolff, 2017).

With respect to changes in the funds' exposures to the risk factors, we obtain some interesting results. Considering funds ranked on CFE alone, we observe increasing performance for funds which change their factor exposure most (from -132 basis points for funds with the smallest exposure changes to +66 basis points for those with the largest changes). Further ranking on both CFE and performance reveals that funds with the worst pervious performance that change their exposures least have an alpha of -264 basis points. In contrast, mutual funds with the highest previous performance that change their factor exposure most have a subsequent average return of 488 basis points. These findings indicate that fund managers with persistent performance who are willing to regularly change their risk exposures outperform in the subsequent month. We next investigate whether these findings hold when we control for other factors previously shown to have predictive power for fund performance.

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

So far, we provided evidence that funds changing their exposures to risk factors to a greater extent generate better alphas than funds experiencing lower levels of CFE. However, it is important to highlight that we employed relative contributions of each risk factor in calculating the CFE. Thus, this evidence could be due to tracking errors of the fund. Hence, the higher the tracking error a fund experiences (that is, the lower the R^2 is), the higher is the overall change in the exposures to the risk factors of this fund. Given the evidence provided in Amihud and Goyenko (2013), this might be a potential drawback of our analysis, and here we determine whether it impacts our findings.

Therefore, we run a similar procedure as in Table 4.4, 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 correlation. Performance results of these portfolios using Model (1) are shown in Table 4.5.

Table 4.5. Fund portfolio performance, double-sorting on previous funds' CFE and R^2

		CFE_{t-1}						
		P1	P2	P3	P4	P5	All	P5-P1
R^2_{t-1}	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)
	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 performance of different hypothetical portfolios during the 1992-2016 period. These portfolios invest equally-weighted in 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 of these portfolios. The independent variables are the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). The performance of each portfolio is then estimated as the intercept of the model, and it is annualised form a daily basis (that is, multiplied by 252). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

In line with Amihud and Goyenko (2013), funds with a high coefficient of determination experience, on average, a negative and statistically significant performance. For instance, the portfolio investing in funds with the highest previous R^2 (column All, raw P5), obtain a significantly alpha of -1.31% per year (t-stat of -4.406). Double sorting on CFE and then R^2, we note that funds with the highest R^2 but changing their exposures little have a significant alpha of -2.06% per annum. Considering funds with the highest previous R^2, we find a statistically significant difference of 2.22% between funds with the greatest and those with the smallest change in CFE. These findings 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 the tracking error that these funds assume. In other words, if a fund altering its tracking error during a period does not experience exactly the same relative contributions from each risk factor to its R^2 during both the end and the beginning of this 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 4.6 shows the main performance results of this analysis.

The evidence in Table 4.6 shows, on the one hand, no statistically significant differences between the portfolios investing in funds with a greater change in their tracking error, that is, reducing (row P1) or increasing (row P5) their coefficients of determination. On the other hand, differences between the portfolios investing in funds that experience the highest and the lowest CFE remain positive and statistically significant, even when controlling for changes in R^2.

Table 4.6. Fund portfolio performance, double-sorting on previous funds' CFE and change in R^2

		CFE_{t-1}						
		P1	P2	P3	P4	P5	All	P5-P1
ΔR^2_{t-1}	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)
	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 performance of different hypothetical portfolios during the 1992-2016 period. These portfolios invest equally-weighted in 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 of these portfolios. The independent variables are the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). The performance of each portfolio is then estimated as the intercept of the model, and it is annualised form a daily basis (that is, multiplied by 252). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

4.4.3. Controlling for the effect of fund size

An alternative explanation for our results is that it stems from a size effect. It has been documented that larger funds (size) 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 4.7 documents the performance results of twenty-five monthly-rebalanced hypothetical portfolios, double-sorting first on the change in the funds' exposures to the risk factors and then on the total net assets under management.

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. Moreover, these portfolios outperform those funds with the lowest changes in their exposures. The differences in the annualised alpha are 2.32% for the smallest funds and 2.28% for the largest funds (t- statistics of 2.607 and 2.064, respectively).

Table 4.7. Fund Size Effect

		CFE_{t-1}						
		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-1}	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 performance of different hypothetical portfolios during the 1992-2016 period. These portfolios invest equally-weighted in 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 of these portfolios. The independent variables are the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). The performance of each portfolio is then estimated as the intercept of the model, and it is annualised form a daily basis (that is, multiplied by 252). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

4.4.4. The relation between the change in the funds' exposure and the subsequent performance in each fund style classification

Funds following different investment strategies tend to focus upon holdings of a particular style. 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 capitalisation of the US market are classified as large cap funds. Instead, small cap funds invest mainly on small stocks (stocks in the bottom 10% of the capitalisation of the US market). Additionally, value funds focus their main investments in value stocks, that is, stocks characterised by a 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 some differences in the change in their exposures among funds with different Morningstar Investment Style Categories. For instance, growth funds should experience, on average, higher variation in the exposures to the risk factors than value funds, given the nature of their investment strategy. In light of the evidence shown in previous studies (Chen *et al*., 2000; Chan *et al*., 2002; Kosowski *et al*., 2006) about the greater results achieved by growth-oriented funds, and as we should expect growth funds to experience higher variation in their exposures, the aforementioned results might be driven by the investment style of the fund.

Figure 4.2. Regarding CFE according to mutual fund investment style.

Figure 4.2.a. The average CFE experienced by Large-Cap, Mid-Cap and Small-Cap funds over time

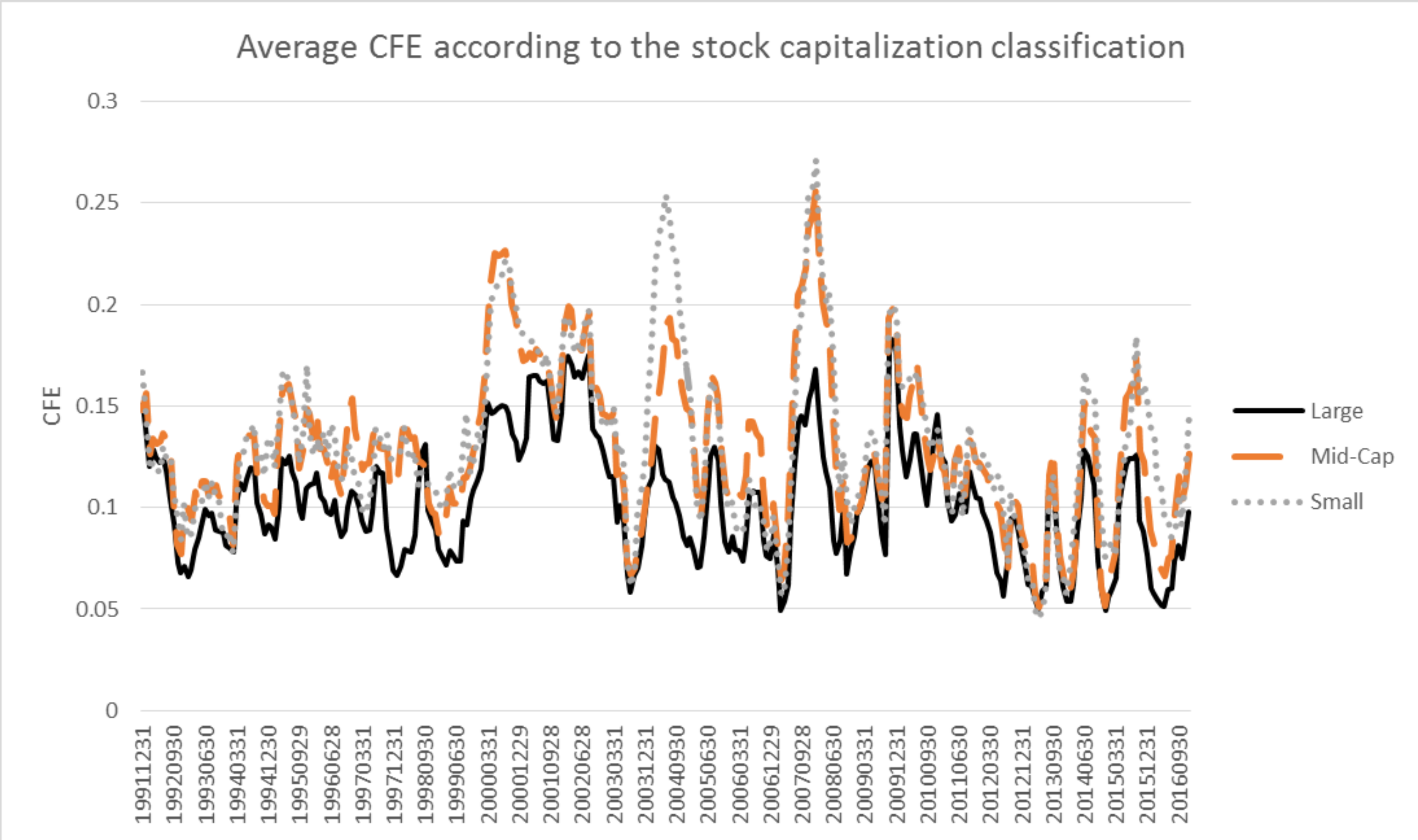
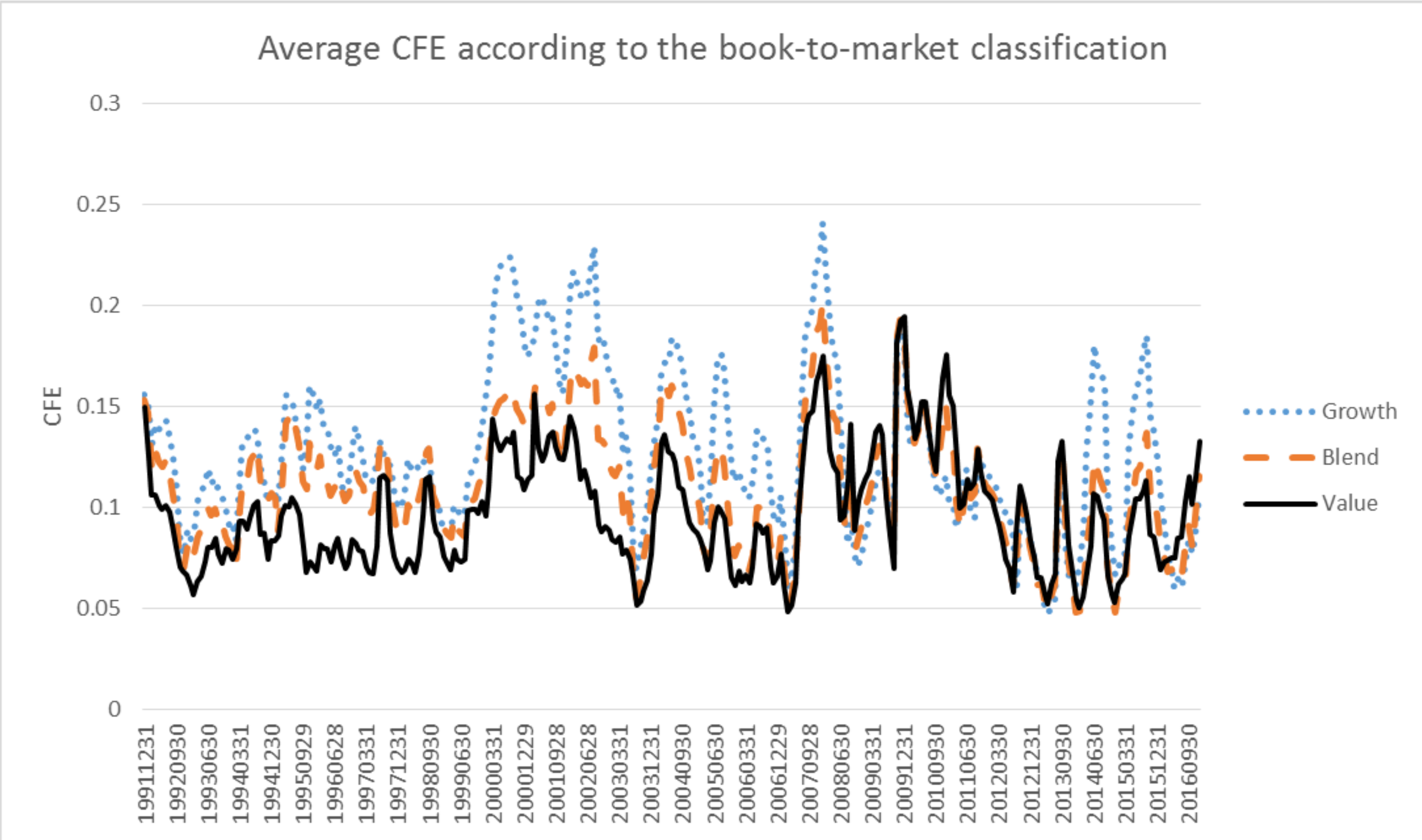


Figure 4.2. (*Continued*)

Figure 4.2.b. The average CFE experienced by Growth, Blend and Value funds over time



Therefore, we sort the 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 capitalisation; 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 4.2 plots the average CFE over time for the funds in each Morningstar Category related to the stock capitalisation (Figure 4.2.a) and book-to-market (Figure 4.2.b) classifications.

As expected, Figure 4.2 shows that growth funds experience the highest overall change in their exposures to the risk factors. In contrast, value funds and large funds show the smallest variation over time.

Similar to the previous analyses, we evaluate the performance of the 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 performance by using the six-factor model. Results are reported in Table 4.8.

Table 4.8. 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-capitalisation 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 performance of different hypothetical portfolios during the 1992-2016 period. These portfolios invest equally-weighted in funds in each Morningstar Category (Growth, Blend, Value, Large Cap, Mid Cap, and Small Cap) 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 the beginning of each month. *All* refers to all the funds in each Morningstar Category, without taking into account the specific level of CFE. The differences between P5 and P1 and their significance are reported in the last column of the Table. The dependent variable is the daily return of each of these portfolios. The independent variables are the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). The performance of each portfolio is then estimated as the intercept of the model, and it is annualised form a daily basis (that is, multiplied by 252). 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 results are in line with those in the previous sections. That is, there is significant evidence of a higher 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 (annualised alpha for P5-P1 of 2.20%, t- statistic of 2.272), large-cap funds (annualised alpha for P5-P1 of 2.23%, t-statistic of 2.319) and small-cap funds (annualised 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. However, funds with relatively low changes in factor exposures, in aggregate, display significant alphas, while the performance of funds with the highest variation is insignificant. Moreover, we observe that growth funds with highest CFE have an outperformance of 1.52% per annum, building on previous findings relating to timing skills for such funds (Chen *et al.*, 2013).

4.4.5. Luck or skill? The performance of predictive portfolios with *m*-months horizon

Up to now, we observed that funds changing their risk factor exposures to a greater extent provide investors with greater alphas than funds that do not experience such variation in exposures. One possible explanation might be that these funds experience luck in the short term that help them to achieve higher performances. Therefore, this outperformance could be due to luck rather than to investment skills or managers' abilities.

In this sense, luck is a temporary phenomenon while investment skills should persist over time. Consequently, and with the aim of differing between luck and skill, we consider the performance persistence for portfolios over the following *m* months. To this end, we consider twelve different windows 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 just the signal provided by CFE at time *t*. Again, all portfolios are monthly rebalanced.

If the evidence in the previous sections is due to luck of the mutual funds, we would expect to observe attenuation in performance for longer windows. In the case that mutual funds varying their exposures to a greater degree were skilled enough to provide investors with better alphas, then these funds should report a persistent higher performance over time. Table 4.9 shows the main results of this analysis as well as the results for the portfolio differences when investing in funds with the highest and the lowest levels of CFE for each windows.

As shown in Table 4.9, the portfolios formed based upon the lowest CFE at time *t* have a significant negative alpha up to 12 months later. Moreover, we find a statistical outperformance of funds with the highest CFE relative to the lowest CFE (P5-P1) for up to 11 months. These findings may indicate that managers who change their exposures persist in doing so in future months, continuing to provide outperformance for their investors.

Table 4.9. 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 performance of different hypothetical portfolios during the 1992-2016 period. In month *t+m*, these portfolios invest equally-weighted in funds according to their change in their exposures to the risk factors (CFE) in month *t*, and are rebalanced monthly. 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. The differences between P5 and P1 and their significance are reported in the last column of the Table. The dependent variable is the daily return of each of these portfolios. The independent variables are the risk-factors considered in the Fama-French (2015) five-factor model plus the momentum factor described in Carhart (1997). The performance of each portfolio is then estimated as the intercept of the model, and it is annualised form a daily basis (that is, multiplied by 252). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

4.4.6. The variation in the fund exposures during shorter periods

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.

In these lines, we should note that the CFE ratio captures the variation in the fund's exposures between the beginning and the end of a given period (for instance, the end of the period t and the end of the period $t+1$), regardless of the specific moment when this change would have happened. Hence, a shorter rolling-window should capture better the interactions between the variation in the funds' exposures and the subsequent performance.

Accordingly, we estimate the CFE during each period considering two consecutive and non-overlapping six-months periods (i.e., 126 days), instead of a whole year of data. We perform analogous analyses than in Section 4.1 and 4.2 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 4.10 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).

Table 4.10. 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-1}						
		P1	P2	P3	P4	P5	All	P5-P1
$alpha_{t-1}$	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)	

Table 4.10 (*Continued*)

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

		CFE_{t-1}						
		P1	P2	P3	P4	P5	All	P5-P1
	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)
R^2_{t-1}	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 performance of different hypothetical portfolios during the 1991-2016 period. These portfolios invest equally-weighted in funds with similar relative levels of variation in their exposures to the risk factors (CFE) and similar alpha (Panel A) or R^2 (Panel B), both measures assessed during the previous six-months. These portfolios are monthly rebalanced. The performance of each portfolio (that is, the intercept obtained by running Model 1) is annualised form a daily basis (that is, multiplied by 252). T-stats (in parentheses) are estimated using Newey-West (1987) HAC standard errors. '*', '**', and '***' denote significance at the 10%, 5%, and 1% levels, respectively.

As shown in Panel A of Table 4.10, the portfolio investing in the previous best-performing funds that experience the highest CFE achieves an annualised alpha of 0.0481 (t-stat of 5.312). In contrast, the portfolio investing in funds with the lowest change but performing similarly during the last six months obtains a significantly negative alpha of -0.0167 per year (t-stat of -2.327). Additionally, the portfolios reporting the worst performance in Panel B are those investing in funds with the lowest levels of previous CFE and the highest levels of previous R^2. Finally, and in line with our expectations, portfolios investing in funds that experience a high change in their exposures during a half-year period provide investors with higher subsequent alphas than portfolios investing in funds that keep similar exposures, regardless of the performance or coefficient of determination achieved previously by the funds. This evidence is significant at the usual levels in most of the cases, with the exception of the portfolios investing in the worst-performing funds (the performance difference between P5 and P1 is positive (0.0105).

4.5. Conclusions

Recent studies provided empirical evidence that some mutual funds are able to beat the benchmark and 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 active management in the mutual fund industry is not a simple issue to address, since a proper definition has not yet been reached in the previous literature. Several authors recently proposed different ratios to capture this fund characteristic, but this question is still far from consensus.

In this chapter, we propose a new measure to estimate this level of active management. This measure is based on the contributions of each risk factor to the explanation of the variability in the 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 altering their exposures to systematic factors achieve better performance.

For a large sample of US domestic equity mutual funds, our results show that funds varying their risk factor exposures to a greater extent achieve higher subsequent alphas. Moreover, investing in the previously best-performing funds that changed their exposures to a large degree leads to positive and statistically significant alphas between 2.60% and 4.80%, in annualised terms. Moreover, this outperformance is not explained by other performance indicators, such as the funds' tracking error, the total net assets under management and the investment style implemented in the portfolio, since similar evidences arise 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 twelve months significantly greater abnormal returns 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 to the abilities of their managers to shift the risk exposure appropriately, rather than being a matter of luck.

Hence, this chapter highlights 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 exposures of the portfolios they manage. Consequently, these funds are able to provide investors with superior abnormal returns relative to passive funds that retain similar exposures. The evidence shown in this chapter, therefore, is of interest to academics, professionals and investors wishing to understand the behaviour and performance of mutual funds over time.

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CHAPTER 5: SUMMARY OF THE THESIS AND CONCLUDING REMARKS

SUMMARY OF THE THESIS AND CONCLUDING REMARKS

5.1. Summary of the doctoral thesis

This doctoral thesis proposes the evaluation of different aspects related to the efficiency and analysis of the behaviour of mutual funds and their demand. The US mutual fund industry is analysed due to its representativeness, since it is the largest fund industry worldwide. The sample analysed focuses on more than 17,000 share-classes related to 5,255 US open-end funds that invest mainly in equities of the same market. Additionally, several economic cycles and other characteristics are taken into account to avoid any potential bias. Thus, this thesis contributes to the extant literature on estimating properly the mutual fund demand and the effect of its determinants, as well as on assessing both the behaviour and the performance of the funds in relation to their level of management activity. The implications of these studies are of interest for investors and managers (in optimizing the financial results of their investments), and for regulators and other stakeholders (in order to conduct the necessary actions to facilitate and improve the publicly available information on equity mutual funds).

5.2. Concluding remarks

This section is devoted to a synthesis of the main conclusions that arise from our results, as well as summarising the discussions and implications of each study included in this doctoral thesis.

The second chapter included in the thesis, '*Investing in mutual funds: the determinants of implied and current net cash flows*', aims to observe the error and noise produced and their potential consequences in estimating the demand for a mutual fund through a rough measure that entails certain implicit assumptions. In this sense, distortions can be generated in the results by employing windows of lower frequency than three-month periods. Such distortions can lead to non-optimal and even detrimental decisions in the mutual fund management. Therefore, investors, professionals and researchers should use in their analyses precise measures to estimate the mutual fund demand. These measures should be directly based on inflows and outflows rather than on assessing the growth of the fund with respect to the growth that would have happened with no flows, and with all the dividends reinvested in the fund. In addition, this evidence should encourage regulators and other governmental agents towards an increase in the transparency, quality and public availability of the information reported in the mutual fund industry, especially in markets where it is still not available.

The following chapter, '*Institutional investment management: An investor's perspective on the relationship between turnover and performance*', considers the turnover ratio as a good proxy of their trading activity, since a higher level of this characteristic implies that managers reach higher levels of purchases and sales in the mutual fund management. That is, a high turnover ratio could be motivated by fund managers aiming to increase their added value through investment opportunities, while bearing high trading costs. Therefore, the main objective of this chapter is to analyse the relationship between turnover and performance in order to evaluate whether a strategy based on this ratio leads to better net results for investors. This study shows that mutual funds experiencing a high turnover in their portfolios do not achieve better risk-adjusted returns than funds that scarcely alter their portfolios' holdings. Moreover, and since this characteristic is persistent on a yearly basis, we observe that a strategy based on investing in funds with previous higher levels of portfolio turnover generally leads to worse financial performances. This relationship between turnover and subsequent performance is not driven by other variables related to the funds' efficiency, behavioural biases or agency problems. Hence, the evidence shown in this study is of interest for managers and investors aiming to enhance their performance, as they should bear in mind the level of transactions reached by the fund in previous periods, and invest accordingly in funds with low turnover ratios, among other characteristics (for instance, good historical performance).

The fourth chapter, '*Mutual fund performance and changes in factor exposures*', shows that funds experiencing a relatively high change in their exposures to the risk factors experience, on average, better risk-adjusted returns or alphas than funds that do not change their exposures to that extent. This evidence is not explained by other factors, and is mainly attributed to the fund manager's abilities, since their financial results are significantly greater up to twelve months after the change. Thus, this study proposes a new measure on the level of activity in the mutual fund management. The evidence shown in this study is of potential interest for investors, managers and academics wishing to understand the evolution and behaviour of mutual funds over time, as well as aiming to forecast fund performance in the short term.

CAPÍTULO 6: RESUMEN Y CONCLUSIONES (EN CASTELLANO)

RESUMEN Y CONCLUSIONES (EN CASTELLANO)[19]

6.1. Introducción

Entender el comportamiento de la demanda de los fondos de inversión ha captado la atención tanto de académicos como de profesionales del sector financiero. El motivo es simple: conocer las características y demás variables que afectan a las decisiones de los inversores, así como estimar correctamente el efecto de cada una de ellas sobre la demanda, permite modificar la gestión del fondo para atraer efectivo y partícipes hacia la cartera de valores gestionada. En consecuencia, muchos autores han estudiado el impacto que ciertos factores (tales como el desempeño previo de la cartera o los gastos asociados a su gestión) tienen sobre la demanda de los fondos de inversión.

Una cuestión relevante sobre estos efectos es la forma en la que se puede medir dicha demanda. Utilizar flujos netos de caja es una medida más que razonable para realizar dicha estimación, pues hace referencia a las entradas y salidas de efectivo experimentadas por el fondo de inversión. En este sentido, la definición estándar de estos flujos netos de efectivo encontrada en la literatura se obtiene al comparar el crecimiento del fondo con respecto al crecimiento que hubiera experimentado sin que hubiera sucedido ninguna entrada ni salida de efectivo, y asumiendo que todos los dividendos se hubieran reinvertido en el fondo. Esta definición imprecisa e indirecta ha sido utilizada por varios autores (por ejemplo, Gruber, 1996; Guercio y Reuter, 2014; Huang *et al.*, 2007) debido principalmente a la falta de información sobre entradas y

[19] Dado que ninguno de los capítulos han sido redactados en ninguna de las dos lenguas oficiales de la Universitat Jaume I, en cumplimiento de lo previsto en el artículo 27 de la Normativa de los estudios de Doctorado, regulados por el RD 99/2011, en la Universitat Jaume I, aprobada por el Consejo de Gobierno núm. 19 de 26 de enero de 2012 y en vigor desde 11 de febrero de 2012, se resumen a continuación los capítulos y se presentan las conclusiones de la tesis en castellano.

salidas de efectivo en las carteras de los fondos durante los años previos al 2000 (en el mercado estadounidense, entre otros).

La definición anterior implica, pues, asumir ciertos supuestos. Por ejemplo, que los flujos netos de caja suceden en el último momento de cada periodo, por lo que no se revalorizan ni generan ningún gasto asociado durante dicho periodo. Por ello, otros autores consideran también que dichos flujos se generen al inicio del periodo a la hora de llevar a cabo sus análisis (Bhattacharya *et al*., 2013; Feng *et al*., 2014; Friesen y Sapp, 2007; Zheng, 1999). A pesar de ello, esta medida sigue siendo una estimación imprecisa y no especifica la cantidad exacta asociada a las entradas y salidas de efectivo de los inversores. Dicha imprecisión puede generar una distorsión en la cuantificación de la demanda proporcional a la ventana de estimación utilizada (mensual, semestral, anual, etc.), lo que implica incurrir potencialmente en un error a la hora de estimar el efecto de sus determinantes.

Por ello, y más recientemente, otros autores enfatizan en la importancia de especificar los flujos netos de caja utilizando información relativa a las entradas y salidas de efectivo (Andreu y Sarto, 2016; Keswani y Stolin, 2008). Es decir, los flujos netos de caja se pueden obtener sencillamente comparando entradas y salidas durante un mismo periodo temporal. No obstante, dicha información no se encuentra siempre disponible para algunas bases de datos y para ciertos países (especialmente, los que se encuentran en desarrollo y en los que la industria de los fondos de inversión crece de manera más exponencial).

En consecuencia, uno de los objetivos principales de esta tesis doctoral es analizar los efectos de los determinantes de los fondos de inversión, y mostrar que el uso de una medida imprecisa puede conducir a un sesgo en la estimación de los flujos netos experimentados por el fondo. Al utilizar una medida directa de estimación, se observa que algunos factores tienen un impacto en la demanda de los fondos, tales como los flujos pasados en el fondo (o fondos similares), el nivel de gastos asociados o la antigüedad del fondo. Sobre todo, mejores resultados en el pasado son clave para atraer la demanda de los fondos, que busca maximizar su rentabilidad en periodos sucesivos.

En esta línea, unas muy buenas revisiones de literatura sobre el desempeño de los fondos de inversión se pueden encontrar en Elton y Gruber (2013) y en Ferson (2010). En relación a ello, en los capítulos de la tesis tratamos de observar qué fondos pueden obtener mejores o peores resultados. Dada la ingente cantidad de estudios que tratan actualmente de medir el grado de gestión activa y su efecto en el desempeño del fondo (Cremers y Petajisto, 2009; Amihud y Goyenko, 2013; Huang *et al*., 2011, entre otros), y la importancia del valor añadido del gestor en la cartera de inversión (en caso contrario, sería preferible invertir mediante estrategias pasivas, a través de, por ejemplo, fondos índice, los cuales soportan menos gastos), procedemos a intentar determinar la relación entre estas variables.

La mayor dificultad a la que cualquier investigador se enfrenta al abordar este tema es la determinación del nivel de actividad en la cartera de los fondos de inversión. Dado que se trata de una idea abstracta y no cuantificable, se deben realizar ciertos supuestos e inferir que ciertas variables asociadas a una característica o rasgo están potencialmente conectadas con el nivel de actividad experimentado por el fondo de inversión. En esta tesis, proponemos dos formas diferentes de medir dicho nivel de actividad de cada cartera.

Por una parte, consideramos que el porcentaje de transacciones realizadas en la cartera está directamente relacionado con el nivel de actividad de la cartera. Este porcentaje de transacciones se puede medir a través de la rotación de la cartera, esto es, el mínimo entre compras y ventas de activos del fondo divididos por el tamaño del mismo durante un periodo. Al usar el mínimo entre compras y ventas, los flujos de los inversores no afectan a la rotación de la cartera. En otras palabras, cuando un fondo experimenta flujos netos de caja positivos o negativos, suele suceder una compra o venta de activos, pero si esta acción no viene acompañada de una venta o compra de otros activos, respectivamente, ésta no se consideran al medir la rotación de la cartera (Lavin y Magner, 2014). Por ello, una elevada rotación de cartera puede ser interpretada por los inversores como el esfuerzo de los gestores de incrementar el valor que añaden al fondo, detectando activos infravalorados o sobrevalorados, y tomando decisiones de compraventa para anticiparse al mercado. No obstante, esto se basa en una creencia del gestor sobre el desempeño futuro, y los costes de transacción pueden jugar un papel importante, deteriorando la rentabilidad neta obtenida.

Por otra parte, el nivel de actividad de un fondo también debería estar directamente relacionado con el cambio en las exposiciones de la cartera a los factores de riesgo comúnmente aceptados (Fama y French, 1993; Carhart, 1997, Fama y French, 2015). Dada la evidencia mostrada en Pástor y Stambaugh (2002) y Matallín-Sáez (2006) sobre el sesgo generado al obviar factores o *benchmarks* relevantes en la evaluación de los fondos de inversión, decidimos utilizar todos los factores considerados en los trabajos citados. Por tanto, si un fondo no experimenta un nivel elevado de gestión activa, las exposiciones a dichos factores deberían ser constantes a lo largo del tiempo, independientemente del nivel de exposición que tengan a cada factor. En cambio, si modifican sus exposiciones a lo largo del tiempo, se podría asumir que están tratando de anticipar ciertos movimientos del mercado para generar mejores resultados financieros en, al menos, el corto plazo. Nuestros resultados confirman dichas expectativas, y los fondos con un mayor cambio en sus exposiciones son capaces de obtener mejores *alphas* hasta después de un año de dicho cambio que los fondos con una menor modificación de sus exposiciones.

6.2. Conclusiones generales

La tesis plantea la evaluación de distintos aspectos relacionados con la eficiencia y el análisis del comportamiento de los fondos de inversión y su demanda. El mercado analizado es el estadounidense, dado que es el mercado que mayor información reporta sobre los fondos de inversión, además de ser el mercado donde más fondos participan (nuestra muestra se centra en más de 17.000 compartimentos relativos a 5.255 fondos de inversión estadounidenses que invierten principalmente en acciones del mismo mercado). Además, diversos ciclos económicos y otras características son tenidos en cuenta para evitar sesgos potenciales.

La tesis contribuye tanto a la estimación de la demanda de los fondos de inversión y al efecto de sus determinantes, como a la evaluación del comportamiento de los fondos relativos a su nivel de actividad y del desempeño de sus carteras. Las implicaciones de estos trabajos afectan a inversores y a gestores (para optimizar los resultados financieros de sus carteras), y a reguladores y otros partícipes (para realizar las acciones necesarias para facilitar y mejorar la información disponible públicamente de los fondos de inversión). Seguidamente, se procede a sintetizar individualmente los trabajos incluidos en esta tesis:

Capítulo 2: ***Investing in mutual funds: the determinants of implied and actual net cash flows.***

Estimar la demanda de los fondos de inversión juega un papel importante en la gestión de los fondos. Así, la demanda de los fondos puede ser medida como los flujos netos de caja totales experimentados por el fondo durante un periodo. Debido a la falta de información de entradas y salidas de efecto en algunos países y bases de datos, algunos autores realizan una estimación indirecta utilizando datos sobre la cantidad de activos netos gestionados por el fondo y su rentabilidad. Dicha medida, a pesar de ser una buena aproximación, asume implícitamente un error en su cálculo. El error generado es mayor en fondos pequeños, en fondos con mayores rentabilidades absolutas y en fondos con un mayor nivel de entradas y salidas de efectivo. Además, se muestra que este error conduce a una distorsión en la estimación del efecto de algunos determinantes de la demanda de los fondos. En este sentido, se puede generar unas distorsiones en los resultados cuando la ventana que se utiliza es de una frecuencia superior a la trimestral. Dichas distorsiones pueden conducir a decisiones no óptimas e incluso perjudiciales en la gestión de los fondos de inversión.

Capítulo 3: ***Institutional investment management: An investor's perspective on the relation between turnover and performance.***

El objetivo principal de este estudio es observar la relación entre el desempeño de los fondos de inversión y el nivel de rotación de cartera que éstos asumen. Para la muestra analizada, se muestra que los fondos de inversión con alta rotación de cartera no consiguen batir a los fondos que rotan poco su cartera. Además, se observa que el nivel relativo de rotación de cartera es persistente a lo largo del año. Por ello, es de interés analizar diferentes estrategias basadas en el nivel previo de compraventas asumido en el fondo, dado que dicho ratio es fácilmente accesible por los inversores a través de la información reportada en el folleto del fondo. Se muestra que un inversor obtendría peores rentabilidades ajustadas al riesgo al invertir en fondos con un alto nivel de rotación de cartera en el pasado, lo que deterioraría su desempeño final.

Capítulo 4: ***Mutual fund performance and changes in factor exposures.***

Este estudio propone una nueva medida para estimar el cambio en las exposiciones de los fondos a los factores de riesgo comúnmente aceptados por la literatura. Además, se examina la relación de este cambio en las exposiciones con el desempeño futuro de los fondos. Se evidencia que los gestores que cambian activamente sus exposiciones generan, en promedio, mejores rentabilidades al riesgo. Esta evidencia no es explicada por otras variables, tales como el desempeño pasado, el tamaño o el estilo de inversión de la cartera, entre otros. Además, no hay evidencia de que se trate de un factor causado por la suerte, por lo que el cambio en las exposiciones y su mejora en las rentabilidades ajustadas al riesgo se asocia con habilidades en la gestión de los fondos de inversión. Dichas habilidades proveen al fondo de *alphas* significativamente mejores hasta doce meses después de experimentar un cambio relevante en sus exposiciones. Por tanto, este capítulo es de interés potencial para inversores, gestores y académicos que quieran entender la evolución y el comportamiento de los fondos de inversión a lo largo del tiempo, así como prever su desempeño en el corto plazo.

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