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THREE ESSAYS ABOUT MUTUAL FUND MANAGER BEHAVIOR

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THREE ESSAYS ABOUT MUTUAL FUND MANAGER BEHAVIOR

MIGUEL SERRANO

THREE ESSAYS ABOUT MUTUAL FUND MANAGER BEHAVIOR

by

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THESIS

Submitted to the Department of Accounting and Finance at University of Zaragoza in order to get the degree of Doctor of Philosophy in Financial Economics.

Zaragoza, March 2017

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MOTIVATION

The development of this Doctoral Thesis is justified given that, in recent years, researchers have analyzed several questions about the behavior of mutual fund managers due to the agency problems that may exist between managers and investors. As a consequence, financial literature, regulators and practitioners has become increasingly interesting in understanding the incentives that explain manager actions, its consequences on collective investment portfolios as well as the effectiveness of different control mechanisms.

Though many authors consider that behavioural finance is still in its infancy, the academic and practitioners' interest is growing rapidly and the current situation justifies the development of this work. It is very interesting, at least for me, to show that participants do not always act as they are supposed to.

Recent research and, apparently, the future in academic research will be based on multi-disciplinary applications. Consequently, researchers must open their minds to related areas such as finance, psychology, operational research, etc. to get more consistent and useful results to the society.

This Doctoral Thesis is composed of three empirical chapters. The first chapter analyses the financial implications of manager replacement in Spanish equity mutual funds. The second chapter studies the performance consequences of different mechanisms of risk shifting used by mutual fund managers as well as the influence of fund manager sociodemographic characteristics on the consequences of risk shifting.

Finally, the third chapter analyses the efficiency of managers through a model of Data Envelopment Analysis (DEA) that focuses on examining the efficiency of managers not only

from a purely financial point of view (ability to maximize the profitability obtained in the largest number of funds and assets under managed assuming the lowest possible risk) but also taking into account manager sociodemographic variables such as their experience, their gender, age, education, etc.

The lack of empirical studies that examine the consequences and implications of manager replacement, the consequences of risk shifting and managers' efficiency in less developed markets and with a financial literature and culture different from the United States leads me to examine these topics in the Spanish mutual fund industry.

The analyses carried out in the thesis can help to understand the effectiveness of some control mechanisms like manager turnover in other less developed markets. Additionally, the thesis reinforces prior studies that examine the performance consequences of risk shifting behavior through a holdings-based measure of risk shifting and introduces the important role of manager sociodemographic variables to detect the consequences of risk shifting. Finally, the thesis also evaluates managers' efficiency depending on sociodemographic characteristics to help management companies in their hiring and remuneration decisions. Hence, this thesis fills this gap detected in international literature.

Another reason that justifies the study of the Spanish mutual fund industry is is because it has been one of the most dynamic financial markets in Europe in recent decades. In addition, this market has some peculiar characteristics that deserve attention. The high number of mutual funds provokes that the average size of Spanish funds is much smaller than the average UK or US fund.[1] This aspect is the result of an excess mutual fund supply probably due to the sales force of banks and saving banks in Spain. Another peculiarity is the high degree of concentration because few management companies manage a high percentage

[1] In December 2016, management companies altogether managed 2 329 mutual funds with a market value of €235 billion.

of the industry. Concretely, the two biggest management companies account for almost 50% of the assets under management.[2]

[2] See, for example, Cambon and Losada (2014) and Golez and Marin (2015) for more details about the Spanish mutual fund industry.

CHAPTER 1:

Implications of manager replacement: evidence from the Spanish mutual fund industry

Summary

This chapter analyzes the financial consequences of manager replacement in a sample that includes all domestic and European equity funds in Spain. Specifically, 104 funds of the sample experience manager turnover over the period 1999-2009. The results show that that underperforming funds in the pre-replacement period experience a significant improvement in the excess returns and the performance after the manager change, an improvement that lasts over time for domestic equity funds. The analysis of the risk profile indicates that funds suffering a manager change do not show significantly different levels of risk before the replacement dates although they tend to show an increase in the level of total risk after the change. Finally, the pool-regression analysis of the investment flows confirms that manager changes tend to impact negatively on subsequent flows of those funds with manager turnover. In spite of this overall negative impact, the event-study approach captures that funds with previous negative performance obtain higher flows than the rest of the portfolios included in the same investment category after the manager change.

1.1 Introduction and literature review

In recent years, the financial literature has become increasingly interesting in understanding the behavior of mutual fund managers. Specifically, researchers, regulators and practitioners have become interesting in understanding the incentives that explain manager actions, its consequences on collective investment portfolios as well as the effectiveness of different control mechanisms. This increase of interest is due to the agency problems that may exist between managers and investors.

Specifically, some authors like Brown *et al*. (1996), Kempf and Ruenzi (2008) and Elton *et al*. (2010) focus their attention on manager behavior due to the portfolio competition during the year. They argue that managers analyze the performance of their portfolios in relation to their competitors in certain reference periods and change their level of risk based on their own interests, mainly personal compensation and career concerns. In spite of the intense debate about the existence of tournament behavior, only recently, the study of Huang *et al*. (2011) examines the consequences of risk shifting. These authors find that funds that increase risk perform worse than funds that keep stable risk levels over time, suggesting that risk shifting is either an indication of inferior ability or is motivated by agency issues in delegated money management.

Another strand of the literature has focused on the analysis of how the personal characteristics of fund managers influence on their behavior. Specifically, Chevalier and Ellison (1999a, 1999b) study the relationship between fund performance and manager replacement with manager age and education. Their findings suggest that older managers have worse performance than younger managers, which can be explained by career concerns. They also find that younger managers are more likely to be replaced if the fund's systematic or unsystematic risk deviates from the average in the industry. Additionally, other authors like Dwyer *et al*. (2002), Gottesman and Morey (2006) and

Watson and McNaughton (2007) also examine the relationship between manager characteristics such as education and gender and mutual fund performance.

Finally, some studies have investigated the organization of mutual and pension fund industries and the effectiveness of some control mechanism like manager replacement.[1] Denis and Denis (1995) study the effects of manager replacement in U.S. mutual funds. They conclude that forced resignations of top managers are preceded by large and significant declines in performance and followed by large improvements while normal retirements are followed by small increases in operating income. Similarly, Khorana (1996) also examines the relationship between manager replacement and their prior performance. He finds an inverse relationship between the probability of manager replacement and fund performance. Later, Khorana (2001) analyzes the performance changes around manager replacement dates, that is, fund performance in pre- and post-replacement periods. Specifically, the author reports substantial improvements after the replacement of poor performing managers along with significant deterioration in performance for the sample of overperforming funds in the pre-replacement period.

The aim of this chapter is to analyze the consequences of manager replacement in the Spanish mutual fund industry. The study firstly examines the performance consequences, that is, whether underperforming funds in the pre-replacement period are able to turn around their performance. Secondly, the study examines whether there are shifts in the risk profile of mutual funds across the pre- and post-replacement periods. Finally, the chapter analyzes the effectiveness of manager replacements by examining the relationship between these changes and the investment flows into the funds.

[1] Agrawal *et al*. (1999) indicate that studies about executive and manager replacement have emerged due to scandals of fraud in some companies.

The lack of empirical studies that examine the consequences and implications of manager replacement in markets outside the US leads me to examine this topic in the Spanish mutual fund industry. This analysis can help researchers and practitioners to understand the effectiveness of some control mechanisms like manager turnover in other less developed markets. Hence, this study allows filling this gap detected in international literature.

The analysis of the topic in the Spanish mutual fund industry, as previously explained in the motivation section, is relevant because this market has been one of the most dynamic financial markets in Europe in recent decades.[2] Additionally, this market has some peculiar characteristics that deserve attention. On the other hand, this chapter will help researchers and practitioners to understand the actions of Spanish mutual fund managers and compare them with those carried out in other markets.

The main contribution of this chapter is to aid in the understanding of the effectiveness of manager replacement as control mechanism in less developed markets since this knowledge is useful for the different agents involved in financial markets. Fund advisors who are compensated based on fund assets may be interested in knowing whether managerial replacement alters the pattern of investment flows in the post-replacement period. Similarly, investors may also want to know whether managerial replacement alters the future fund performance and the risk level. Finally, market regulators may want to examine the performance before and after the change to better understand the efficiency of the industry and to monitor mutual funds more efficiently.

Using a sample of 354 equity mutual funds, where 104 funds suffer manager replacement over the period 1999-2009, the study documents that underperforming funds in the pre-replacement period experience a significant improvement in the

[2] The assets under management in Spanish mutual funds have grown more than 25% in the last two decades.

performance that lasts over time in the case of domestic equity funds. The analysis of the risk profile documents that the level of risk assumed by funds that experience manager replacement does not differ significantly from the level of the remaining funds before the change. However, this analysis reports a statistically significant decrease in the level of total risk in the short-term just after the manager change, which can reflect a prudential management of new managers during their initial period as managers and a significant increase when long-term periods are considered. Finally, manager changes lead mutual funds with manager turnover to obtain lower investment flows than those received over the rest of their time life. However, funds with previous negative performance improve their investment flows compared to the remaining funds of the sample when comparing the flows to those obtained by the rest of the sample around the managerial turnover dates.

The remainder of the chapter is organized as follows. Section 1.2 describes the data sources and the sample selection procedure. Section 1.3 outlines the underlying hypotheses and the methodology used. Section 1.4 provides a discussion of the empirical results and Section 1.5 concludes.

1.2 Data

The empirical study of the consequences of manager replacement in the Spanish mutual fund industry mainly relies on two data sources. First, the official supervisor of the market, the *Spanish Securities Exchange Commission* (CNMV) provides information on fund returns, total net assets, investment objectives and other fund characteristics of Spanish mutual funds. CNMV provides a free of survivorship bias database that includes all the mutual funds commercialized in Spain. Specifically, this chapter focuses on actively managed funds that belong to the domestic and European equity investment

vocation using the CNMV categories to define the market segment in which a fund operates.

Second, the database includes hand-collected information on replaced fund managers' from Morningstar website which provides information on the manager's name and the date on which a manager assumed responsibility for the fund. Finally, the funds from CNMV database are matched to the funds in the Morningstar database using the ISIN code and the fund name.

The sample consists of 354 equity mutual funds: 173 domestic equity mutual funds and 181 European equity mutual funds. Morningstar website reports manager replacements in 104 funds of the sample, 57 in the domestic equity sample and 47 in the European equity sample. The sample period goes from June 1999 to December 2009. However, this study analyzes the manager replacements that occur from September 1999 because a minimum of information for the pre-replacement period is needed.

Table 1.1 reports some descriptive statistics for funds that have experienced manager replacement and for the remaining funds existing in the investment vocations analyzed over the period 1999-2009. The table shows that manager replacements are not evenly distributed over the calendar years examined. In fact, the changes are concentrated in 2009.[3] The table also shows that the average size of the funds that suffer manager replacement is bigger than the average size of the remaining funds. Similarly, the average number of investors of funds suffering manager replacement is higher than for the others funds in both samples (see, Panel A and Panel B). The Appendix 1.1 lists some additional information about those funds with manager replacement in the sample period. This table provides valuable information to know that manager changes occur in

[3] This concentration of manager replacements at the end of the sample period can be related, to some extent, to other restructuring processes of the Spanish mutual fund industry such as mergers, which have become common after the global financial crisis.

a wide variety of management companies. Therefore, manager turnovers are not concentrated in the largest or smallest management companies.

Table 1.1 - Distribution of mutual funds with manager replacement by investment objective and year

This table lists the sample of 104 mutual funds that have suffered a manager replacement over the period June 1999 to December 2009 as well as the other funds existing in each year. The table also reports the average fund assets in € million and the average number of investors for fund that has replaced the fund manager and for the other funds of the dataset. The information is reported separately for domestic equity mutual funds (Panel A) and for European equity mutual funds (Panel B).

Panel A: Domestic Equity funds						
	# Funds with manager replacement	**# of others Funds**	**Average TNA Funds with manager replacement**	**Average TNA other funds**	**Average # investors Funds with manager replacement**	**Average # investors other funds**
1999	-	-	-	-	-	-
2000	3	102	134	82	4,692	3,100
2001	-	-	-	-	-	-
2002	1	92	33	56	100	2,774
2003	2	100	74	39	1,338	2,773
2004	-	-	-	-	-	-
2005	1	108	72	78	3,063	3,014
2006	6	106	40	88	1,296	3,257
2007	5	108	183	89	7,324	2,886
2008	4	104	9	24	837	1,535
2009	35	41	34	22	2,446	1,301
Average			72	60	2,637	2,580
Panel B: European Equity funds						
1999	1	72	18	69	685	3,116
2000	-	-	-	-	-	-
2001	-	-	-	-	-	-
2002	-	-	-	-	-	-
2003	-	-	-	-	-	-
2004	-	-	-	-	-	-
2005	3	98	78	55	4,375	2,418
2006	1	104	13	71	1,624	2,824
2007	3	108	635	75	26,652	2,613
2008	3	104	73	53	4,457	2,163
2009	36	46	15	28	1,114	1,760
Average			139	59	6,485	2,482

To measure the return of mutual funds involved in manager replacements, daily net asset values are obtained from the CNMV dataset. Additionally, to evaluate the portfolio management and therefore, the value added by the managers before the charge of different fees and commercial costs, daily gross returns are calculated as follows:

$$(1+\mathrm{NR}_{\mathrm{it}}) = (1+\mathrm{GR}_{\mathrm{it}}) \cdot (1-\mathrm{f}_{\mathrm{it}}) \tag{1.1}$$

where NR_{it} is the net return obtained by mutual fund i in period t, GR_{it} is the gross return of mutual fund i in period t and f_{it} is the percentage of management and custodial fees charged by fund i in period t.

In addition, for the purpose of constructing objective-adjusted performance benchmarks, daily returns for the entire population of funds in each investment category analyzed are calculated. Finally, to estimate multifactor models of fund performance, daily returns on the Spanish value-weighted index and on the Fama-French factors from MSCI and returns on 1-day Treasury Bill Repos from Bank of Spain are obtained.

The chapter examines the implications and consequences of manager replacement not only in the long-term but also in the short-term. In spite of the availability of daily data, the study examines weekly data to avoid the noise attributable to high frequency data. Specifically, periods of 13, 52 and 104 weeks are considered to examine the consequences in the short-term period (3 months) and in the long-term period (12 and 24 months). Note that daily data is used only to calculate the total risk and to estimate the 1-factor model and 3-factor model in the short-term period to obtain robust parameters. With the analysis of these pre- and post-replacement periods, this study contributes to the literature since the majority of previous articles use monthly data and therefore only study the long-term financial consequences of manager replacement. Therefore, the findings of this chapter may shed more robust results than previous studies.

According to Khorana (2001), past performance of mutual funds can be seen as a reasonable proxy for the reason behind replacement. For that reason, the sample of 104 manager replacements is decomposed based on their objective-adjusted fund performance in the 24, 12 and 3 months preceding the replacement.[4] Funds having negative objective-adjusted performance are placed in the negative performance sample (NP) and those exhibiting positive objective-adjusted performance are placed in the positive performance sample (PP). Note that the analyses are performed for the whole sample and then split in both groups to examine the consequences of manager replacement according to the performance prior to the replacement. Hence, the split can be seen as a robustness test to examine the differences between both groups.

1.3 Hypotheses and methodology

1.3.1 Performance

Question 1: Does the performance of a mutual fund improve after the manager replacement?

The impact of manager replacement in the performance obtained by those mutual funds that have suffered a manager change is analyzed. Hence, if poor performance in the pre-replacement period is attributable to managerial abilities, one would expect an improvement in post-replacement performance for the NP sample. On the other hand, in the PP sample, the ability to maintain or improve the performance depends on the skills of the new manager. If the new manager is successful, he/she will generate persistence in fund performance while if the post-replacement performance decreases it will be caused by inferior management skills of the new manager.

[4] Objective-adjusted performance measures are computed as the difference between a fund's performance and the average performance of all funds in that investment objective. It is interesting to make this distinction, since a fund may improve after the change, but the industry average do better than the fund, and therefore the concrete mutual fund has not improved as much as previously thought.

The return consequences are examined through the use of the following excess return measures:

– Gross excess return over the market: the MSCI Spain/Emu index is used as the market benchmark depending on the investment category studied.

– Net Excess return over the market: the MSCI Spain/Emu index is used as the market benchmark depending on the investment category studied.

The analysis of the performance is carried out through the Jensen (1968) one-factor model and the Fama and French (1993) three-factor model. Specifically, the models are as follows:

$$r_{it} - r_{ft} = \alpha_i^1 + \beta_i^{Mkt}(r_{Mkt,t} - r_{ft}) + \varepsilon_{it} \qquad (1.2)$$

$$r_{it} - r_{ft} = \alpha_i^3 + \beta_i^{Mkt}(r_{Mkt,t} - r_{ft}) + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{it} \qquad (1.3)$$

where, r_{it} is the return of fund i in period t, $r_{f,t}$ is the return of the risk-free rate (one-day Spanish Treasury Bill Repos) in period t, $r_{Mkt,t} - r_{ft}$ is the excess return of the market in period t. SMB and HML are the returns of factor-mimicking portfolios. In particular, the size factor, SMB, is calculated as the return difference between small and large Spanish capitalization stocks, and the value factor, HML, is calculated as the return difference between high and low book-to-market Spanish stocks.

Additionally, the pre- and post-replacement changes in objective-adjusted performance measures are also examined to take into account not only those mutual funds with manager change but also the other funds in the investment category. As previously said, these objective-adjusted performance measures are defined as the performance of a given fund less the corresponding performance of the benchmark portfolio composed of the other funds within the same investment objective. Hence, these measures implicitly adjust for sector, industry, or style-specific factors that may exogenously affect all funds in the same investment category. The different measures

used are computed for periods of 24, 12 and three months surrounding the date of manager replacement.

1.3.2 Risk Level

Question 2: Does the risk level of a mutual fund change after the manager replacement?

In this section, the impact of manager replacement on the level of risk assumed by mutual funds is examined. In this sense, the tournament behavior theory (see, e.g. Brown *et al*., 1996) suggests that, in an attempt to maximize their expected compensation, underperforming fund managers tend to increase the overall volatility of their portfolios. By contrast, Busse (2001) and Taylor (2003) also justify that funds that are ranked above the median fund in their category increase total risk more than below-median funds, especially when stocks offer high returns and low volatility.

The risk level of mutual funds is measured through the calculation of the total risk and the systematic risk. Specifically, the following risk measures are used:

- Total risk: calculated as the standard deviation of a fund's raw returns (σ_{it})
- Systematic risk: calculated through the Jensen (1968) one-factor model and the Fama and French (1993) three-factor model.

Objective-adjusted risk metrics are also computed considering periods of 24, 12 and 3 months surrounding the date of manager replacement.

1.3.3 Investment Flows

Question 3: Do the investment flows of a mutual fund improve after the manager replacement?

This section studies the pattern of investment flows in the pre- and post-replacement periods. This analysis is interesting for several reasons. First, it allows researchers to detect whether the new manager is able to capture more investment flows than previously and therefore, the manager is able to improve the market share of the mutual fund. Those funds with bad performance in the pre-replacement are expected to have difficulties to attract more inflows than the remaining funds and therefore, increase their market share. Khorana (2001) documents that the replacement of the poorly performing fund managers is significantly preceded by lower asset flows. Hence, it is critical for the investment advisors of poorly performing funds to generate improvements in post-replacement performance. Second, the analysis of the relation between performance and investment flows for the overperforming sample provides evidence on market participants' beliefs with regard to funds ability to exhibit performance persistence.

In contrast to previous studies, the magnitude of investment flows in the pre- and post-replacement periods is measured using data of both fund assets and number of investors. The only use of money flows might provide misleading information in an industry where investors are quite heterogeneous.[5] Furthermore, management companies are not only interested in attracting money flows but also investors flows due to the spillover effects and the benefits that new investors can provide to the financial group. Therefore, the analysis of investor flows can add relevant information to examine the investment behavior of individual investors. Consequently, this chapter is one of the few studies that work with money flows as well as investors flows (see, e.g. Guercio

[5] This is the case in the Spanish mutual fund market, where around 98% of investors are retail investors and the remaining investors manage approximately a 25% of the industry in terms of money (see, e.g. Vicente *et al*. 2011).

and Tkac, 2002; Vicente *et al*., 2011 and Andreu *et al*., 2012). The following investment flow measures are used:

- Percentage money flow: defined as the monthly change in total net assets (TNA) net of fund returns during the month.

$$PMF_{i,t} = \frac{TNA_{it} - TNA_{it-1} \cdot (1 + r_{i,t}) - MGTNA_{it}}{TNA_{i,t-1}} \tag{1.4}$$

where PMF_{it} is the net percentage money flow in fund i in period t, TNA_{it} is the total net assets in fund i in period t, TNA_{it-1} is the total net assets in fund i in period $t-1$, $r_{i,t}$ is the return in fund i in period t and $MGTNA_{it}$ indicates the increase in total net assets of fund i due to mergers during month t, if applicable.

- Percentage investor flow: defined as the monthly change in the number of investors.

$$PIF_{i,t} = \frac{I_{it} - I_{i,t-1} - MGI_{it}}{I_{i,t-1}} \tag{1.5}$$

where PIF_{it} is the net percentage investor flows in fund i in period t, I_{it} is the number of investors in fund i in period t, I_{it-1} is the number of investors in fund i in period $t-1$ and MGI_{it} indicates the increase in the number of investors of fund i due to mergers during month t, if applicable.

The investment flow patterns before and after the manager replacement are examined through two different methodologies. First, in order to be consistent with previous analyses, the event-study methodology is considered. This analysis allows to consider not only the investment flow patterns around different event-windows of those mutual funds that have suffered a manager change but also the difference in the flows attracted by funds with manager change in relation to the remaining funds of the sample since objective-adjusted flow measures are calculated as the difference between a funds' investment flow and the average flow on all funds in that investment category.

The investment flow measures are computed for periods of 24, 12 and 3 months surrounding the date of manager replacement. Additionally, since it is well-known that investment flows are highly influenced by past performance (see, e.g., Sirri and Tufano, 1998 and Cooper *et al*., 2005, among others), an event-study analysis splitting the sample into the NP sample and the PP sample is carried out to control for the previous performance of mutual funds.

Second, the investment flow patterns before and after the manager replacement is analyzed through a pool regression since this method allows to control for past performance from a quantitative perspective instead of the qualitative perspective considered in the event-study approach (this method only split the sample into positive and negative performance subsamples while the pool regression takes into account the magnitude of the performance). Moreover, this methodology also allows to control for other financial variables such as risk level, fund size, etc. Therefore, the pool regression takes into account the entire time period of life of each mutual fund as opposed to the event-study method which only considers some event windows around the manager change dates. Additionally, this method only considers those mutual funds that have suffered a manager changed as opposed to the event-study methodology which also takes into account the remaining funds. Specifically, the following regression is carried out:

$$NETFLOW_{i,t+j} = f[\text{Objective Flow}_{t+j}; \text{Fund Performance}_{i,t-h}; Risk_{i,t-h}; Log(Size)_{i,t}; \text{Post-replacement indicator}_{i,t+j}] \quad (1.6)$$

where $Netflow_{i,t+j}$ refers to percentage money flows and percentage investor flows depending on the analysis carried out of fund i in period $t+j$ (j=3, 12 and 24 months). $Objective\ Flow_{t+j}$ is included to control for the effect of the overall flow in the investment category in the period $t+j$. $Fund\ Performance_{i,t-h}$ is included to capture the

effect of lagged fund performance (h=3 and 12 months) on subsequent investment flows. Performance is measured based on alphas from one-factor and three-factor models depending on the regression. $Risk_{i,t-h}$: is included to capture the effect of the total risk level on subsequent investment flows. Risk is measured as the standard deviation of gross returns. $Log(Size)_{i,t}$: is a control variable that captures the size of the fund. It considers Log assets and Log number of Investors when percentage money flows and percentage investor flows are studied, respectively. *Post-replacement* $indicator_{i,t+j}$: is a dummy that captures differences in the performance-flow relationship between the pre- and post-replacement periods. The indicator equals 1 for *j* months after the manager change and zero otherwise.

1.4 Results

1.4.1 Performance changes surrounding manager replacement

Table 1.2 shows the average fund performance measures for the four-year period surrounding the replacement (Columns 2-7) and the performance changes across various event windows around the change (Columns 8-13). In relation to the changes, the table firstly compares pre-replacement and post-replacement performance considering periods with identical time range (Columns 8-10). Secondly, the table shows the results considering wider post-replacement periods than pre-replacement periods (Columns 11-13) to examine the consequences in the long-term. The table is split into two panels. Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity mutual funds. Excess return is measured by both the gross and the net excess return over the market while performance is measured by the alphas of single- and three-factor models. These four measures are also calculated in terms of objective-adjusted measures (see section 1.3).

The performance analysis in pre-replacement periods does not provide any significant result while the analysis of the post-replacement periods shows, for domestic equity funds, that both the excess returns and the alphas of funds with manager change are significantly above to the measures of the remaining funds in the long-term analysis. Therefore, it seems that manager change has a positive effect but only in the long run.

The analysis of performance changes around manager replacement dates that take into account equal periods of time before and after the replacement (columns 8 to 10) only reports a significant improvement in the short-term performance of those managers with managerial turnover in the case of European equity funds (Panel B).

On the other hand, assorted results are obtained when analyzing wider post-replacement periods (columns 11-13). Panel A shows that the alphas of domestic equity funds improve after the manager replacement, being these values significantly higher than the average if the turnover is carried out in the short-term (see e.g. the analysis -3m to +12m or -3m to +24m) while Panel B shows that manager changes cause a significant decrease in the excess returns of those funds that have undergone a manager change. Furthermore, adjusted measures indicate that funds with manager change evolve significantly worse than the average. Note that these assorted results can be explained due to the different reasons behind manager replacements. Hence, the split of the dataset into the NP and the PP sample should provide more precise results. These results are provided in Table 1.3.

Table 1.2 – Performance measures surrounding manager replacement

This table shows the average performance of funds for the four-year period surrounding the manager replacement (columns 2-7) as well as the changes in these measures across various event windows around the managerial turnover (columns 8-13). The table is split into two panels: Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity funds. Returns are measured by the Gross excess return over the market and the Net excess return over the market while performance is measured by the alphas of the single- and multifactor models. These four measures are also calculated in terms of objective-adjusted measures. Objective-adjusted measures are computed as the difference between a funds' performance and the average performance of all funds in that investment objective. ***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

Panel A: Domestic equity funds	**-24 m**	**-12 m**	**-3 m**	**+3 m**	**+12 m**	**+24 m**	**-3 to +3**	**-12 to +12**	**-24 to +24**	**-3 to +12**	**-3 to +24**	**-12 to +24**
Gross Excess Market Return												
Funds with Manager Replacement	0.0007	0.0002	-0.0012	-0.0015	-0.0001	0.0003	-0.0003	-0.0003	-0.0004	0.0003	0.0000	-0.0003
Obj. adjusted measure Funds with Manager Replacement	0.0006	0.0002	0.0002	0.0002	0.0003	0.0006***	0.0000	0.0000	0.0000	0.0003	0.0002	0.0000
Net Excess Market Return												
Funds with Manager Replacement	0.0004	-0.0002	-0.0015	-0.0018	-0.0005	0.0000	-0.0003	-0.0003	-0.0004	0.0003	0.0000	-0.0003
Obj.Adjusted measure Funds with Manager Replacement	0.0006	0.0002	0.0002	0.0002	0.0003	0.0006**	0.0000	0.0000	0.0000	0.0003	0.0003	0.0001
α^1												
Funds with Manager Replacement	0.0005	-0.0001	0.0000	0.0000	0.0006	0.0008	0.0000	0.0006	0.0002	0.0007	0.0007	0.0005
Obj. Adjusted measure Funds with Manager Replacement	0.0002	0.0000	0.0000	0.0001	0.0007	0.0009*	0.0000	0.0007	0.0007	0.0007*	0.0009**	0.0009
α^3												
Funds with Manager Replacement	0.0002	0.0002	-0.0001	-0.0001	0.0002	0.0006	0.0000	0.0000	0.0005	0.0002	0.0006**	0.0005
Obj. Adjusted measure Funds with Manager Replacement	0.0002	0.0000	0.0000	0.0000	0.0003	0.0006**	0.0000	0.0003	0.0004	0.0004	0.0006***	0.0005
Panel B: European equity funds												
Gross Excess Market Return												
Funds with Manager Replacement	0.0005	0.0006	-0.0012	-0.0002	0.0004	0.0000	0.0010	-0.0002	-0.0005	-0.0013	-0.0021*	-0.0008
Obj.-Adjusted measure Funds with Manager Replacement	0.0008	0.0010***	0.0001	0.0001	0.0003	0.0000	0.0001	-0.0007	-0.0008	-0.0016*	-0.0025*	-0.0011
Net Excess Market Return												
Funds with Manager Replacement	0.0001	0.0003	-0.0016	-0.0006	0.0001	-0.0004	0.0010	-0.0002	-0.0004	-0.0013	-0.0021*	-0.0007
Obj.-Adjusted measure Funds with Manager Replacement	0.0008	0.0009	0.0000	0.0001	0.0002	0.0000	0.0001	-0.0007	-0.0007	-0.0016*	-0.0025*	-0.0011
α^1												
Funds with Manager Replacement	0.0008	0.0008	-0.0001	0.0001	0.0004	-0.0004	0.0002**	-0.0004	-0.0012	0.0001	-0.0008	-0.0015
Obj. Adjusted measure Funds with Manager Replacement	0.0009	0.0011	0.0000	0.0000	0.0004	-0.0003	0.0000	-0.0007	-0.0012	0.0000	-0.0008	-0.0016
α^3												
Funds with Manager Replacement	0.0007	0.0007	0.0000	0.0001	0.0005	0.0001	0.0002**	-0.0002	-0.0006	0.0004	-0.0002	-0.0008
Obj. Adjusted measure Funds with Manager Replacement	0.0008	0.0009	0.0000	0.0000	0.0005	0.0002	0.0000	-0.0004	-0.0006	0.0003	-0.0001	-0.0009

Similarly to Table 1.2, Table 1.3 reports the average performance measures of funds for the four-year period surrounding the replacement and the changes across various event windows around the change date divided into those funds classified as negative performance sample (NP) and positive performance sample (PP). This split is based on the objective-adjusted performance measures in the pre-replacement period. Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity mutual funds.

Panel A shows that funds exhibiting positive performance in the pre-replacement period still perform better than underperforming funds after the manager change. This difference tends to gain statistical significance over time. For example, managers in the NP sample of domestic equity funds exhibit an objective-adjusted gross excess return over the market of -0.0005 in +3 months while the PP sample exhibit a figure of 0.0010, being the difference of 0.0015 statistically significant at 1%. However, the superior results of the PP sample compared to the NP sample in the post-replacement period is only observed when using the excess returns in the European equity fund dataset (Panel B).

Table 1.3 - Detailed analysis of performance around manager replacement: Negative performance and positive performance

This table shows the average performance of funds for the four-year period surrounding the manager replacement as well as the changes in these measures across various events windows around the managerial turnover. The table is split into two panels: Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity funds. Returns are measured by the Gross excess return over the market and the Net excess return over the market while performance is measured by the alpha of the single-and multifactor models. These four measures are also calculated in terms of objective-adjusted measures. Objective-adjusted measures are computed as the difference between a funds' performance and the average performance on all funds in that investment objective. These objective-adjusted measures are used to split the sample into NP sample -if they were negative in the pre-replacement- and PP sample -if they were positive in the pre-replacement.***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

Panel A: Domestic equity funds	**-24 m**	**-12 m**	**-3 m**	**+3 m**	**+12 m**	**+24 m**	**-3 to +3**	**-12 to +12**	**-24 to +24**	**-3 to +12**	**-3 to +24**	**-12 to +24**
Gross Excess Market Return												
Funds with Manager Replacement NP	-0.0003	-0.0009	-0.0023	-0.0019	-0.0001	0.0000	0.0004	0.0007	0.0004	0.0021***	0.0011**	0.0008**
Obj-Adjusted measure Funds with Manager Replacement NP	-0.0004	-0.0007	-0.0012	-0.0005	0.0002	0.0003	0.0006	0.0010***	0.0007***	0.0018***	0.0011***	0.0009***
Funds with Manager Replacement PP	0.0033	0.0015	0.0000	-0.0011	-0.0001	0.0011	-0.0011*	-0.0017	-0.0022	-0.0019	-0.0028	-0.0029
Obj-Adjusted measure Funds with Manager Replacement PP	0.0030	0.0015	0.0016	0.0010	0.0003	0.0012	-0.0006	-0.0012	-0.0017	-0.0017	-0.0024	-0.0024
Funds with Manager Replacement PP-NP	0.0036*	0.0024**	0.0023***	0.0008	0.0000	0.0011						
Obj-Adjusted measure Funds with Manager Replacement PP-NP	0.0034*	0.0022**	0.0028***	0.0015***	0.0001	0.0009*						
Net Excess Market Return												
Funds with Manager Replacement NP	-0.0007	-0.0010	-0.0027	-0.0023	-0.0006	-0.0003	0.0004	0.0004	0.0003	0.0016***	0.0011**	0.0004*
Obj-Adjusted measure Funds with Manager Replacement NP	-0.0004	-0.0006	-0.0011	-0.0005	0.0002	0.0003	0.0006	0.0007**	0.0007***	0.0014***	0.0012***	0.0007***
Funds with Manager Replacement PP	0.0029	0.0024	-0.0003	-0.0013	-0.0003	0.0008	-0.0011	-0.0026	-0.0021	-0.0023	-0.0027	-0.0029
Obj-Adjusted measure Funds with Manager Replacement PP	0.0030	0.0027	0.0017	0.0010	0.0005	0.0012	-0.0006	-0.0022	-0.0017	-0.0022	-0.0024	-0.0024
Funds with Manager Replacement PP-NP	0.0036*	0.0034*	0.0024***	0.0010	0.0003	0.0011*						
Obj-Adjusted measure Funds with Manager Replacement PP-NP	0.0034*	0.0033**	0.0028***	0.0016***	0.0004	0.0009*						
α^1												
Funds with Manager Replacement NP	-0.0002	-0.0005	-0.0002	0.0000	0.0002	-0.0001	0.0002**	0.0007*	0.0001	0.0005	0.0001	0.0002
Obj. Adjusted measure Funds with Manager Replacement NP	-0.0005	-0.0006	-0.0002	0.0000	0.0002	0.0003	0.0003***	0.0008***	0.0009***	0.0005*	0.0005***	0.0009***
Funds with Manager Replacement PP	0.0023	0.0006	0.0001	-0.0001	0.0012	0.0029	-0.0002	0.0006	0.0006	0.0023	0.0036**	0.0022
Obj. Adjusted measure Funds with Manager Replacement PP	0.0022	0.0010	0.0002	0.0001	0.0014	0.0025	-0.0001	0.0004	0.0003	0.0018	0.0029**	0.0014
Funds with Manager Replacement PP-NP	0.0025***	0.0011**	0.0003***	-0.0001	0.0010	0.0030*						
Obj. Adjusted measure Funds with Manager Replacement PP-NP	0.0027***	0.0016***	0.0004***	0.0001	0.0012	0.0022						
α^3												
Funds with Manager Replacement NP	-0.0004	-0.0004	-0.0002	0.0000	-0.0003	0.0002	0.0002***	0.0000	0.0006**	0.0002	0.0002	0.0006**
Obj. Adjusted measure Funds with Manager Replacement NP	-0.0004	-0.0005	-0.0002	0.0000	-0.0001	0.0002	0.0002***	0.0004**	0.0007***	0.0001	0.0003**	0.0007***
Funds with Manager Replacement PP	0.0016	0.0010	0.0001	-0.0001	0.0010	0.0016	-0.0002**	0.0000	0.0000	0.0021***	0.0017***	0.0005
Obj. Adjusted measure Funds with Manager Replacement PP	0.0017	0.0009	0.0002	0.0000	0.0011	0.0016	-0.0001	0.0001	-0.0002	0.0019**	0.0014**	0.0000
Funds with Manager Replacement PP-NP	0.0020***	0.0014***	0.0003***	-0.0001	0.0013**	0.0014***						
Obj. Adjusted measure Funds with Manager Replacement PP-NP	0.0021***	0.0014***	0.0004***	0.0000	0.0011*	0.0013*						

(Continued)

Panel B: European equity funds	-24 m	-12 m	-3 m	+3 m	+12 m	+24 m	-3 to +3	-12 to +12	-24 to +24	-3 to +12	-3 to +24	-12 to +24
Gross Excess Market Return												
Funds with Manager Replacement NP	-0.0006	-0.0006	-0.0032	-0.0010	0.0006	-0.0001	0.0022***	0.0012	0.0005	-	-	0.0011
Obj-Adjusted measure Funds with Manager Replacement NP	-0.0002	-0.0001	-0.0019	-0.0006	-0.0004	0.0001	0.0013***	-0.0003	0.0003	-	-	0.0003
Funds with Manager Replacement PP	0.0019	0.0008	0.0017	0.0009	0.0004	0.0002	-0.0008	-0.0004	-0.0017	-0.0020*	-0.0039	-0.0019
Obj-Adjusted measure Funds with Manager Replacement PP	0.0022	0.0011	0.0029	0.0012	0.0003	0.0000	-0.0017*	-0.0008	-0.0022	-0.0021*	-0.0044	-0.0025
Funds with Manager Replacement PP-NP	0.0025	0.0014	0.0049***	0.0019***	-0.0002	0.0003						
Obj-Adjusted measure Funds with Manager Replacement PP-NP	0.0024	0.0012	0.0048***	0.0018**	0.0007	-0.0001						
Net Excess Market Return												
Funds with Manager Replacement NP	-0.0010	-0.0011	-0.0036	-0.0014	0.0001	-0.0005	0.0022***	0.0012	0.0005	-	-	0.0011
Obj-Adjusted measure Funds with Manager Replacement NP	-0.0003	-0.0002	-0.0019	-0.0006	-0.0005	0.0000	0.0013***	-0.0003	0.0003	-	-	0.0003
Funds with Manager Replacement PP	0.0016	0.0004	0.0014	0.0006	0.0000	-0.0001	-0.0008	-0.0003	-0.0017	-0.0020*	-0.0039	-0.0020
Obj-Adjusted measure Funds with Manager Replacement PP	0.0022	0.0011	0.0029	0.0011	0.0003	0.0001	-0.0017*	-0.0008	-0.0021	-0.0021*	-0.0044	-0.0024
Funds with Manager Replacement PP-NP	0.0026	0.0015	0.0050***	0.0020***	-0.0001	0.0004						
Obj-Adjusted measure Funds with Manager Replacement PP-NP	0.0025	0.0013	0.0048***	0.0017**	0.0008	0.0001						
α^1												
Funds with Manager Replacement NP	-0.0010	-0.0011	-0.0004	0.0001	0.0011	0.0001	0.0005***	0.0022	0.0011*	-	0.0002	0.0012
Obj. Adjusted measure Funds with Manager Replacement NP	-0.0009	-0.0009	-0.0003	0.0000	0.0009	0.0002	0.0003***	0.0018	0.0011**	-	0.0004	0.0010
Funds with Manager Replacement PP	0.0032	0.0013	0.0002	0.0002	0.0002	-0.0010	0.0000	-0.0011	-0.0042**	-0.0004	-0.0022*	-0.0043
Obj. Adjusted measure Funds with Manager Replacement PP	0.0032	0.0016	0.0004	0.0001	0.0002	-0.0010	-0.0002	-0.0014	-0.0043**	-0.0005	-0.0023*	-0.0045*
Funds with Manager Replacement PP-NP	0.0042***	0.0024	0.0006***	0.0002	-0.0009	-0.0011						
Obj. Adjusted measure Funds with Manager Replacement PP-NP	0.0041**	0.0025	0.0007***	0.0002	-0.0007	-0.0012						
α^3												
Funds with Manager Replacement NP	-0.0009	-0.0005	-0.0003	0.0003	-0.0002	0.0000	0.0006***	0.0004	0.0009	-	-	0.0003
Obj. Adjusted measure Funds with Manager Replacement NP	-0.0008	-0.0005	-0.0003	0.0002	0.0000	0.0002	0.0005***	0.0005	0.0010	-	-	0.0005
Funds with Manager Replacement PP	0.0019	0.0010	0.0001	0.0001	0.0007	0.0002	-0.0001	-0.0003	-0.0018	0.0005	-0.0003	-0.0017
Obj. Adjusted measure Funds with Manager Replacement PP	0.0020	0.0013	0.0002	0.0000	0.0007	0.0002	-0.0002***	-0.0006	-0.0018	0.0004	-0.0004	-0.0020
Funds with Manager Replacement PP-NP	0.0028*	0.0015	0.0004***	-0.0002*	0.0009	0.0002						
Obj. Adjusted measure Funds with Manager Replacement PP-NP	0.0028*	0.0018	0.0005***	-0.0001	0.0007	0.0000						

The analysis of performance changes around manager replacement dates shows that both domestic and European equity funds that belong to the NP sample tend to improve their performance after the manager replacement, exhibiting better results than those reported by the investment vocation analyzed. Note, however, that this improvement is generally shown in the short-term for European equity funds while it last over time for domestic equity funds. On the other hand, the results for the PP sample tend to exhibit a statistically significant deterioration in the short-term performance (-3m to +3m) for both samples. However, the consequences in the long-term are different depending on the investment category examined. It seems that it takes some time for new managers in the PP sample of domestic equity funds to improve their results while the erosion in the performance of European equity funds seems to last over time.

These results are consistent with Denis and Denis (1995) who document that forced resignations (NP proxy) are followed by large improvements in post-replacement performance. Hence, the results of this study confirm the idea that control mechanisms are effective for underperforming funds.

1.4.2 Risk changes surrounding manager replacement

Table 1.4 shows the average risk measures for the four-year period surrounding the manager replacement (Columns 2-7) and the changes across various event windows around the replacement (Columns 8-13). The table is split into two panels. Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity mutual funds. Risk is measured by the standard deviation of gross excess return over the market and by the beta of the single- and multifactor models. These three measures are also calculated in terms of objective-adjusted measures.

Panels A and B of Table 1.4 show that mutual funds that have suffered a manager replacement do not show risk levels (total and systematic risk) statistically different from the remaining funds before the changes. However, this table reveals that the replacement of the manager has led to a statistically significant decrease in the total risk assumed by the funds in the short-term which can reflect a prudential management of new managers during their initial period as manager of the funds and to a statistically significant increase in the long-term in an attempt to achieve higher levels of performance when managers are more established in their new position.

Next, Table 1.5 reports the results distinguishing between the NP and the PP samples. The table shows that funds included in the NP sample tend to present higher levels of systematic risk in the pre-replacement period than funds in the PP sample (see Panels A and B). However, the study fails to find significant changes in the systematic risk after the manager replacement. Similarly, the analysis of the total risk does not provide conclusive results.

Table 1.4 - Risk measures surrounding manager replacement

This table shows the average risk level of funds for the four-year period surrounding the manager replacement (columns 2-7) as well as the changes in these measures across various event windows around the managerial turnover (columns 8-13). The table is split into two panels: Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity funds. Risk is measured by the standard deviation of Gross excess return over the market and systematic risk (beta of the single- and multifactor models). These three measures are also calculated in terms of objective-adjusted measures. Objective-adjusted measures are computed as the difference between a funds' level of risk and the average risk level of all funds in that investment objective. ***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

Panel A: Domestic equity funds	-24 m	-12 m	-3 m	+3 m	+12 m	+24 m	-3 to +3	-12 to +12	-24 to +24	-3 to +12	-3 to +24	-12 to +24
Total Risk (standard deviation)												
Funds with Manager Replacement	0.0165	0.0230	0.0149	0.0122	0.0259	0.0252	-0.0027*	0.0179***	0.0195***	-0.0001	0.0096***	0.0081**
Obj. Adjusted Funds with Manager Replacement	-0.0014	0.0005	0.0001	0.0030	0.0006	-0.0010	0.0029	0.0006	0.0003	0.0010	0.0010	0.0002
Systematic Risk (Jensen)												
Funds with Manager Replacement	0.8069	0.8700	0.8519	0.8593	0.8386	0.8029	0.0074	-0.0314	-0.0040	-0.0219	-0.0342	0.0000
Obj. Adjusted Funds with Manager Replacement	-0.0814	-0.0210	-0.0008	0.0007	-0.0480	-0.0927	0.0015	-0.0269	-0.0113	-0.0159	-0.0053	-0.0078
Systematic Risk (Fama & French)												
Funds with Manager Replacement	0.8986	0.9486	0.9116	0.9331	0.9126	0.8887	0.0216	-0.0360	-0.0099	-0.0273	0.0090	0.0012
Obj. Adjusted Funds with Manager Replacement	-0.0318	0.0162	-0.0071	0.0012	-0.0234	-0.0623	0.0084	-0.0396	-0.0304	-0.0229	-0.0129	-0.0306
Panel B: European equity funds	**-24 m**	**-12 m**	**-3 m**	**+3 m**	**+12 m**	**+24 m**	**-3 to +3**	**-12 to +12**	**-24 to +24**	**-3 to +12**	**-3 to +24**	**-12 to +24**
Total Risk (standard deviation)												
Funds with Manager Replacement	0.0172	0.0168	0.0180	0.0127	0.0281	0.0257	-0.0053***	0.0113*	0.0085*	0.0186***	0.0197***	0.0114**
Obj. Adjusted Funds with Manager Replacement	0.0012	0.0003	0.0007	0.0005	0.0005	-0.0006	-0.0002	0.0002	-0.0018	-0.0002	-0.0011	-0.0004
Systematic Risk (Jensen)												
Funds with Manager Replacement	0.9045	0.9297	0.9045	0.9346	0.8983	0.8743	-0.0301	-0.0315	-0.0302	-0.0615	-0.0606	-0.0327
Obj. Adjusted Funds with Manager Replacement	-0.0179	-0.0061	0.0194	0.0169	-0.0301	-0.0570	-0.0024	-0.0240	-0.0390	-0.0555	-0.0609	-0.0211
Systematic Risk (Fama & French)												
Funds with Manager Replacement	0.9162	0.9378	0.8800	0.8914	0.8814	0.8969	0.0114	-0.0564	-0.0193	-0.0816	-0.0544	-0.0268
Obj. Adjusted Funds with Manager Replacement	-0.0043	0.0068	0.0170	0.0081	-0.0325	-0.0187	-0.0089	-0.0392	-0.0144	-0.0713	-0.0493	-0.0037

Table 1.5 - Detailed analysis of risk measures around manager replacement: Negative performance and positive performance

This table shows the average risk of funds for the four-year period surrounding the manager replacement as well as the changes in these measures across various events windows around the managerial turnover. The table is split into two panels: Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity funds. Risk is measured by the standard deviation of Gross excess return over the market and systematic risk (beta of the single- and multifactor models). These three measures are also calculated in terms of objective-adjusted measures. Objective-adjusted measures are computed as the difference between a funds' level of risk and the average risk level on all funds in that investment objective. ***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

Panel A: Domestic equity funds	-24 m	-12 m	-3 m	+3 m	+12 m	+24 m	-3 to +3	-12 to +12	-24 to +24	-3 to +12	-3 to +24	-12 to +24
Total Risk (standard deviation)												
Funds with Manager Replacement NP	0.0170	0.0263	0.0144	0.0118	0.0284	0.0295	-0.0026	0.0021	0.0125***	0.0196**	0.0224***	0.0074
Obj. Adjusted Funds with Manager Replacement NP	0.0010	0.0016	-0.0003	0.0006	0.0017	0.0000	0.0009	0.0001*	-0.0010	0.0021	0.0001	-0.0014
Funds with Manager Replacement PP	0.0153	0.0187	0.0154	0.0126	0.0226	0.0147	-0.0028	0.0040	-0.0006	0.0144	0.0082**	-0.0022
Obj. Adjusted Funds with Manager Replacement PP	-0.0075	-0.0011	0.0005	0.0003	-0.0009	-0.0036	-0.0003	0.0002	0.0039	0.0003	0.0010	0.0028
Funds with Manager Replacement PP-NP	-0.0017	-0.0076	0.0010	0.0008	-0.0058	- 0.0148***						
Obj. Adjusted Funds with Manager Replacement PP-NP	-0.0085	-0.0028	0.0009	-0.0004	-0.0026	-0.0036						
Systematic Risk (Jensen)												
Funds with Manager Replacement NP	0.9405	0.8936	0.8639	0.8521	0.8564	0.8914	-0.0117	-0.0372	-0.0490	-0.0399	-0.0470	-0.0313
Obj. Adjusted Funds with Manager Replacement NP	0.0421	-0.0111	0.0026	-0.0054	-0.0511	-0.0129	-0.0080	-0.0400	-0.0550	-0.0390	-0.0491	-0.0364
Funds with Manager Replacement PP	0.4731	0.8315	0.8438	0.8641	0.8097	0.5815	0.0203	-0.0218	0.1085	0.0014	0.1150	0.0767
Obj. Adjusted Funds with Manager Replacement PP	-0.3900	-0.0372	-0.0032	0.0048	-0.0428	-0.2921	0.0079	-0.0057	0.0979	0.0257	0.0996	0.0524
Funds with Manager Replacement PP-NP	-0.4674**	-0.0621	-0.0201	0.0120	-0.0467	-0.3099						
Obj. Adjusted Funds with Manager Replacement PP-NP	-0.4321**	-0.0261	-0.0058	0.0102	0.0083	-0.2792						
Systematic Risk (Fama & French)												
Funds with Manager Replacement NP	0.9667	0.9801	0.9293	0.9146	0.9360	0.9393	-0.0147	-0.0441	-0.0274	-0.0645	-0.0297	-0.0252
Obj. Adjusted Funds with Manager Replacement NP	0.0364	0.0532	-0.0018	-0.0106	0.0004	-0.0199	-0.0088	-0.0528	-0.0563*	-0.0532	-0.0531	-0.0624
Funds with Manager Replacement PP	0.7284	0.8976	0.8967	0.9487	0.8747	0.7621	0.0520	-0.0228	0.0337	0.0813	0.1333	-0.0134
Obj. Adjusted Funds with Manager Replacement PP	-0.2024	-0.0439	-0.0116	0.0112	-0.0621	-0.1683	0.0228	-0.0182	0.0341	0.0602	0.1094	-0.0357
Funds with Manager Replacement PP-NP	-0.2383***	-0.0825	-0.0326	0.0341	-0.0613	-0.1772						
Obj. Adjusted Funds with Manager Replacement PP-NP	-0.2388***	-0.0971	-0.0098	0.0218	-0.0625	-0.1484						

(Continued)

Panel B: European equity funds	-24 m	-12 m	-3 m	+3 m	+12 m	+24 m	-3 to +3	-12 to +12	-24 to +24	-3 to +12	-3 to +24	-12 to +24
Total Risk (standard deviation)												
Funds with Manager Replacement NP	0.0189	0.0211	0.0192	0.0133	0.0458	0.0266	-0.0059***	0.0247	0.0077	-	-	0.0284
Obj. Adjusted Funds with Manager Replacement NP	0.0034	0.0025	-0.0003	0.0001	0.0076	0.0026	0.0004	0.0051	-0.0008	-	-	0.0053
Funds with Manager Replacement PP	0.0149	0.0163	0.0163	0.0118	0.0261	0.0245	-0.0045*	0.0098	0.0096	0.0142**	-0.0075*	0.0104*
Obj. Adjusted Funds with Manager Replacement PP	-0.0017	0.0001	0.0022	0.0013	-0.0003	-0.0049	-0.0010	-0.0003	-0.0032	-0.0002	-0.0046	-0.0026
Funds with Manager Replacement PP-NP	-0.0040	-0.0048	-0.0029	-0.0015	-0.0197	-0.0021						
Obj. Adjusted Funds with Manager Replacement PP-NP	-0.0051**	-0.0024	0.0026*	0.0012*	-0.0079**	-0.0075*						
Systematic Risk (Jensen)												
Funds with Manager Replacement NP	1.1118	1.1673	0.8406	0.8233	1.0155	0.9816	-0.0194	-0.1518	-0.1301	-	-0.2124	-0.1647
Obj. Adjusted Funds with Manager Replacement NP	0.1863	0.2308	0.0268	0.0219	0.0708	0.0553	-0.0049	-0.1601	-0.1310	-	-0.2264	-0.1576
Funds with Manager Replacement PP	0.6280	0.8704	0.9268	0.9182	0.8690	0.7311	-0.0085	-0.0014	0.1030	-0.0306	0.0036	0.0589
Obj. Adjusted Funds with Manager Replacement PP	-0.2902	-0.0653	0.0109	0.0113	-0.0554	-0.2067	0.0004	0.0099	0.0835	-0.0174	0.0047	0.0675
Funds with Manager Replacement PP-NP	-0.4838***	-0.2969	0.0862	0.0949	-0.1465	-0.2505*						
Obj. Adjusted Funds with Manager Replacement PP-NP	-0.4765***	-0.2961*	-0.0159	-0.0106	-0.1262	-0.262**						
Systematic Risk (Fama & French)												
Funds with Manager Replacement NP	1.1213	1.1470	0.7889	0.8163	0.8869	0.9522	0.0274	-0.2601	-0.1692	-	-	-0.2280
Obj. Adjusted Funds with Manager Replacement NP	0.2009	0.1893	-0.0651	-0.0586	-0.0327	0.0347	0.0065	-0.2220	-0.1662	-	-	-0.1981
Funds with Manager Replacement PP	0.7623	0.8855	0.9317	0.9340	0.8800	0.8555	0.0023	-0.0055	0.0932	-0.0587	-0.0209	0.0612
Obj. Adjusted Funds with Manager Replacement PP	-0.1582	-0.0389	0.0635	0.0459	-0.0324	-0.0588	-0.0176	0.0065	0.0994	-0.0445	-0.0134	0.0834
Funds with Manager Replacement PP-NP	-0.359**	-0.2615*	0.1428***	0.1177***	-0.0069	-0.0967						
Obj. Adjusted Funds with Manager Replacement PP-NP	-0.3591**	-0.2282	0.1286***	0.1045**	0.0003	-0.0935						

1.4.3 Investment flow changes surrounding manager replacement

Table 1.6 shows the analysis of investment flows around manager replacement dates through the event-study methodology. The table is organized as previous tables of the chapter. Columns 2-4 show the investment flows received by the funds before the manager change. However, according to the purposes of the study, this section focuses the attention on the post-replacement flows (Columns 5-7) and on the investment flow changes over the event-windows considered (Columns 8-13).

A positive relationship between performance in the pre-replacement period and investment flows after the change is observed. That is, outperforming funds before the manager change (PP sample) obtain subsequently higher investment flows. However, this positive relationship is only statistically significant for Spanish domestic equity funds (Panel A) for both money and investor flows. Note, however, that this finding can be just the result of the performance-flow relationship previously documented in financial literature (see, e.g. Sirri and Tufano, 1998) regardless of the existence of manager replacement.

Additionally, the analysis of the patterns of investment flows around manager replacement dates shows that the manager change has led to a significant improvement in the money flows attracted by the funds belonging to the NP sample compared to those obtained by the investment vocation although the money flows attracted are still negative. This result is observed in both domestic and European equity funds, especially in the long-term analysis, and can be related to the significant performance improvement in the NP sample after the manager change since recent past performance is the major determinant of investment flows. This finding is really relevant from a management perspective due to its financial implications for the fund family given that

the higher the investment flows are the higher the incomes of the management company.

When investors' flows are examined the findings are less conclusive. Only the results for the domestic mutual funds (Panel A) are quite similar to those obtained with money flows. Hence, it seems that institutional investors are more sensitive to manager replacements than individual investors, a relevant finding since they are probably better informed about these control mechanisms of management companies.

Given that previous findings can be biased since they only considers the performance in a qualitative perspective (Negative or Positive but not its level), Table 1.7 shows the relationship between investment flows and managerial replacement after controlling for lagged fund performance, risk level, fund size and contemporaneous flows in the investment objective using a pool regression. Nevertheless, it is important to note the differences between this methodology and the event-study, since here, only those mutual funds with manager replacement during their entire time period are examined and therefore, the dataset is different in both analyses. As previously explained, an indicator variable is used to distinguish between pre- and post-replacement flows. Hence, Table 1.7 shows the results of equation 1.6 for both, domestic equity funds (Panel A) and European equity funds (Panel B).

Similar to Sirri and Tufano (1998) and Khorana (2001), Table 1.7 reports that contemporaneous flows in the investment objective and lagged fund performance measured from one- and three-factor models have a positive and statistically significant impact to investment flows (money and investor flows) while higher past return volatility have a negative and usually significant impact. In addition, smaller funds in terms of money and number of investors tend to attract larger net percentage flows.

Table 1.6 - Detailed analysis of flow measures around manager replacement: Negative performance and positive performance

This table shows the average investment flows for the four-year period surrounding the manager replacement as well as the changes in these measures across various events windows around the managerial turnover. The table is split into two panels: Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity funds. The analysis of the investment flows is carried out considering both money flows and investor flows. These two measures are also calculated in terms of objective-adjusted measures. Objective-adjusted measures are computed as the difference between a funds' flow and the average flows on all funds in that investment objective. The table splits the results into the Negative Performance sample (NP) and Positive Performance sample (PP). ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Domestic equity funds	**-24 m**	**-12 m**	**-3 m**	**+3 m**	**+12 m**	**+24 m**	**-3 to +3**	**-12 to**	**-24 to**	**-3 to +12**	**-3 to +24**	**-12 to**
Asset Flows												
Funds with Manager Replacement NP	-0.0188	-0.0198	-0.0281	0.0003	-0.0112	-0.0224	0.0284	0.0086	-0.0036	0.0305	0.0343	0.0014
Objective-Adjusted measure Funds with Manager Replacement NP	-0.0237	-0.0122	-0.0100	0.0039	0.0005	-0.0022	0.0138	0.0127	0.0215**	0.0360	0.0432	0.0193**
Funds with Manager Replacement PP	0.0470	0.0148	-0.0150	0.0020	-0.0008	0.0291	0.0170	-0.0156	-0.0180	0.0059	-0.0055	-0.0384
Objective-Adjusted measure Funds with Manager Replacement PP	0.0408	0.0267	0.0054	0.0028	0.0011	0.0265	-0.0026	-0.0256	-0.0142	-0.0017	-0.0223	-0.0479
Funds with Manager Replacement PP-NP	0.0658*	0.0347	0.0131	0.0017	0.0104	0.0515**						
Objective-Adjusted measure Funds with Manager Replacement PP-NP	0.0644*	0.0389*	0.0154	-0.0011	0.0006	0.0287**						
Investor Flows												
Funds with Manager Replacement NP	-0.0087	-0.0187	-0.0297	-0.0163	-0.0133	-0.0226	0.0134	0.0053	-0.0139**	0.0204	0.0464	-0.0113
Objective-Adjusted measure Funds with Manager Replacement NP	-0.0176	-0.0139	-0.0165	-0.0148	-0.0044	-0.0072	0.0017	0.0095	0.0104*	0.0248	0.0557*	0.0058
Funds with Manager Replacement PP	0.0584	0.0259	-0.0155	-0.0021	0.0074	0.0494	0.0133	-0.0185	-0.0090	0.0193	0.0018	-0.0455
Objective-Adjusted measure Funds with Manager Replacement PP	0.0518	0.0331	-0.0002	-0.0004	0.0034	0.0442	-0.0002	-0.0297	-0.0076	0.0130	-0.0121	-0.0575
Funds with Manager Replacement PP-NP	0.0671**	0.0445*	0.0142	0.0142	0.0207	0.0720**						
Objective-Adjusted measure Funds with Manager Replacement PP-NP	0.0694**	0.0470**	0.0163	0.0144*	0.0078	0.0514**						
Panel B: European equity funds	**-24 m**	**-12 m**	**-3 m**	**+3 m**	**+12 m**	**+24 m**	**-3 to +3**	**-12 to**	**-24 to**	**-3 to +12**	**-3 to +24**	**-12 to**
Asset Flows												
Funds with Manager Replacement NP	0.0056	-0.0126	0.0005	-0.0196	-0.0226	0.0019	-0.0201	-0.0100	-0.0038	-	-	0.0229**
Objective-Adjusted measure Funds with Manager Replacement NP	-0.0025	-0.0145	0.0165	-0.0207	-0.0355	-0.0006	-0.0371	-0.0210	0.0020	-	-	0.0108**
Funds with Manager Replacement PP	0.0304	0.0167	-0.0236	0.0042	0.0059	-0.0020	0.0278	-0.0108	-0.0325	0.0247	0.0060	-0.0481
Objective-Adjusted measure Funds with Manager Replacement PP	0.0222	0.0174	-0.0086	0.0028	0.0192	0.0082	0.0114	0.0018	-0.0140	0.0144	0.0185	-0.0280
Funds with Manager Replacement PP-NP	0.0248	0.0293	-0.0241	0.0238	0.0285	-0.0039						
Objective-Adjusted measure Funds with Manager Replacement PP-NP	0.0248	0.0319	-0.0251	0.0235	0.0547	0.4050						
Investor Flows												
Funds with Manager Replacement NP	-0.0090	-0.0166	0.0001	-0.0093	-0.0084	-0.0207	-0.0095	0.0082	-0.0117	-	-	0.0046
Objective-Adjusted measure Funds with Manager Replacement NP	-0.0153	-0.0161	0.0159	-0.0097	-0.0256	-0.0255	-0.0257**	-0.0096	-0.0102	-	-	-0.0117
Funds with Manager Replacement PP	0.0447	0.0146	-0.0175	-0.0022	-0.0057	-0.0088	0.0153	-0.0202	-0.0535	0.0078	-0.0063	-0.0465
Objective-Adjusted measure Funds with Manager Replacement PP	0.0365	0.0129	-0.0033	-0.0042	0.0027	-0.0033	-0.0009	-0.0102	-0.0398	-0.0017	0.0024	-0.0313
Funds with Manager Replacement PP-NP	0.0537	0.0311	-0.0176	0.0071	0.0027	0.0119						
Objective-Adjusted measure Funds with Manager Replacement PP-NP	0.0518	0.0290	-0.0192	0.0055	0.0283	0.0222						

Table 1.7 –Analysis of flow measures around manager replacement using pool regressions

This table shows the results of pool OLS regressions of the percentage money flow (PMF) and the percentage investor flow (PIF) on: objective flows, fund performance, volatility of the fund's return, size of the fund and an indicator variable to distinguish between the pre- and post-replacement periods. The table is split into two panels: Panel A reports the figures for domestic equity mutual funds while Panel B reports the figures for European equity funds. Columns 2-5 show the results when j and h=3, columns 6-9 show the results when j=3 and h=12, columns 10-13 show the results when j=12 and h=3 and columns 14-17 shows the results when j and h=12. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively considering White standard errors since the panel data do not show significant fund or time-fixed effects.

	+3 -3				+3 -12				+12 -3				+12 -12			
Panel A	**PMF**		**PIF**		**PMF**		**PIF**		**PMF**		**PIF**		**PMF**		**PIF**	
Intercept	0.0832***	0.0830***	0.0362***	0.0363***	0.0771***	0.0772***	0.0261***	0.0294***	0.0638***	0.0399***	0.0386***	0.0333***	0.0816***	0.0823***	0.0261***	0.0291***
Objective Flow	0.8347***	0.8890***	0.8180***	0.8671***	0.8223***	0.9348***	0.7842***	0.8869***	0.9056***	0.9134***	0.8716***	0.8792***	0.8743***	0.9405***	0.8212***	0.8890***
Risk	0.0888	-0.0815	-0.0552	-0.1496**	0.1873***	-0.069	0.1140***	-0.0773*	-0.4189***	-0.3622***	-0.2365***	-0.0755	0.0451	-0.1175**	0.0929***	-0.0409
Log(Assets)	-0.0183***	-0.0179***			-0.0178***	-0.0164***			-0.0126***	-0.0078***			-0.0178***	-0.0169***		
Log(Investors)			-0.0113***	-0.0111***			-0.0094***	-0.0089***			-0.0110***	-0.0099***			-0.0089***	-0.0086***
α^1	17.8186***		12.4607***		8.6187***		6.7687***		-3.0755***		1.4067***		6.4827***		5.5211***	
α^3		13.7037***		10.4331***		7.9438***		5.9926***		9.8196***		7.1907***		7.2533***		5.7283***
Post	-0.0038	-0.0024	-0.0075***	-0.0066**	-0.0027	-0.0043	-0.0070**	-0.0085***	-0.0001	0.0007	-0.0043***	-0.0052***	-0.0006	-0.0039***	-0.0039***	-0.0067***
R^2	18.43%	17.58%	17.49%	17.06%	18.96%	18.09%	17.80%	16.97%	27.07%	27.06%	25.12%	25.51%	36.16%	36.31%	29.28%	28.85%
Panel B																
Intercept	0.0510***	0.0502***	0.0241***	0.0230***	0.0293***	0.0299***	0.0133***	0.0134***	0.0444***	0.0442***	0.0185***	0.0181***	0.0343***	0.0349***	0.0143***	0.0145***
Objective Flow	1.0060***	1.0139***	0.9163***	0.9268***	0.9946***	0.9890***	0.9355***	0.9318***	1.0358***	1.0428***	0.9804***	0.9936***	1.0078***	1.0091***	0.9702***	0.9764***
Risk	-0.3129**	-0.1996	-0.3193***	-0.1749	-0.1276*	-0.1244*	-0.1430**	-0.1366**	-0.1396*	-0.1025	-0.2420***	-0.1839**	0.0437	0.0432	0.0016	-0.0016
Log(Assets)	-0.0099***	-0.0100***			-0.0054***	-0.0055***			-0.0087***	-0.0088***			-0.0073***	-0.0074***		
Log(Investors)			-0.0067***	-0.0069***			-0.0037***	-0.0038***			-0.0052***	-0.0053***			-0.0051***	-0.0051***
α^1	7.9307***		9.9557***		1.9279***		2.2796***		3.4559***		4.8858***		1.4686***		1.4202***	
α^3		1.9486		2.267		2.9084***		2.8076***		1.5548		1.5496		1.3495***		0.7581**
Post	-0.0069	-0.0068	0.0006	0.0006	-0.0070*	-0.0071*	0.001	0.0012	-0.0036**	-0.0030**	0.0006	0.0014	-0.0037***	-0.0037***	0.0002	0.0004
R^2	21.29%	20.84%	22.05%	21.06%	19.43%	19.61%	20.68%	20.75%	33.93%	33.75%	31.78%	31.19%	32.62%	32.48%	30.79%	30.37%

More importantly, this table shows that investment flows to a fund are negatively related to manager replacement. The post-replacement indicator is negative and significant when investor flows are analyzed in domestic equity funds (Panel A) and when money flows are analyzed in European equity funds (Panel B).

1.5 Conclusions

The chapter analyzes the impact of manager replacement on the subsequent performance, the risk level and the investment flows of Spanish equity mutual funds. Concretely, a total of 104 manager turnovers have been examined over the 1999-2009 period.

The study documents that those manager replacements carried out in underperforming funds lead to significant improvements in the performance that lasts over time in the case of domestic equity funds. Hence, the monitoring mechanism of managerial replacement is effective for those funds with bad records. On the contrary, those funds with positive performance in the pre-replacement period tend to suffer deterioration in the performance that last over time in case of European equity funds but that is only observed in the short-term for domestic equity funds. Therefore, it seems that it takes some time for new managers in the PP sample to improve their results.

The analysis of the risk level assumed by mutual funds around manager replacement dates shows that these funds do not report risk levels significantly different from those reported by funds without manager replacement in the pre-replacement period. However, as a consequence of the manager change, the total risk level tends to increase in the long-term probably in an attempt to achieve higher levels of performance.

Finally, the analysis of the investment flow patterns shows that manager changes, in general, have a negative impact on subsequent investment flows when considering the entire

time period of each mutual fund. However, taking into account not only those funds with manager replacement but all the mutual funds in the investment category, an improvement in the money flows attracted by mutual funds with negative performance in the pre-replacement period is observed. Hence, the results of this investigation are of great interest for investment advisors and mutual fund unit-holders because they demonstrate that the control mechanism of manager replacement have positive consequences for underperforming funds not only in a developed market like US but also in growing markets like Spain.

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APPENDIX 1.1 - List of funds with manager replacement by investment objective and year

Table A1.1 - List of funds with manager replacement by investment objective and year.
This table lists the sample of 104 mutual funds that have experienced a manager replacement over the period June 1999 to December 2009. The table reports the fund family, the fund Id as well as the inception date of the fund and the manager replacement date organized by manager replacement date. The information is reported separately for European equity mutual funds (Panel A) and for domestic equity mutual funds (Panel B).

Panel A: European Equity funds

Fund Family	Fund	Inception	Manager Replacement
CEP GESTORA	1525	16/07/1998	sept-99
GESBANKINTER	489	30/05/1994	jan-05
GES FIBANC	1637	05/11/1998	jul-05
GESBANKINTER	59	01/04/1991	aug-05
RENTA 4 GESTORA	1134	13/08/1997	sept-06
BESTINVER GESTION	377	13/01/1993	jan-07
BANKINTER GESTION DE ACTIVOS	3167	02/05/2005	jan-07
BBVA GESTION	973	14/05/1997	nov-07
SANTANDER ASSET MANAGEMENT	26	01/04/1991	feb-08
SANTANDER ASSET MANAGEMENT	1058	20/06/1997	feb-08
AVIVA GESTION SGIIC	3034	04/11/2004	mar-08
INVERCAIXA GESTION, S.A., SGIIC	2522	02/04/2002	jan-09
INVERCAIXA GESTION, S.A., SGIIC	3244	04/08/2005	jan-09
CREDIT AGRICOLE ASSET MANAGEMENT FONDOS, SGIIC,	41	01/04/1991	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	262	01/08/1991	apr-09
PRIVAT BANK PATRIMONIO S.A. S.G.I.I.C.	296	13/01/1992	apr-09
MAPFRE INVERSION DOS, SGIIC, S.A.	532	22/12/1994	apr-09
INVERCAIXA GESTION, S.A., SGIIC	562	27/03/1995	apr-09
BANKPYME, S.A., S.G.I.I.C.	922	04/04/1997	apr-09
GESMADRID, S.A., S.G.I.I.C.	1137	13/08/1997	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	1243	21/11/1997	apr-09
GESDUERO, S.G.I.I.C., S.A.	1414	27/04/1998	apr-09
POPULAR GESTION, S.A., S.G.I.I.C.	1452	01/06/1998	apr-09
GESTORA NAVARRA DE INVERSIONES, S.A. ´GESNAVARRA´,	1497	26/06/1998	apr-09
CAJA ESPAÑA FONDOS, S.A., S.G.I.I.C.	1502	02/07/1998	apr-09
BANKPYME, S.A., S.G.I.I.C.	1554	07/08/1998	apr-09
GESINTER, S.G.I.I.C., S.A.	1560	13/08/1998	apr-09
EUROAGENTES GESTION, S.A., S.G.I.I.C.	1593	25/09/1998	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	1615	19/10/1998	apr-09
POPULAR GESTION, S.A., S.G.I.I.C.	1665	04/12/1998	apr-09
SEGUROS BILBAO FONDOS, S.G.I.I.C., S.A.	1687	30/12/1998	apr-09
GESCOOPERATIVO, S.A., S.G.I.I.C.	1822	21/05/1999	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	1871	16/07/1999	apr-09
ESPIRITO SANTO GESTION, S.A., SGIIC	2008	28/01/2000	apr-09
GVC GAESCO GESTIÓN, SGIIC, S.A.	2040	13/01/2000	apr-09
G.I.I.C. FINECO, S.A., S.G.I.I.C.	2050	13/03/2000	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	2095	28/04/2000	apr-09
SANTANDER ASSET MANAGEMENT	2268	01/12/2000	apr-09
GESTIFONSA, S.G.I.I.C., S.A.	2327	15/03/2001	apr-09
B.MADRID GESTION DE ACTIVOS, SGIIC, S.A.	2978	17/08/2004	apr-09
BANSABADELL INVERSION, S.A., S.G.I.I.C.	3000	02/09/2004	apr-09
BBK GESTION, S.A., S.G.I.I.C.	3221	17/06/2005	apr-09
CONSULNOR GESTION, S.G.I.I.C., S.A	3857	20/07/2007	apr-09
GESMADRID, S.A., S.G.I.I.C.	3861	13/07/2007	apr-09
BANSABADELL INVERSION, S.A., S.G.I.I.C.	4045	18/07/2008	apr-09
CAJASTUR GESTION, S.G.I.I.C., S.A.	1234	21/11/1997	jul-09
GESIURIS, S.A., S.G.I.I.C.	2671	28/01/2003	aug-09

Table A1.1 Continued

Panel B: Domestic Equity funds

Fund Family	Fund id	Inception Date	Manager Replacement Date
AB GESTION FONDOS	164	01/04/1991	jan-00
GESMADRID, S.A., S.G.I.I.C.	1131	13/08/1997	jan-00
DB GESTION	477	21/04/1994	sept-00
INVERSEGUROS GESTION	787	01/12/1996	jan-02
BESTINVER GESTION	377	13/01/1993	mar-03
BESTINVER GESTION	502	29/06/1994	mar-03
METAGESTION	104	01/04/1991	jun-05
DWS INVESTMENTS SGIIC	477	21/04/1994	jan-06
GESBANKINTER	1641	11/11/1998	jan-06
AVIVA GESTION SGIIC	2379	05/10/2001	jan-06
AVIVA GESTION SGIIC	3033	04/11/2004	jan-06
RENTA 4 GESTORA	428	12/11/1993	sept-06
CREDIT SUISSE GESTION	1270	12/12/1999	oct-06
BBVA GESTION	131	01/04/1991	jan-07
BANKINTER GESTION DE ACTIVOS	1000	01/06/1997	jan-07
LLOYDS INVESTMENT	538	12/01/1995	jan-07
GESMADRID, S.A., S.G.I.I.C.	186	01/04/1991	mar-07
AHORRO CORPORACION GESTION	475	07/04/1994	jul-07
INVERCAIXA GESTION SGIIC	1878	21/07/1999	oct-08
INVERCAIXA GESTION SGIIC	2833	14/08/2003	oct-08
INVERCAIXA GESTION SGIIC	3351	04/01/2006	oct-08
INTERDIN SGIIC	3868	06/08/2007	oct-08
BBVA ASSET MANAGEMENT, S.A., SGIIC	131	01/04/1991	jan-09
SANTANDER ASSET MANAGEMENT, S.A., SGIIC	1581	10/09/1998	jan-09
INVERCAIXA GESTION SGIIC	2523	04/02/2002	jan-09
INVERCAIXA GESTION SGIIC	2549	08/03/2002	jan-09
SANTANDER ASSET MANAGEMENT, S.A., SGIIC	58	01/04/1991	apr-09
SEGUROS BILBAO FONDOS, S.G.I.I.C., S.A.	134	01/04/1991	apr-09
POPULAR GESTION, S.A., S.G.I.I.C.	136	01/04/1991	apr-09
GESCONSULT, S.A., S.G.I.I.C.	183	01/04/1991	apr-09
SANTANDER ASSET MANAGEMENT, S.A., SGIIC	228	01/04/1991	apr-09
GESCONSULT, S.A., S.G.I.I.C.	336	26/06/1992	apr-09
POPULAR GESTION, S.A., S.G.I.I.C.	351	24/09/1992	apr-09
MAPFRE INVERSION DOS, SGIIC, S.A.	381	18/01/1993	apr-09
GVC GAESCO GESTIÓN, SGIIC, S.A.	487	03/05/1994	apr-09
SANTANDER ASSET MANAGEMENT, S.A., SGIIC	506	18/07/1994	apr-09
CAJA LABORAL GESTION, S.G.I.I.C., S.A.	511	28/07/1994	apr-09
IBERCAJA GESTION, SGIIC, S.A.	539	12/01/1995	apr-09
BBK GESTION, S.A., S.G.I.I.C.	621	07/03/1996	apr-09
SANTANDER ASSET MANAGEMENT, S.A., SGIIC	702	26/09/1996	apr-09
GESNAVARRA´, S.G.I.I.C.	941	24/04/1997	apr-09
CAJA ESPAÑA FONDOS, S.A., S.G.I.I.C.	959	08/05/1997	apr-09
GESMADRID, S.A., S.G.I.I.C.	1235	21/11/1997	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	1239	21/11/1997	apr-09
BANCAJA FONDOS, S.G.I.I.C., S.A.	1528	22/07/1998	apr-09
MARCH GESTION DE FONDOS, S.G.I.I.C., S.A.	1579	09/09/1998	apr-09
ALLIANZ GESTION, S.A., S.G.I.I.C.	1557	07/08/1998	apr-09
GESTIFONSA, S.G.I.I.C., S.A.	1678	23/12/1998	apr-09
GESPASTOR, S.A., S.G.I.I.C.	1706	22/01/1999	apr-09
ESPIRITO SANTO GESTION, S.A., SGIIC	1786	15/04/1999	apr-09
POPULAR GESTION, S.A., S.G.I.I.C.	2348	20/04/2001	apr-09
BANSABADELL INVERSION, S.A., S.G.I.I.C.	2430	12/07/2001	apr-09
BANSABADELL INVERSION, S.A., S.G.I.I.C.	2572	23/05/2002	apr-09
GESIURIS, S.A., S.G.I.I.C.	2688	19/02/2003	apr-09
GESDUERO, S.G.I.I.C., S.A.	2989	27/07/2004	apr-09
CAJA INGENIEROS GESTION, S.G.I.I.C., S.A.	3231	02/08/2002	apr-09
CAJASTUR GESTION, S.G.I.I.C., S.A.	989	21/05/1997	jul-09

CHAPTER 2:

RISK SHIFTING CONSEQUENCES DEPENDING ON MANAGER CHARACTERISTICS

Summary

This chapter investigates the performance consequences of the risk shifting behavior shown by domestic equity mutual funds through the analysis of monthly portfolio holdings. The objective of the study is to assess the implications of risk shifting for mutual fund investors. Specifically, the chapter studies the performance consequences of different mechanisms of risk shifting such as the change in the composition between equity and cash holdings and the change of the systematic or idiosyncratic risk within the equity positions. The findings suggest that funds that increase their risk level obtain significantly better performance than funds with stable or reduced risk levels. Additionally, the chapter examines whether the performance consequences of risk shifting depends on fund manager characteristics. Manager gender, education and level of specialization are revealed as important variables to differentiate the performance consequences of risk shifting.

2.1 Introduction and literature review

The financial literature has deeply analyzed the causes and incentives of mutual fund managers to change risk since the seminal paper of Brown *et al*. (1996). These authors found evidence that portfolio managers increase the volatility of their portfolio in the second half of the year when they underperform in the first half. The incentive to shift risk is the disproportionately large amount of money flows into top performing funds compared to the outflows of poorly performing funds. The researchers argue that this asymmetry creates a tournament in which the winner is compensated by management fees earned on the assets acquired; managers of poorly performing funds can increase their chances of winning the tournament by increasing their portfolio volatility. If these managers perform well, they win more than they could lose if they perform poorly.[1] Similarly, Taylor (2003) also suggests that the optimal response of a fund manager to the fund's interim performance is an adjustment of its risk taking, because this maximizes the fund's probability of achieving a top position at the end of the year.

Later, other studies also highlight the important role of compensation incentives in explaining risk taking and risk shifting behavior. Specifically, Kempf *et al*. (2009) examine the influence of employment risk and compensation incentives on risk taking. The researchers find that, when employment risk is more important than compensation incentives, fund managers with a poor midyear performance tend to decrease risk relative to leading managers to prevent potential job loss. However, if employment risk is low, compensation incentives become more relevant and fund managers with a poor midyear performance increase risk to match the midyear winners. Similarly, Massa and Patgiri (2009) also test how incentives affect performance and risk taking in the US mutual fund industry. They show that contractual

[1] Later, Chevalier and Ellison (1997) and Sirri and Tufano (1998), among others, also demonstrate that fund investors tend to chase past performance investing in portfolios with good records but do not penalize poor performance equally.

incentives play an important role in increasing the risk taking and performance of mutual funds. The higher performance is due not only to the higher risk of the fund strategies but also to an improvement in fund management.

More recently, Lee *et al*. (2016) also argue that the compensation contracts of portfolio managers can be as important as the response of flows to past performance to determine risk shifting behavior, because the vast majority of US portfolio managers have a contract with variable compensation based on the mutual fund's performance relative to their benchmark.[2] However, these contracts are asymmetric; therefore, the manager is not penalized if the fund underperforms the benchmark. Therefore, portfolio managers have incentives to shift the volatility of the fund to maximize the value of their compensation. Additionally, fund managers can change risk to impress fund investors (see, e.g. Chevalier and Ellison, 1997; Sias, 2007; and Huang *et al*., 2011) or to manipulate taxes.

Overall, previous studies tend to hypothesize that risk shifting behavior is harmful to investors without focusing on its performance consequences. However, risk shifting behavior can be driven by very different reasons; therefore, the consequences can also be different. Obviously, risk shifting is undesirable for financial investors whether this behavior is motivated by the trades of unskilled fund managers or agency-prone managers who trade to increase their personal compensation. However, risk shifting can also be the result of trades of skilled managers who trade to take advantage of their stock selection and/or market timing abilities. In this case, risk shifting behavior would be desirable for fund investors, because they would benefit from superior performance. In fact, there is evidence that more active fund managers have superior investment abilities (see, e.g. Kacperczyk *et al*., 2005; Cremers and Petajisto, 2009 and Fama and French, 2010).

[2] Ma *et al*. (2016) investigates portfolio manager compensation in the US mutual fund industry.

The objective of this chapter is twofold. First, the objective is to examine the performance consequences of the risk shifting behavior shown by Spanish domestic equity mutual funds through the analysis of monthly portfolio holdings to assess the implications to fund investors. The prior literature has only focused on analyzing the existence of risk shifting or tournament behavior through risk measures mainly based on fund returns (see, e.g., Daniel and Wermers, 2000). Therefore, it is important to extend previous evidence to investigate the performance consequences of risk shifting behavior using a holdings-based measure of risk; only the recent paper of Huang *et al*. (2011) addresses this issue. The second aim is to detect whether performance consequences are the same or different depending on the mechanisms of risk shifting used, because the portfolio risk level can shift due to the change in the composition between equity and cash holdings or by changing the systematic or idiosyncratic risk within the equity positions. Finally, this study differs from Huang *et al*. (2011) because the performance consequences of risk shifting are analyzed not only based on the mechanisms used by managers but also depending on fund manager characteristics such as age, gender, tenure, and education.[3]

As opposed to the findings obtained in the US market, the findings show that funds that increase risk tend to perform better than funds that reduce or maintain stable risk levels. Hence, risk shifting appears to be an indicator of skilled fund managers adjusting their portfolio composition to take advantage of investment skills. This finding is robust using different performance measures and several risk shifting proxies or mechanisms. Therefore, all mechanisms of risk shifting are important. Finally, the main finding of the paper is also robust when examining the performance consequences of risk shifting depending on manager characteristics. Specifically, the results provide evidence that, although increasing the risk

[3] The financial literature has previously investigated the impact of these characteristics on fund performance and the level of risk. However, there are no studies examining the consequences of risk shifting depending on them.

level tends to always provide better performance than stable or decreasing risk levels, the decision of increasing risk is better when it is made by a female, specialist or more educated manager.

The study contributes to several strands of the financial literature. First, the study reinforces prior studies that examine the performance consequences of risk shifting behavior through a holdings-based measure of risk shifting. This study provides a more powerful test of the performance consequences by using monthly portfolio holdings and the daily return data of the portfolios, which can provide more robust results than the previous paper by Huang *et al*. (2011) analyzing semiannual or quarterly holdings, as well as monthly returns. Second, as far as I am concerned, this is the first paper outside the US market that analyzes the performance consequences of risk shifting. Moreover, this paper is the first analyzing the performance consequences of risk shifting depending on the sociodemographic characteristics of fund managers.

The remainder of the chapter is organized as follows. Section 2.2 introduces the holdings-based measure of risk shifting and describes the methodology used. Section 2.3 describes the data. Section 2.4 documents the main findings obtained in the study and Section 2.5 concludes.

2.2 Methodology: The Risk Shifting measure

2.2.1 Portfolio Holdings Returns and Volatility

Mutual fund managers can change the risk level of their portfolio by holding assets with different risk characteristics or by changing the asset allocation of the portfolio. These two different strategies also allow fund managers to time the market through an appropriate decision of the securities that must be overweighted/underweighted in the first case or by an

appropriate asset mix (proportion in equities vs proportion in fixed-income and cash) in the second case. The financial literature has traditionally focused on managers' motivation to shift risk by comparing the standard deviations of fund returns over two non-overlapping time periods (see, e.g., Brown *et al*., 1996; Busse, 2001 and Elton *et al*., 2003). Certain exceptions are the studies by Chevalier and Ellison (1997) and Kempf *et al*. (2009) who use mutual fund holding data to compute changes in risk levels. However, as stated by Huang *et al*. (2011), the comparison of risk levels between two non-overlapping time periods may capture exogenous changes in market conditions in addition to manager intentional changes in portfolio risk.[4] Therefore, in accordance with Huang *et al*. (2011), the risk shifting behavior of mutual funds is calculated through the analysis of their portfolio holdings using identical time periods to estimate the realized volatility and the current holdings volatility. Consequently, the risk shifting measure will be able to capture the risk changes induced by changes in the portfolio composition and will be unbiased by changes in market conditions.

To calculate the current holdings volatility, the fund holdings return over time is calculated. The return of the fund portfolio holdings represents the return of a buy-and-hold strategy, because it captures the return that the fund would have achieved if the holdings of the disclosed portfolios were maintained for the time period analyzed. The holdings returns can be calculated using portfolio weights or using the number of securities held (see, e.g., Meier and Schaumburg, 2006).

This study uses the number of securities held in the last trading day of the month for which the portfolio is disclosed instead of the portfolio weights, because portfolio weights capture both the active trading and the passive changes that occur because of stock price

[4] Kempf *et al*. (2009) find that, in bear markets, employment risk is more important than the compensation incentives for fund managers. Hence, fund managers with poor midyear performance tend to decrease the risk level to prevent the potential job loss. However, in bull markets where the employment risk is low, managers with poor midyear performance tend to increase the risk to match the midyear winners.

changes. Hence, this study differentiates from Huang *et al*. (2011), because these authors use constant portfolio weights to measure the current holdings volatility. The approach proposed here is more accurate, since the portfolio weights of the assets are time-varying depending on the manager decision to overweight/underweight a security and depending on the returns of the assets.

The database shows, for each reported portfolio, the money invested in each asset in the last trading day of the month. Therefore, setting that day as *t=0*, the number of securities held in each asset by each fund is calculated. This calculation is only valid on the reporting day *t=0*. The prices of securities vary over time; therefore, the number of securities is also changeable. Using the daily price information of the securities, the money invested in each security by each mutual fund from reporting day *t=0* to day *t= -62* is calculated to consider the days of a given quarter and have sufficient observations to perform the estimation.[5] Once the money invested in each asset is calculated from *t=0* to *t= -62*, the daily total assets under management (AUM) of mutual fund *p* in day *t* is calculated as follows:

$$AUM^{H}_{p,t} = \sum_{j=1}^{n} AUM_{j,t} \tag{2.1}$$

where $AUM_{j,t}$ captures the money invested in security *j* in day *t*, and $AUM^{H}_{p,t}$ captures the money invested in mutual fund *p* in day *t* according to the most recent portfolio holdings.

Hence, the daily return of the portfolio holdings of mutual fund *p* in day *t* ($R^{H}_{p,t}$) is calculated as follows:

$$R^{H}_{p,t} = \frac{AUM^{H}_{p,t} - AUM^{H}_{p,t-1}}{AUM^{H}_{p,t-1}} \tag{2.2}$$

[5] Stock splits, reserve splits and other capital operations are considered when calculating the number of securities in a given asset.

Note that the variance of the holdings' return of mutual fund *p* at day *t* depends on the money invested in the various securities held by the fund and on the NxN variance-covariance matrix of the individual securities. However, to facilitate the calculation of the current holdings volatility, the standard deviation of the return of a hypothetical portfolio that held the most recently disclosed positions over the prior 3 months (i.e., the prior quarter or prior 62 days in this study) is calculated in accordance with the approach of Huang *et al*. (2011), since it is computationally easier to calculate the volatility of a time series of portfolio returns than to estimate a variance-covariance matrix of stock returns. Hence, the standard deviation of R_{pt}^{H} daily returns from day *t= 0* to *t= -62* is calculated to capture the current holdings volatility (σ_{pt}^{H}). Therefore, the volatility patterns associated with risk shifting are examined in an interval that begins three months before each reporting date (month) and ends in the reporting date.

2.2.2 Realized Fund Returns and Volatility

From the database of the daily net asset values (NAV) of mutual funds, the daily fund return is calculated for each fund as the relative change in NAV. However, the NAV return is net of the different fees charged by the fund while the return of fund holdings does not consider these expenses. Thus, the gross daily return of a given mutual fund *p* in day *t* is calculated as follows:

$$R_{p,t}^{R} = \frac{1 + NetReturn_{p,t}^{R}}{1 - Fees_{p,t}} - 1 \qquad (2.3)$$

where $R_{p,t}^{R}$ is the realized gross return of mutual fund *p* in day *t*, and $Fees_{p,t}$ compiles both management and custodial fees charged by mutual fund *p* in day *t*.

Then, the realized volatility of fund p at time t (σ_{pt}^{P}) is calculated as the standard deviation of the actual daily gross returns over the prior 3 months (62 days). Hence, this volatility captures the total risk assumed by the fund. The use of daily instead of monthly returns as in previous studies allows the consideration of the recent past of the mutual fund and not 3 years of monthly data to have sufficient observations to calculate the realized volatility.

2.2.3 Risk Shifting Measure

As in Huang *et al*. (2011), the risk shifting of a mutual fund p at time t is measured through the following expression:

$$RS_{p,t} = \sigma_{p,t}^{H} - \sigma_{p,t}^{R} \tag{2.4}$$

where σ_{pt}^{H} is the current holdings volatility based on the fund's most recently disclosed portfolio, and σ_{pt}^{R} is the past realized volatility based on the fund's realized returns.

The realized volatility would be identical to the current holdings volatility only if the fund maintains constant portfolio weights over the prior 3 months. In this case, there is no risk shifting. In contrast, the risk shifting measure $RS_{p,t}$ is positive if the most recently disclosed holdings exhibit a higher volatility than the actual holdings over the prior 3 months and is negative otherwise. Thus, a positive risk shifting measure indicates that a mutual fund has increased the portfolio risk during the time period analyzed, which can be achievable either by holdings assets with higher risk levels or by changing the asset allocation of the portfolio.

The use of identical time periods to estimate both volatilities allows to capture the changes in risk induced by changes in the portfolio holdings and is unaffected by changes in market conditions. Nevertheless, the *RS* measure can be biased due to the following reasons. First, the measure may capture the impact of interim trades, window dressing or other

unobserved actions of fund managers because the current holdings volatility is based on disclosed portfolio holdings (see, e.g., Kacperczyk *et al*., 2008). However, the use of monthly portfolio holdings instead of semi-annual or quarterly holdings as in previous studies reduces this problem.[6] Second, the *RS* measure is defined as the difference between two volatility measures; therefore, it can be affected by the volatility level of the fund. However, this problem can be addressed by defining the metric as a ratio, as discussed later.

2.3 Data

The study focuses on the performance consequences of risk shifting of actively managed Spanish domestic equity funds from December 1999 to December 2011. However, since daily return data of a quarter is needed to compute the risk shifting measure of each mutual fund, the first three months of the return and holdings information of all funds are lost. Thus, the final time period covers from March 2000 to December 2011.

For the empirical study, the portfolio holdings information of the mutual fund database provided by the Spanish Securities Exchange Commission (*CNMV*) and the Morningstar Direct database are merged. Specifically, the *CNMV* database has information on daily returns and monthly/yearly fund characteristics such as the total net assets, the number of investors, the management fees and the name of the management company for all Spanish mutual funds. This database also contains quarterly portfolio holdings' information for all Spanish mutual funds over time. Therefore, this database is free of survivorship bias.

In addition to this information, *CNMV* provided monthly portfolio holdings from December 1999 to December 2006 for research purposes; this overcomes any problem of

[6] Note that Spanish management companies must only report their holdings to fund investors on a quarterly basis. Hence, monthly holdings are not available for individual investors, and they should not suffer from window dressing practices.

reporting selection bias that can be present in previous literature using high frequency portfolios where management companies voluntarily supply the portfolio holdings of their funds to private data providers (see, e. g., Elton *et al*. 2010).[7] Consequently, the Morningstar Direct database is only used to complete the *CNMV* quarterly portfolio holdings from January 2007 onwards with monthly holdings when available. As stated by Elton *et al*. (2012), Morningstar as well as *CNMV* holdings data not only include holdings of traded equity but also holdings of bonds, preferred stock, other mutual funds, nontraded equity, derivatives and cash. Both databases were matched by fund names and fund ISIN code (International Securities Identification Numbering).

The study focuses on actively managed Spanish domestic equity funds. Therefore, balanced, bond, international or index funds were eliminated. The initial sample includes 173 funds that report at least one year of daily returns and 11 portfolio holdings. From this sample funds that do not fulfil the official investment requirement of this investment category were eliminated to ensure that all portfolios analyzed were appropriately classified as Spanish domestic equity funds.[8] The final sample consists of 144 Spanish domestic equity funds. The removal of these misclassified funds implies no bias in the sample. The matching of *CNMV* and Morningstar datasets have allowed to analyze a total number of 10,730 portfolio holdings, which represent 81.9% of all the fund-months in the sample period.

In relation to the security returns, the study mainly relies on DataStream, which provides daily information regarding the returns of domestic and foreign stocks considering capital operations such as stock splits, the payment of dividends and seasoned equity offering. Hence, daily returns of stocks across the entire sample period are used. The ISIN code of each

[7] Monthly portfolio holdings provided by *CNMV* contains disclosed and undisclosed months, since management companies in Spain must report to investors on a quarterly basis, which is more frequent than the European Union's requirement of semiannual portfolio reports. The fiscal year of Spanish management companies is the natural year. Therefore, mandatory reports are those at the end of each quarter.

[8] These funds must invest at least 75% of their assets in equities in any month.

stock is used to link portfolio holdings with the stock returns. Additionally, the returns of Treasury Bills and other fixed-income securities are calculated using indices published by *Analistas Financieros Internacionales* (AFI). Finally, a low percentage of fund total assets (see Table 2.1) are non-controlled securities, which, together with cash and cash equivalents, receive a zero return. The Ibex-35 total return index is used as a proxy for the market return, while one-day T-bill Repos yield is the proxy for the risk-free rate.

Table 2.1 reports summary statistics for the 144 distinct funds in the sample of Spanish domestic equity funds during the 2000-2011 period. The number of funds ranges from 102 in 2000 to 72 in 2011. Specifically, Table 2.1 summarizes statistics on fund total net assets (TNA), percentage money flow (PMF), number of investors, average number of stocks held in the portfolios, annual turnover, active share (computed as in Cremers and Petajisto, 2009 using the Ibex35 as equity benchmark), age and annual management and custodial fees.

Table 2.1 also summarizes information regarding the portfolio holdings of Spanish domestic equity funds. The holdings database includes not only the long positions in domestic common stocks but also other non-equity holdings. Since the analysis is focused on equity mutual funds, the average percentage of the portfolios invested in stocks (79%) represents the most important asset class, with the remaining assets invested in fixed-income, other mutual fund units and cash or cash equivalents. Non-controlled securities only take an average value of 3.4% of the portfolios. This low percentage reinforces the quality of the database.

Table 2.1 - Summary statistics of Spanish domestic equity fund

This table summarizes the characteristics of mutual funds in the sample over the time period analyzed: March 2000-December 2011. The table reports the mean and median values of the variables and their standard deviation over the time. Specifically, the table shows the number of funds analyzed, their size (TNA), the monthly percentage money flows (PMF), the number of investors, the average number of distinct stocks held by the portfolios, the annual turnover, the active share and the age of the portfolios as well as the distribution of the portfolio holdings into the different asset classes (% invested in stocks, fixed-income securities, other fund units and cash and cash equivalents).

Variables	Mean	Median	Std. Dev.
Number of Funds	91	96	12
Total Net Asset (thousand €)	56,913.8	26,045.1	89,164.9
Monthly Percentage Money Flow (thousand €)	-927.9	-168.6	7,461.7
Number of Investors	2,352	832	3,873
Average No. of stocks held	35.7	35.0	11.51
Annual Turnover (%)	43.6%	35.5%	31.9%
Active Share (%)	39.3%	34.8%	19.7%
Age (in Years)	9.2	9.1	4.9
Annual Management Fees (%)	1.9%	2.0%	0.5%
Stock Proportion (%)	78.8%	80.0%	14.6%
Fixed-Income Securities (%)	14.8%	11.8%	12.3%
Other Mutual Fund Units (%)	5.2%	4.4%	4.5%
Cash and Cash Equivalents (%)	19.9%	18.2%	13.5%
Non-controlled Securities (%)	3.4%	1.4%	5.9%

2.4 Empirical Findings

2.4.1 Characteristics of risk shifters

Table 2.2 summarizes the characteristics of risk shifters by averaging funds in five portfolios sorted according to the most recent *RS* measure. Portfolio 1 gathers those funds that have reduced their risk level the most (decile 1), while Portfolio 5 compiles those mutual funds that have increased their risk level the most (decile 10). Specifically, funds in portfolio 1 decrease risk on average by 0.46% per month. Conversely, funds in portfolio 5 increase risk by 0.39% per month. Thus, funds exhibit significant changes in their overall risk levels over time. The table also shows that funds in portfolio 5 exhibit the highest current holdings volatility, and

their realized volatility is not very different from the mean realized volatility. In contrast, funds in portfolio 1 have the highest realized volatility, and their current holdings volatility is not substantially different from the mean holdings volatility.

Table 2.2 also reports that funds that increase risk share similar characteristics to funds that decrease risk. Funds that increase risk (funds in decile 10) are smaller and younger than funds with more stable risk levels.

Table 2.2 - Fund characteristics by risk shifting

This table summarizes the average characteristics of portfolios of mutual funds sorted according to the most recent risk shifting measure. The difference in current holdings volatility and past realized volatility is defined as the risk shifting measure (*RS*). TNA is measured in thousands of Euros, # of investors represents the number of people putting their money in the mutual fund, and age is defined in years.

Portfolio	RS Range	RS Mean	Current Holdings Volatility	Past Realized Volatility	TNA	# of Investors	Age
1	Decile 1	-0.0046	0.0095	0.0141	54,748	2,709	7.54
2	Deciles 2-3	-0.0023	0.0109	0.0131	90,694	4,226	9.22
3	Deciles 4-7	0.0000	0.0122	0.0121	63,239	2,915	8.36
4	Deciles 8-9	0.0025	0.0127	0.0102	48,937	1,607	7.85
5	Decile 10	0.0039	0.0136	0.0097	34,185	1,064	8.03

2.4.2 Performance consequences of risk shifting

Several performance measures are used to evaluate the performance consequences of shifting risk. Hence, the performance of funds that increase or decrease the risk level of the portfolio is compared with the performance of funds with more stable risk properties.

The financial literature usually adjusts for risk and style by estimating the factor loadings for each fund over a rolling window using prior data and then computing abnormal returns in the subsequent period as the difference between the actual fund return and the expected fund return based on the estimated factor loadings. As stated by Huang *et al*. (2011), this methodology is not appropriate in this research, since it is focused on funds that change

their risk exposures over time. The factor loadings estimated over prior windows may not be accurate for funds that shift risk levels. Therefore, this chapter uses a portfolio approach. The previously explained five portfolios of funds with similar risk shifting levels are constructed according to their most recent RS measure. The risk exposures of these portfolios are estimated in the sample based on the returns of these portfolios.

Six different performance measures are used. Gross returns and net returns (the former are relevant to evaluate the management performance, while the latter are relevant from an investors' perspective) and excess market returns are computed to evaluate the performance against the value-weighted market portfolio. Additionally, to adjust for risk and style effects, the one-factor CAPM alpha, the Fama and French (1993) alpha and the Carhart (1997) alpha are examined.[9]

Portfolio returns are computed as the equal-weighted mean returns of all funds in the corresponding *RS* portfolio over the next month ($t+1$) and the next quarter ($t+3$). The alphas of the portfolios are estimated using the time-series of fund portfolio gross returns. The results are summarized in Panels A and B of Table 2.3.

Table 2.3 shows that funds that reduce the risk level the most obtained a negative and statistically significant performance regardless of the time period examined ($t+1$ and $t+3$). In contrast, funds that assumed the highest risk level (portfolio 5) obtained a positive but not significant performance, while funds in portfolio 4 achieve a positive and statistically significant performance. This finding indicates that the improvement in performance is not sequential. This fact is observed in the different performance measures (CAPM, Fama and French and Carhart alpha) and in both panels.

[9] The factors of size, book to market and momentum have been calculated in accordance with the same procedure detailed on the website of Kenneth French considering the stocks traded in the Spanish stock market (see, e.g., http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

This finding of superior performance for funds increasing the risk level contrasts with the result in the US market where increasing risk is harmful for financial investors (see, e.g., Huang, Sialm and Zhang; 2011). The table also shows that funds that increase risk experience better subsequent abnormal performance than funds with stable or reduced risk levels. This finding provides evidence that risk shifting is not harmful to investors; instead, it is the opposite.

Table 2.3 - Performance consequences of risk shifting

This table reports the performance of mutual fund portfolios sorted according to the most recent risk shifting measure (*RS* measure). Panel A summarizes the performance consequences of risk shifting in the short-term (next month), while Panel B summarizes the results in the next quarter. All measures are expressed in % terms. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:			**t+1**			
RS Portfolio	**Gross Return**	**Net Return**	**Excess Market**	**CAPM**	**Fama-French**	**Carhart**
1	0.11%	-0.05%	-0.13%*	-0.15%***	-0.17%***	-0.20%***
2	0.28%	0.11%	0.03%	0.04%	0.02%	0.04%
3	0.19%	0.03%	-0.05%	-0.03%	-0.07%	-0.06%
4	0.41%	0.25%	0.16%	0.21%**	0.11%	0.11%
5	0.29%	0.13%	0.04%	0.10%	0.02%	0.06%
# 5-1	0.17%	0.18%	0.17%	0.24%***	0.19%***	0.26%***
# 5-3	0.09%	0.10%	0.09%	0.13%**	0.09%	0.12%**
# 1-3	-0.08%	-0.08%	-0.08%	-0.11%*	-0.10%*	-0.14%**
Panel B:			**t+3**			
RS Portfolio	**Gross Return**	**Net Return**	**Excess Market**	**CAPM**	**Fama-French**	**Carhart**
1	0.35%	-0.13%	-0.53%***	-0.59%***	-0.70%***	-0.90%***
2	0.88%	0.40%	0.00%	0.02%	-0.02%	0.05%
3	0.74%	0.26%	-0.15%	-0.09%	-0.21%**	-0.20%**
4	1.36%*	0.90%	0.48%**	0.61%***	0.30%**	0.31%**
5	1.01%	0.54%	0.12%	0.29%	0.07%	0.20%
# 5-1	0.65%	0.67%	0.65%**	0.88%***	0.77%***	1.11%***
# 5-3	0.27%	0.28%	0.27%	0.39%***	0.28%***	0.40%***
# 1-3	-0.39%	-0.40%	-0.40%**	-0.49%***	-0.49%***	-0.70%***

2.4.3 Mechanisms of risk shifting

Mutual funds can change the risk level of their portfolios through several mechanisms. First, mutual funds can change the composition between equity holdings and cash holdings. Second, within their equity holdings, funds can change their exposure to systematic risk by switching between stocks with high or low beta; they can change their idiosyncratic risk exposures by deviating from their benchmarks or by changing the portfolio concentration in particular industries and styles.

Alternative *RS* measures are proposed to consider some of these mechanisms of risk shifting and investigate the performance consequences using each alternative measure. These alternative *RS* measures are detailed below.

- *Risk Shifting Ratio:* defined as the ratio between the current holdings volatility and the past realized volatility.

$$RS\ Ratio_{p,t}^{H} = \frac{\sigma_{p,t}^{H}}{\sigma_{p,t}^{R}} \tag{2.6}$$

- *Systematic Risk Shifting:* Fund managers may shift risk in an effort to take advantage of investment opportunities due to their management skills. Fund managers may change their exposure to systematic risk if they believe that they have superior market timing abilities. The systematic risk shifting measure is defined as follows:

$$RS_{p,t}^{\beta} = \beta_{p,t}^{H} - \beta_{p,t}^{R} \tag{2.7}$$

where $\beta_{p,t}^{H}$ is the weighted average of the CAPM, Fama and French and Carhart market beta of the most recently disclosed holdings[10], and $\beta_{p,t}^{R}$ is the CAPM, Fama and French and Carhart market beta of the daily realized returns over the prior year.

[10] The betas of individual stocks are estimated using the one-factor model, 3-factor model or 4-factor model with one year daily returns prior to the portfolio reporting date.

- *Idiosyncratic Risk Shifting:* Fund managers may change the idiosyncratic risk of their portfolio if they believe that they have stock selection ability. Specifically, the idiosyncratic risk shifting measure is defined as follows:

$$RS_{p,t}^{idiosync} = \sigma_{p,t}^{H,idiosync} - \sigma_{p,t}^{R,idiosync} \tag{2.8}$$

where $\sigma_{p,t}^{H,idiosync}$ is the idiosyncratic volatility of the most recently disclosed fund holdings return, and $\sigma_{p,t}^{R,idiosync}$ is the idiosyncratic volatility of the past realized fund return. The idiosyncratic volatilities are computed as the standard deviations of the residuals from the CAPM, Fama and French or the Carhart factor regressions over the prior year.

- *Equity-based Risk Shifting*: Fund managers can also modify the risk level through a change in the composition of the portfolios. Specifically, by increasing the percentage that equity holdings represent in the portfolios, fund managers increase the risk level and vice versa. Therefore, the equity-based risk shifting measure is defined as follows:

$$RS_{p,t}^{equity} = w_{p,t}^{equity} - \overline{w}_{p,t}^{equity} \tag{2.9}$$

where $w_{p,t}^{equity}$ is the most recently disclosed proportion invested in equity securities, and $\overline{w}_{p,t}^{equity}$ is the average percentage invested in equity securities over the prior quarter.[11]

Table 2.4 reports the performance consequences of risk shifting based on the abovementioned four alternative *RS* measures. Panel A shows the consequences in the next month *(t+1)*, while Panel B shows the consequences in the next quarter *(t+3)*. The first column compiles the five *RS* portfolios analyzed. These portfolios are formed as in Table 2.3. Columns 2-4 report the results for the *RS* ratio; columns 5-7 report the results for the

[11] The consideration of the prior quarter implies the consideration of a minimum of three and a maximum of nine portfolio holdings depending on the frequency of portfolio reporting.

systematic *RS* measure. Columns 8-10 report the results for idiosyncratic *RS* measure, while columns 11-13 report the results for the equity-based *RS* measure. The table shows the CAPM, Fama and French and Carhart alphas as a measure of abnormal performance for fund portfolios formed according to each of these alternative *RS* measures.

Table 2.4 shows that the results are not affected qualitatively by using the *RS* ratio. The results of the *RS* ratio are consistent with those obtained in Table 2.3. The findings indicate that funds that reduce risk have poor subsequent performance both in the next month and in the next quarter (see Panel A and B, respectively). Comparing the portfolios, it can be observed that funds that increase risk obtain a positive and statistically significant outperformance compared with funds that maintain stable risk levels and funds that reduce their risk. Note that the results in Panel B of Table 2.4 are more significant than the findings in Panel A.

Similar to the RS measure and the RS ratio, the results show that those funds that decrease their risk level through alternative measures tend to experiment negative performance that is statistically significant in some cases. Furthermore, the table also reports a positive and statistically significant difference in the performance among funds that increase and reduce the risk through the systematic and equity-based RS measures when examining the consequences in the next quarter.

However, the findings obtained when using the idiosyncratic risk are slightly different. Table 2.4 shows that increasing the idiosyncratic risk, which occurs when funds increase their portfolio concentration, leads to underperformance. This finding is consistent with the paper by Huang *et al*. (2011) and suggests that the driver of the poor performance for increasing idiosyncratic risk is the poor stock-picking abilities.[12]

[12] Ang *et al*. (2006) report that stocks with high idiosyncratic volatility based on daily returns tend to exhibit relatively poor abnormal returns in the subsequent month.

Table 2.4 - Performance consequences using alternative risk shifting measures

This table reports the CAPM, Fama and French and Carhart alphas of portfolios of mutual funds sorted according to the most recent risk shifting measure. Four different measures of risk shifting are calculated: the ratio between the current holdings volatility and the past realized volatility, the systematic risk shifting, the idiosyncratic risk shifting, and the equity-based risk shifting measures. Panel A shows the results for the next month (period *t+1*), and Panel B shows the results for the next quarter (period *t+3*). *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A	**t+1**											
RS Portfolio	**RS ratio**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
	CAPM	**Fama-French**	**Carhart**	**CAPM**	**Fama-French**	**Carhart**	**CAPM**	**Fama-French**	**Carhart**	**CAPM**	**Fama-French**	**Carhart**
1	-0.07%	-0.09%	-0.13%**	0.01%	0.00%	0.02%	0.02%	0.00%	-0.01%	-0.12%	-0.17%**	-0.19%**
2	0.01%	-0.01%	0.01%	0.01%	-0.01%	0.01%	0.03%	0.00%	0.01%	0.04%	0.00%	0.01%
3	-0.03%	-0.07%	-0.06%	0.00%	-0.04%	-0.04%	0.06%	0.02%	0.03%	0.02%	-0.04%	-0.03%
4	0.16%	0.07%	0.07%	0.21%**	0.12%	0.12%	0.11%	0.04%	0.07%	0.00%	-0.06%	-0.05%
5	0.15%	0.06%	0.09%	0.08%	0.00%	0.06%	0.00%	-0.10%	-0.07%	-0.04%	-0.10%	-0.10%
# 5-1	0.21%***	0.14%***	0.22%***	0.07%**	0.00%	0.04%	-0.02%	-0.10%	-0.06%	0.08%	0.08%	0.08%
# 5-3	0.18%***	0.13%**	0.15%***	0.09%	0.05%	0.10%*	-0.06%	-0.12%**	-0.09%*	-0.06%	-0.06%	-0.07%
# 1-3	-0.03%	-0.02%	-0.06%	0.01%	0.04%	0.06%	-0.04%	-0.02%	-0.03%	-0.14%**	-0.13%**	-0.15%***

Panel B	**t+3**											
RS Portfolio	**RS ratio**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
	CAPM	**Fama-French**	**Carhart**	**CAPM**	**Fama-French**	**Carhart**	**CAPM**	**Fama-French**	**Carhart**	**CAPM**	**Fama-French**	**Carhart**
1	-0.30%***	-0.37%***	-0.50%***	-0.11%	-0.13%*	-0.12%*	0.04%	-0.04%	-0.03%	-0.29%**	-0.39%***	-0.51%***
2	-0.11%	-0.167%*	-0.14%	-0.07%	-0.11%	-0.04%	0.03%	-0.02%	-0.01%	0.07%	-0.04%	0.00%
3	-0.09%	-0.21%**	-0.20%**	-0.02%	-0.14%	-0.12%	0.13%	-0.01%	0.00%	0.03%	-0.14%	-0.16%
4	0.47%***	0.19%	0.21%	0.68%***	0.37%***	0.35%**	0.29%*	0.11%	0.19%	-0.08%	-0.29%***	-0.29%**
5	0.46%**	0.20%	0.31%*	0.15%	-0.06%	0.12%	-0.05%	-0.36%*	-0.23%	0.06%	-0.11%	-0.11%
# 5-1	0.75%***	0.57%***	0.81%***	0.25%***	0.07%	0.25%***	-0.09%	-0.32%***	-0.20%*	0.35%***	0.28%**	0.40%***
# 5-3	0.55%***	0.41%***	0.51%***	0.17%	0.07%	0.24%**	-0.19%*	-0.35%***	-0.23%***	0.03%	0.03%	0.05%
# 1-3	-0.21%**	-0.16%*	-0.30%***	-0.09%	0.00%	-0.01%	-0.09%	-0.03%	-0.03%	-0.32%***	-0.25%***	-0.35%***

2.4.4 Performance consequences of risk shifting depending on manager characteristics.

Previous studies such as those by Chevalier and Ellison (1999b), Prather and Middleton (2002), and Bliss *et al*. (2008) indicate that manager characteristics such as age, gender and tenure can affect the risk profiles of the portfolios managed.

Chevalier and Ellison (1999b) find that younger managers take on less unsystematic risk than older managers. Chevalier and Ellison (1999a) also find that mutual fund managers who attended more selective undergraduate institutions have higher performance than mutual fund managers who attended less selective undergraduate institutions. Menkhoff *et al*. (2006) argue that experienced fund managers are less overconfident and take lower risks.

As can be observed, there is a large variety of studies analyzing the impact of manager characteristics on performance and risk taking. This study contributes to this literature by going a step forward through the analysis of the performance consequences of risk shifting depending on certain characteristics of fund managers.

This chapter focuses on those fund-periods where mutual funds from the sample are single managed, since the objective is to analyze the performance consequences of risk shifting depending on manager characteristics.[13] Therefore, fund-month observations for which Morningstar reports a management team or provides multiple manager names for a given date are excluded. Morningstar Direct provides information on the managers' name and the date on which the manager assumed responsibility for the fund. All funds from the *CNMV* database are matched to the funds in the Morningstar database using the fund ISIN code. For certain mutual funds, Morningstar does not report the manager name. Hence, in this section, the study only considers those fund-observations where Morningstar reports the manager name. This fact does not bias the findings, as shown in Appendix 2.1.

[13] Baer *et al*. (2011) show that team managed funds and single managed funds behave differently, and it is not clear how the skills of single team members translate into the skills of a team.

Appendix 2.1 shows the performance consequences of risk shifting for those funds where Morningstar provides manager information. Panel A of Table A2.1 in Appendix 2.1 suggests the same conclusions as Tables 2.3 and 2.4. Those mutual funds that increase their risk level obtained significantly better performance than funds with stable or decreased risk. Panels B and C disaggregate the results in Panel A splitting those fund-months with team managed funds and single managed funds, respectively. The findings once more confirm the outperformance of managers with an increase in the risk level.

Similar conclusions are obtained in Table A2.2 when the alternative *RS* measures are examined. Finally, it is important to highlight the increase experienced by the performance values for those funds for which Morningstar provides managers' information; this appears to suggest that poor performing funds do not have incentives to report their managers' names.

The manager characteristics that are studied in this chapter include gender (female vs male managers), level of specialization (generalists versus specialists' managers), tenure in the industry, age, and education (managers with a master degree or without).

2.4.4.1 Performance consequences of risk shifting depending on gender

Whether women behave differently from men has been extensively studied and reveals robust gender differences. The literature in economics and finance has concluded that women are more risk averse than men. Schmidt and Traub (2002) show women to be more loss averse than men. Beckmann and Menkhoff (2008) show that women are significantly more risk averse, tend to be less overconfident and behave less competitively oriented. More recently, Welch and Wang (2013) also find evidence that suggests that female managers have a lower risk tolerance than males.

The financial literature has not only researched gender differences in manager decisions but also investor decisions. Jianakoplos and Bernasek (1998) find that single women exhibit relatively more risk aversion in financial decision making than single men. Conversely, Dwyer, Gilkeson and List (2002) find that women exhibit less risk taking than men in their most recent and riskiest fund investment decisions.

Due to the abovementioned evidence, the chapter analyzes whether the performance consequences of risk shifting are different depending on manager gender. One could expect better performance results when women increase the risk of the portfolios due to their lower tolerance to risk. Women's lower tolerance to risk will only lead them to increase their risk exposure when they have clearly detected an investment opportunity. Table 2.5 summarizes the performance consequences using the *RS* measure and the alternative metrics depending on the manager gender for the next month.

First, Table 2.5 shows that the performance consequences of increasing risk are positive regardless of manager gender and the risk shifting mechanism examined, although this figure only tends to be statistically significant for male managers. Second, Panel A (CAPM alpha) reveals that the consequences of increasing risk (*RS* measure) are stronger for male than for female managers, while it is the opposite in Panel B (Carhart alpha). This finding appears to suggest that male managers obtain superior performance when increasing the risk level of their portfolios following investment strategies based on size, book to market or momentum. However, when these factors are considered, the male managers' alphas suffer a relevant decrease. Therefore, as expected, women obtain better performance results than men when increasing the risk level of the overall portfolio, if the performance is calculated using the Carhart alpha; however, the difference is not statistically significant.

Table 2.5 - Performance consequences of risk shifting by gender.

This table reports the future performance of portfolios of mutual funds sorted according to their level of risk shifting and the manager gender. Specifically, Panel A reports the CAPM alphas for the next month (period *t+1*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into male and female groups; then, they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A	RS measure			Systematic RS			Idiosyncratic RS			Equity-based RS		
RS Portfolio	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**
1	0.01%	-0.08%	0.09%	0.04%	0.08%	-0.04%	0.32%*	-0.02%	0.35%***	0.46%***	-0.27%	0.73%
2	-0.05%	0.11%*	-0.16%***	-0.05%	0.03%	-0.08%	0.18%	0.10%	0.08%	0.29%**	0.06%	0.23%
3	0.29%**	-0.12%	0.41%***	0.28%**	-0.02%	0.30%**	0.46%***	-0.01%	0.46%***	0.32%**	0.10%	0.22%**
4	0.65%***	0.00%	0.65%**	0.76%***	0.00%	0.76%**	0.26%**	0.55%**	-0.29%	0.20%*	-0.01%	0.21%
5	0.51%***	0.21%	0.31%	0.41%***	0.07%	0.34%	0.18%	-0.43%	0.61%	0.31%**	0.06%	0.25%
# 5-1	0.50%***	0.28%***	0.22%***	0.37%***	-0.01%	0.38%***	-0.14%	-0.40%***	0.27%	-0.15%	0.33%**	-0.48%***
# 5-3	0.22%*	0.33%***	-0.10%	0.13%	0.09%	0.04%	-0.27%**	-0.42%***	0.15%	-0.01%	-0.04%	0.03%
# 1-3	-0.28%**	0.04%	-0.32%***	-0.23%**	0.10%	-0.34%***	-0.13%	-0.02%	-0.12%	0.14%	-0.37%***	0.51%***

Panel B	RS measure			Systematic RS			Idiosyncratic RS			Equity-based RS		
RS Portfolio	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**
1	0.02%	-0.08%	0.10%	0.04%	0.11%	-0.07%	0.23%	-0.01%	0.25%***	0.33%**	-0.24%	0.56%***
2	-0.06%	0.14%**	-0.2%***	-0.02%	0.04%	-0.06%	0.17%	0.16%	0.01%	0.20%	0.16%	0.05%
3	0.13%	-0.12%	0.26%**	0.11%	-0.03%	0.14%	0.31%***	0.03%	0.27%***	0.10%	0.12%	-0.02%
4	0.45%***	0.29%	0.16%	0.59%***	0.26%	0.33%	0.17%	0.89%***	-0.73%***	0.10%	-0.10%	0.20%
5	0.36%***	0.48%	-0.12%	0.27%**	-0.07%	0.34%	0.00%	-0.04%	0.03%	0.15%	0.17%	-0.02%
# 5-1	0.35%***	0.56%***	-0.21%***	0.23%***	-0.18%*	0.41%***	-0.24%	-0.03%	-0.21%	-0.17%	0.41%**	-0.59%***
# 5-3	0.23%**	0.60%***	-0.38%***	0.16%	-0.05%	0.20%**	-0.31%***	-0.07%	-0.24%**	0.05%	0.05%	-0.01%
# 1-3	-0.12%	0.04%	-0.16%	-0.07%	0.13%	-0.20%**	-0.07%	-0.05%	-0.03%	0.22%**	-0.36%***	0.58%***

Finally, Table 2.5 also highlights the timing ability of male managers (Equity-based *RS* measure); especially in bear markets since it can be observed a positive and statistically significant performance of male managers when reducing their exposure to the equity market.

2.4.4.2 Performance consequences of risk shifting depending on level of specialization

Management companies can have incentives to assign portfolio managers depending on their abilities and level of specialization. Zambrana and Zapatero (2015) show that it is optimal to assign managers with market timing ability to generalist responsibilities (generalist managers are those who run funds comprising several investment objectives) and managers with stock-picking ability to specialist responsibilities (they run portfolios on one investment objective).[14] Consequently, the underlying idea is that specialist managers are those with superior stock picking abilities and therefore, the managers who obtain better results when modifying the idiosyncratic risk of their portfolios. Similarly, one would expect that generalist managers exhibit more skills to time the market (i.e., to modify the portfolio asset allocation).

In accordance with Zambrana and Zapatero (2015), the degree of specialization of the manager in each time period is measured by the difference between the overall number of funds managed by the manager and the number of funds managed in an investment vocation (in this thesis domestic equity mutual funds). When all mutual funds managed (or all expect one) belong to domestic equity funds, this manager is classified as a specialist; otherwise, the manager is classified as a generalist. Table 2.6 summarizes the performance consequences of risk shifting depending on the level of the managers' specialization. This table reinforces, once more, the main finding of this chapter. That is, increasing the risk level of portfolios has positive performance consequences regardless of the level of specialization of the fund

[14] Fang *et al*. (2014) also indicate that fund families allocate managers to market segments depending on their management skills. Specifically, fund families allocate their most skilled managers to inefficient markets to exploit the inefficiencies and generate higher performance.

managers. Similar to Table 2.5, different behavior between specialist and generalist managers that increase risk (portfolio 5) is observed whether CAPM alpha (Panel A) or Carhart alpha (Panel B) are examined. When considering the CAPM alpha, generalist managers tend to outperform specialist managers although without statistical significance. This finding appears reasonable because generalist managers are expected to be more skilled when following size, book to market or momentum investment strategies. Hence, it is not surprising that the generalist managers' performance decreases when Carhart alphas are examined. Concretely, specialist managers are those that outperform when increasing the overall and systematic risk level of the portfolios considering the Carhart alpha. Hence, Table 2.6 shows that specialist managers are able to add value in their portfolios when they increase the risk level even when controlling for the 4-factors.

However, Table 2.6 does not exhibit a superiority of specialist managers' vs generalists in increasing the idiosyncratic risk. Similarly, Table 2.6 does not exhibit outperformance of generalist managers compared with specialists in terms of their abilities to time the market (increase or decrease the percentage invested in equity holdings).

Table 2.6 - Performance consequences of risk shifting by level of specialization.

This table reports the future performance of portfolios of mutual funds sorted according to their level of risk shifting and the type of responsibilities of fund managers. Managers are classified as generalist whether they run funds belonging to several investment objectives while they are classified as specialists whether they run funds on just one investment objective. Specifically, Panel A reports the CAPM alphas for the next month (period *t+1*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into specialist and generalist groups and then they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**
1	-0.02%	0.13%	-0.15%	0.06%	-0.04%	0.11%*	-0.02%	0.09%	-0.11%	0.33%**	-0.04%	0.37%***
2	0.06%	0.00%	0.06%	0.10%	-0.06%	0.16%**	0.19%	0.20%	-0.01%	0.27%*	0.15%	0.12%
3	0.12%	0.25%***	-0.13%	0.17%	0.21%**	-0.04%	0.26%**	0.34%***	-0.08%	0.21%*	0.25%*	-0.04%
4	0.45%***	0.47%***	-0.02%	0.53%***	0.71%***	-0.17%	0.47%***	0.14%	0.33%***	0.00%	0.25%*	-0.25%*
5	0.39%**	0.46%***	-0.07%	0.38%**	0.35%**	0.03%	-0.02%	0.16%	-0.18%	0.32%*	0.02%	0.30%
# 5-1	0.41%***	0.33%*	0.08%	0.32%***	0.39%***	-0.07%	0.00%	0.07%	-0.07%	-0.01%	0.05%	-0.07%
# 5-3	0.27%**	0.21%**	0.06%	0.21%	0.14%	0.07%	-0.28%**	-0.18%	-0.10%	0.10%	-0.23%*	0.33%***
# 1-3	-0.14%	-0.12%	-0.02%	-0.11%	-0.25%***	0.14%	-0.28%**	-0.25%**	-0.03%	0.12%	-0.29%**	0.40%***

Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**
1	-0.01%	0.16%	-0.17%	0.07%	-0.05%	0.12%*	-0.09%	0.08%	-0.16%	0.34%**	-0.08%	0.42%***
2	0.07%	0.00%	0.07%	0.12%	-0.07%	0.18%***	0.19%	0.15%	0.04%	0.34%**	-0.01%	0.34%***
3	0.02%	0.15%	-0.13%	0.07%	0.07%	0.00%	0.26%**	0.17%	0.10%	0.10%	0.06%	0.05%
4	0.45%***	0.36%**	0.09%	0.54%***	0.56%***	-0.02%	0.41%***	0.10%	0.31%***	-0.11%	0.20%	-0.31%**
5	0.40%***	0.22%	0.18%	0.34%**	0.20%	0.14%	-0.22%	0.09%	-0.31%**	0.15%	-0.12%	0.27%
# 5-1	0.42%***	0.07%	0.35%***	0.27%***	0.25%***	0.02%	-0.13%	0.02%	-0.15%	-0.19%	-0.04%	-0.15%
# 5-3	0.39%***	0.07%	0.31%***	0.27%*	0.13%	0.14%	-0.48%***	-0.07%	-0.40%***	0.05%	-0.18%	0.23%*
# 1-3	-0.03%	0.01%	-0.04%	0.00%	-0.12%	0.12%	-0.35%***	-0.09%	-0.26%**	0.23%*	-0.14%	0.37%***

2.4.4.3 Performance consequences of risk shifting depending on manager tenure

Several empirical studies have analyzed whether risk taking changes with manager experience. Graham (1999), Li (2002) and Boyson (2003) find that risk aversion increases with manager experience. Similarly, Clement and Tse (2005) and Menkhoff *et al*. (2006) also highlight that experienced managers are less overconfident and take fewer risks. However, other studies observe a positive relation between risk taking and experience (see, Chevalier and Ellison, 1999b; Hong *et al*. 2000 and Lamont, 2002).

Conversely, prior literature also indicates that managers with more industry tenure are more aware of the true volatility of asset prices which might lead to better investment decisions. Hence, despite the contradictory evidence about the relationship between risk taking and manager tenure, this study hypothesizes that should observe superior performance consequences when more experienced managers increase the risk level of their portfolios because they have "more to lose" in personal wealth and reputation than less experienced managers if they fail.

Tenure in the industry is calculated from the first year that Morningstar reports for a manager in the database. Then, mutual funds in each period are divided into two groups depending on whether the manager tenure is above or below the median value. In a second step, the two groups of funds are further divided into five portfolios according to their most recent *RS* measure. Finally, the CAPM and Carhart alphas of the portfolios formed are calculated.

Table 2.7 - Performance consequences of risk shifting by tenure.

This table reports the future performance of the portfolios of mutual funds sorted according to their level of risk shifting and the level of tenure of fund managers. Managers are classified by high and low tenure to form two equal-sized groups according to whether the characteristic is above or below its median value. Specifically, Panel A reports the CAPM alphas for the next month (period *t+1*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into high and low tenure groups and then they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**
1	0.09%	-0.09%	0.18%	0.04%	0.02%	0.02%	0.02%	0.12%	-0.10%	0.18%	0.04%	0.14%
2	-0.02%	0.13%*	-0.16%**	0.02%	-0.04%	0.07%	0.09%	0.25%	-0.16%	0.29%**	0.10%	0.19%
3	0.30%***	0.06%	0.24%*	0.25%**	0.13%	0.12%	0.43%***	0.19%	0.25%**	0.27%**	0.17%	0.11%
4	0.32%*	0.64%***	-0.32%	0.53%***	0.57%***	-0.04%	0.18%	0.41%***	-0.23%	0.19%	-0.03%	0.23%
5	0.46%***	0.43%***	0.03%	0.33%**	0.42%**	-0.10%	-0.06%	0.01%	-0.07%	0.11%	0.30%	-0.19%
# 5-1	0.37%***	0.52%***	-0.15%***	0.29%***	0.41%***	-0.12%**	-0.08%	-0.11%	0.03%	-0.07%	0.26%	-0.33%**
# 5-3	0.16%*	0.37%***	-0.21%***	0.08%	0.30%**	-0.22%**	-0.49%***	-0.17%	-0.32%***	-0.17%	0.13%	-0.30%**
# 1-3	-0.21%***	-0.15%	-0.06%	-0.21%**	-0.11%	-0.10%	-0.41%***	-0.07%	-0.35%***	-0.10%	-0.13%	0.03%

Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**
1	0.15%*	-0.12%	0.27%*	0.07%	0.03%	0.04%	0.01%	0.13%	-0.12%	0.12%	0.06%	0.07%
2	-0.02%	0.14%*	-0.16%**	0.03%	-0.05%	0.07%	-0.01%	0.24%	-0.25%	0.21%	0.15%	0.06%
3	0.20%***	-0.06%	0.26%**	0.12%	0.01%	0.10%	0.28%***	0.14%	0.14%	0.05%	0.06%	-0.01%
4	0.06%	0.53%***	-0.47%**	0.31%*	0.51%**	-0.20%	0.14%	0.33%**	-0.19%	0.10%	-0.08%	0.18%
5	0.36%**	0.45%***	-0.09%	0.19%	0.32%**	-0.13%	-0.15%	-0.14%	-0.01%	0.02%	0.18%	-0.16%
# 5-1	0.21%***	0.57%***	-0.36%***	0.12%**	0.29%***	-0.17%***	-0.16%	-0.27%**	0.11%	-0.10%	0.13%	-0.23%*
# 5-3	0.17%**	0.51%***	-0.35%***	0.07%	0.31%***	-0.24%**	-0.43%***	-0.27%**	-0.15%	-0.03%	0.12%	-0.15%
# 1-3	-0.04%	-0.06%	0.01%	-0.05%	0.02%	-0.07%	-0.27%***	0.00%	-0.27%***	0.07%	0.00%	0.08%

Table 2.7 summarizes the performance consequences of risk shifting depending on manager tenure. The table first shows that there are few statistically significant differences between more and less experienced managers.[15] Second, it is observed that experienced managers tend to obtain significantly better performance when they maintain stable risk levels in the overall portfolio and according to the idiosyncratic risk (see, e.g., Panels A and B). Third, Table 2.7 also confirms the main finding of this chapter; increasing the overall level of risk and the systematic risk of fund portfolios leads to better performance than stable or decreasing risk levels being this improvement in performance higher in less experienced managers.

2.4.4.4 Performance consequences of risk shifting depending on manager age

As with previous manager characteristics, the financial literature has also analyzed whether risk taking increases or decreases with manager age. Chevalier and Ellison (1999b) find that younger managers take on less unsystematic risk than older managers. The researchers argue that younger managers have implicit labor market incentives, i.e., they are more likely to lose their jobs if their fund's beta or unsystematic risk level deviates from the mean of their objective group. Similarly, Avery and Chevalier (1999) also indicate that managers herd early in their careers and diverge in their actions later.

As the managers' age is not explicitly provided in the Morningstar database, the age is calculated by collecting the birth dates from specialized websites such as citywire or LinkedIn when available.[16] Similar to industry tenure, mutual funds in each period are divided into two groups depending on whether manager age is above or below the median value. In a second

[15] Note that the differences increase their significance when examining the consequences in the next quarter as shown in Appendix 2.2.

[16] Following Chevalier and Ellison (1999b), whether the birth date was not available but there was information about the year in which a manager got their university degree and assume that a manager was 21 upon university graduation.

step, the two groups of funds were divided into five portfolios according to their most recent *RS* measure and estimate the CAPM and Carhart alphas of the portfolios formed.

Table 2.8 summarizes the performance consequences of risk shifting depending on manager age. Similar to previous analyses, Table 2.8 also highlights the superior performance consequences of those portfolios increasing the total risk level. However, in contrast with previous manager characteristics, manager age is not revealed as an important variable to differentiate the performance consequences of risk shifting. Few statistically significant differences in the future performance between young and old managers have occurred. The only remarkable finding is that old managers outperform young managers when they maintain stable risk levels. This finding is very similar to that obtained with manager tenure.

Table 2.8 - Performance consequences of risk shifting by manager age.

This table reports the future performance of portfolios of mutual funds sorted according to their level of risk shifting and the age of fund managers. Managers are classified as young and old to form two equal-sized groups according to whether the characteristic is above or below its median value. Specifically, Panel A reports the CAPM alphas for the next month (period *t+1*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into young and old manager groups; then, they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**
1	0.02%	0.04%	-0.02%	0.01%	0.15%	-0.14%	0.08%	0.75%	-0.67%	0.21%	0.13%	0.09%
2	0.00%	-0.06%	0.07%	-0.01%	-0.02%	0.01%	0.43%	0.38%	0.04%	0.10%	0.26%	-0.16%
3	0.11%	0.60%***	-0.49%***	0.17%*	0.54%***	-0.38%**	0.41%	0.76%*	-0.34%	0.09%	0.69%***	-0.60%***
4	0.41%***	0.74%***	-0.33%	0.47%**	0.81%***	-0.34%	0.67%	0.23%	0.44%	-0.04%	0.34%*	-0.38%**
5	0.57%	0.55%	0.02%	0.58%	0.41%	0.17%	0.47%	0.20%	0.28%	0.64%	0.26%	0.38%
# 5-1	0.55%***	0.52%***	0.03%	0.57%	0.26%*	0.30%***	0.39%	-0.56%	0.95%	0.42%***	0.13%	0.29%**
# 5-3	0.46%***	-0.04%	0.50%***	0.41%***	-0.13%	0.54%***	0.06%	-0.56%	0.62%	0.54%***	-0.44%**	0.98%***
# 1-3	-0.09%	-0.56%***	0.47%***	-0.15%	-0.39%**	0.24%**	-0.33%	0.00%	-0.33%	0.12%	-0.57%***	0.69%***
Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**
1	0.03%	0.08%	-0.05%	0.03%	0.13%	-0.10%	0.06%	1.25%	-1.19%	0.12%	0.08%	0.03%
2	-0.01%	-0.02%	0.02%	0.01%	0.00%	0.00%	0.24%	0.39%	-0.15%	0.20%	0.03%	0.17%
3	0.01%	0.35%*	-0.34%*	0.02%	0.28%	-0.27%	0.42%	0.66%	-0.25%	-0.02%	0.32%*	-0.34%*
4	0.28%**	0.42%*	-0.14%	0.43%**	0.48%**	-0.05%	0.63%	0.30%	0.33%	-0.09%	0.19%	-0.28%
5	0.45%	0.40%	0.04%	0.37%	0.31%	0.06%	0.38%	-0.19%	0.57%	0.45%	0.16%	0.30%
# 5-1	0.42%***	0.32%**	0.10%	0.34%***	0.18%	0.16%***	0.32%	-1.44%	1.76%***	0.33%**	0.07%	0.26%*
# 5-3	0.43%***	0.05%	0.38%***	0.36%***	0.03%	0.32%***	-0.03%	-0.85%*	0.82%*	0.47%***	-0.17%	0.63%***
# 1-3	0.02%	-0.27%	0.28%***	0.01%	-0.15%	0.16%*	-0.35%	0.59%	-0.94%**	0.13%	-0.24%	0.37%***

2.4.4.5 Performance consequences of risk shifting depending on manager education

Prior studies have also investigated the importance of manager education and how it affects portfolio performance and risk. Chevalier and Ellison (1999a) find that mutual fund managers who attended more selective undergraduate institutions have higher performance than mutual fund managers who attended less selective undergraduate institutions. These authors argue that this difference is due to educational training, reinforcing that systematic risk is the sole type of risk that is compensated (not unsystematic risk).

Gottesman and Morey (2006) find that managers who held MBAs from the highest ranked schools outperformed those with MBAs from unranked schools and those without MBAs entirely. Switzer and Huang (2007) show that managers with an MBA degree are more likely to take on extra risk by investing in high beta funds because they know that only systematic risk pays as a compensation for the risk assumed. Dincer *et al*. (2010) examine portfolio managers based on three educational factors (CFA, MBA, and experience) and determine their performance while controlling for risk and style methods. The researchers conclude that those managers with CFAs reduced portfolio risk while those with MBAs increased it. Andreu and Pütz (2017) compare the investment risk and style of managers with both a CFA designation and an MBA degree to managers with only one of these qualifications. They document that managers with both degrees take fewer risks, follow less extreme investment styles, and achieve less extreme performance outcomes than managers with only one degree.

As occurred with industry tenure, one should expect that the level of education impacts the risk shifting strategies of fund managers; consequently, more educated managers (managers with a master degree) should be more aware of the true volatility of asset prices;

this may lead to superior investment decisions and therefore, superior performance consequences (see, e.g., Menkhoff *et al.*, 2006).

Table 2.9 summarizes the performance consequences of risk shifting depending on manager education (managers with a master degree versus managers without a master degree) Manager education appears to be an important variable to discriminate the performance consequences of risk shifting. First, Table 2.9 shows that both managers holding a master's degree and those without significantly outperform when increasing the overall risk level and systematic risk (see, e.g., the comparison of portfolio 5 vs 1 and portfolio 5 vs 3). Second, the use of the *RS* measure or the Systematic *RS* provides evidence in favor of managers with a master degree, because these managers significantly outperform the remaining managers both when they increase their risk level and particularly when they maintain stable risk levels. However, this performance improvement disappears when the 4-factor alphas are considered. Conversely, the findings also reveal that managers with a master's significantly increase the value added to their portfolios when they decrease the idiosyncratic risk; that is, when they diversify their portfolios.

Although this section only reports the results obtained when analyzing the performance consequences for the next month (t+1). All the analyses have also been performed considering the consequences for the next quarter (t+3). These results are reported in the different tables of Appendix 2.2.

Table 2.9 - Performance consequences of risk shifting by education.

This table reports the future performance of the portfolios of mutual funds sorted according to their level of risk-shifting and the education of the fund managers. Managers are classified based on their education into two groups: managers with a master degree and managers without master degree. Specifically, Panel A reports the CAPM alphas for the next month (period *t+1*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into Master and No Master groups; then, they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**
1	0.07%	-0.10%	0.17%	0.10%	-0.12%	0.21%**	0.29%*	-0.08%	0.37%***	0.12%	0.17%	-0.04%
2	-0.02%	0.12%*	-0.15%**	0.05%	-0.02%	0.07%	0.20%	0.09%	0.11%	0.28%*	0.19%	0.09%
3	0.29%*	-0.02%	0.31%***	0.27%*	0.07%	0.20%**	0.43%***	0.05%	0.38%***	0.43%***	-0.09%	0.52%***
4	0.64%***	0.15%	0.49%***	0.69%***	0.24%*	0.44%***	0.43%***	0.20%	0.22%*	0.24%*	0.03%	0.20%
5	0.78%	0.17%	0.62%	0.58%	0.13%	0.45%	0.01%	0.24%	-0.23%	0.20%	0.08%	0.13%
# 5-1	0.72%***	0.27%	0.45%***	0.49%***	0.25%**	0.24%***	-0.28%*	0.31%***	-0.60%***	0.08%	-0.09%	0.17%
# 5-3	0.50%***	0.19%**	0.31%**	0.31%**	0.06%	0.25%*	-0.42%***	0.19%	-0.61%***	-0.22%	0.17%*	-0.39%***
# 1-3	-0.22%	-0.08%	-0.14%	-0.17%	-0.19%**	0.01%	-0.13%	-0.12%	-0.01%	-0.30%**	0.26%***	-0.56%***

Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**
1	0.11%*	-0.24%	0.35%	0.12%**	-0.13%	0.24%**	0.27%	-0.09%	0.36%***	0.09%	0.17%	-0.09%
2	-0.04%	0.12%	-0.15%*	0.06%	-0.02%	0.09%	0.14%	0.20%**	-0.06%	0.19%	0.24%*	-0.06%
3	0.10%	-0.03%	0.13%	0.04%	0.05%	-0.01%	0.27%***	0.06%	0.21%*	0.20%	-0.11%	0.31%***
4	0.40%***	0.23%*	0.17%	0.48%**	0.26%**	0.22%*	0.28%*	0.20%	0.08%	0.14%	-0.11%	0.24%
5	0.47%	0.17%	0.30%	0.35%	0.12%	0.23%	-0.21%	0.14%	-0.35%	-0.01%	-0.04%	0.03%
# 5-1	0.36%***	0.41%*	-0.05%	0.23%***	0.24%**	-0.01%	-0.48%***	0.23%***	-0.71%***	-0.09%	-0.21%	0.12%
# 5-3	0.37%***	0.20%**	0.17%	0.31%**	0.07%	0.24%*	-0.48%***	0.08%	-0.56%***	-0.21%	0.07%	-0.28%**
# 1-3	0.01%	-0.21%**	0.22%	0.07%	-0.17%**	0.25%*	0.00%	-0.15%	0.15%	-0.12%	0.28%***	-0.40%***

2.5 Conclusions

This chapter analyzes the performance consequences of risk shifting through the analysis of monthly portfolio holdings to detect whether this behavior is explained by unskilled or agency-prone fund managers who trade for personal motivations, such as promotion or compensation, or is the result of skilled managers who trade to take advantage of their investment skills.

This study documents that funds that increase risk obtain a positive and statistically significant outperformance compared to funds that maintain stable risk levels and funds that reduce their risk in subsequent periods. This finding, in contrast to previous evidence in the US mutual fund industry, provides evidence that risk shifting is not harmful to investors in less developed markets; instead, it is the opposite. This finding is very robust regardless of the mechanism of risk shifting used by managers (mainly changes in asset allocation and changes in the systematic risk). The findings obtained when using the idiosyncratic risk are slightly different. Increasing the idiosyncratic risk, which occurs when funds increase their portfolio concentration, leads to underperformance. This finding suggests that the driver of poor performance for increasing idiosyncratic risk is poor stock-picking abilities.

Finally, the chapter also documents that the positive performance consequences of increasing risk are robust to manager sociodemographic variables, such as age, gender, tenure, level of specialization and education. However, there are statistically significant differences depending on manager characteristics. Specifically, the decision of increasing risk is better when it is made by a female, a specialist or a more educated manager.

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Appendix 2.1: Analysis of risk shifting consequences in funds with manager information

Table A2.1 - Performance consequences of risk shifting in period t+1 for those funds with manager information

Panel A: Funds with manager information						
RS Portfolio	**Gross Return**	**Net Return**	**Excess Market**	**CAPM**	**Fama-French**	**Carhart**
1	0.15%	0.00%	-0.09%	-0.10%*	-0.12%**	-0.11%*
2	0.31%	0.15%	0.07%	0.07%	0.06%	0.08%*
3	0.26%	0.10%	0.02%	0.03%	-0.01%	-0.01%
4	0.67%*	0.51%	0.42%**	0.48%***	0.35%***	0.33%***
5	0.65%	0.49%	0.41%**	0.46%***	0.37%***	0.40%***
# 5-1	0.50%	0.49%	0.50%	0.56%***	0.48%***	0.51%***
# 5-3	0.39%	0.39%	0.39%	0.43%***	0.38%***	0.41%***
# 1-3	-0.11%	-0.10%	-0.11%	-0.13%***	-0.11%***	-0.10%***
Panel B: Team Managed Funds						
RS Portfolio						
1	0.00%	-0.14%	-0.26%***	-0.26%***	-0.27%***	-0.28%***
2	0.26%	0.10%	0.02%	0.03%	0.02%	0.07%
3	0.24%	0.08%	0.02%	0.04%	0.01%	0.03%
4	0.35%	0.20%	0.11%	0.14%	0.08%	0.13%
5	0.51%	0.36%	0.22%	0.27%*	0.17%	0.23%*
# 5-1	0.50%	0.50%	0.48%	0.53%***	0.44%***	0.52%***
# 5-3	0.27%	0.28%	0.20%	0.24%***	0.16%***	0.20%***
# 1-3	-0.24%	-0.22%	-0.28%	-0.29%***	-0.28%***	-0.32%***
Panel C: Single Managed Funds						
RS Portfolio						
1	0.24%	0.09%	0.00%	-0.01%	-0.04%	-0.01%
2	0.20%	0.05%	0.04%	0.04%	0.03%	0.04%
3	0.40%	0.25%	0.16%	0.19%**	0.11%	0.07%
4	0.66%	0.50%	0.50%***	0.54%***	0.41%***	0.39%***
5	0.63%	0.46%	0.38%**	0.44%***	0.34%***	0.35%***
# 5-1	0.38%	0.37%	0.38%	0.45%***	0.38%***	0.36%***
# 5-3	0.22%	0.21%	0.22%	0.24%***	0.24%***	0.28%***
# 1-3	-0.16%	-0.16%	-0.16%	-0.21%***	-0.15%***	-0.08%***

Table A2.2 - Performance consequences using alternative risk shifting measures in period t+1 for those funds with manager information

Panel A: Funds with manager information												
RS Portfolio	RS ratio			Systematic RS			Idiosyncratic RS			Equity-based RS		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
1	-0.11%*	-0.11%**	-0.12%**	0.01%	0.00%	0.03%	0.11%	0.08%	0.07%	-0.05%	-0.09%	-0.07%
2	0.07%	0.04%	0.08%	0.04%	0.02%	0.04%	0.16%**	0.12%	0.14%*	0.14%*	0.11%	0.12%*
3	0.05%	0.01%	0.01%	0.05%	0.01%	0.02%	0.19%***	0.14%**	0.13%**	0.16%**	0.09%	0.06%
4	0.42%***	0.31%***	0.28%**	0.59%***	0.45%***	0.41%***	0.28%***	0.21%**	0.22%**	0.12%	0.04%	0.04%
5	0.55%***	0.42%***	0.44%***	0.33%***	0.22%*	0.26%**	0.10%	-0.03%	0.00%	0.15%	0.09%	0.08%
# 5-1	0.65%***	0.53%***	0.56%***	0.31%***	0.22%***	0.22%***	-0.01%	-0.11%	-0.07%	0.19%**	0.17%**	0.15%*
# 5-3	0.50%***	0.41%***	0.43%***	0.28%***	0.21%***	0.24%***	-0.09%	-0.16%***	-0.13%**	-0.01%	0.00%	0.02%
# 1-3	-0.15%**	-0.12%**	-0.13%**	-0.03%	-0.01%	0.01%	-0.08%	-0.06%	-0.06%	-0.21%***	-0.17%***	-0.14%**
Panel B	**Team Managed Funds**											
RS Portfolio	RS ratio			Systematic RS			Idiosyncratic RS			Equity-based RS		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
1	-0.27%***	-0.29%***	-0.31%***	-0.09%	-0.10%	-0.07%	0.04%	0.02%	-0.01%	-0.18%	-0.20%*	-0.19%
2	0.17%*	0.14%	0.18%*	0.08%	0.06%	0.08%	0.05%	0.05%	0.07%	0.08%	0.06%	0.08%
3	0.00%	-0.02%	0.00%	0.08%	0.05%	0.10%	-0.01%	-0.04%	-0.01%	0.05%	0.00%	0.04%
4	0.10%	0.05%	0.10%	0.17%	0.10%	0.12%	0.23%*	0.19%	0.27%**	0.02%	-0.02%	0.00%
5	0.28%*	0.18%	0.24%*	0.19%	0.11%	0.16%	0.15%	0.06%	0.16%	-0.05%	-0.08%	-0.05%
# 5-1	0.55%***	0.47%***	0.55%***	0.29%***	0.20%**	0.23%**	0.10%	0.04%	0.17%*	0.13%	0.12%	0.15%
# 5-3	0.27%***	0.20%***	0.24%***	0.12%	0.06%	0.05%	0.16%**	0.10%	0.17%**	-0.10%	-0.08%	-0.09%
# 1-3	-0.27%***	-0.27%***	-0.31%***	-0.17%**	-0.15%*	-0.18%**	0.05%	0.06%	0.00%	-0.23%***	-0.20%***	-0.23%***

(continued)

Panel C: Single Managed Funds

RS Portfolio	RS ratio			Systematic RS			Idiosyncratic RS			Equity-based RS		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
1	-0.06%	-0.08%	-0.08%	0.04%	0.03%	0.06%	0.11%	0.06%	0.08%	0.11%	0.05%	0.07%
2	0.08%	0.05%	0.09%	0.00%	-0.04%	-0.01%	0.20%*	0.15%	0.17%	0.23%**	0.19%*	0.20%*
3	0.16%	0.08%	0.05%	0.21%**	0.13%	0.09%	0.31%***	0.23%***	0.19%**	0.21%**	0.12%	0.06%
4	0.50%***	0.37%***	0.36%***	0.62%***	0.49%***	0.48%***	0.34%***	0.26%***	0.25%**	0.15%	0.06%	0.04%
5	0.52%***	0.41%***	0.40%***	0.31%**	0.21%*	0.22%*	0.01%	-0.12%	-0.13%	0.13%	0.02%	0.02%
# 5-1	0.57%***	0.48%***	0.48%***	0.27%***	0.19%***	0.16%***	-0.10%	-0.19%**	-0.22%**	0.02%	-0.03%	-0.05%
# 5-3	0.36%***	0.33%***	0.35%***	0.10%	0.08%	0.13%	-0.30%***	-0.35%***	-0.32%***	-0.09%	-0.09%	-0.03%
# 1-3	-0.21%**	-0.16%*	-0.13%	-0.17%*	-0.10%	-0.03%	-0.20%**	-0.16%*	-0.11%	-0.10%	-0.06%	0.01%

Appendix 2.2: Performance consequences of risk shifting in next quarter depending on manager characteristics

Table A2.3 - Performance consequences of risk shifting in next quarter by gender

This table reports the future performance of portfolios of mutual funds sorted according to their level of risk shifting and the manager gender. Specifically, Panel A reports the CAPM alphas for the next quarter (period *t+3*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into male and female groups; then, they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**
1	-0.02%	-0.26%	0.24%	0.15%	0.15%	0.00%	1.07%***	-0.10%	1.18%***	1.03%***	-0.32%	1.35%***
2	0.00%	0.25%**	-0.25%**	-0.08%	-0.03%	-0.05%	0.66%***	0.38%*	0.28%	0.87%***	0.21%	0.66%**
3	0.93%***	-0.50%***	1.43%***	0.89%***	-0.30%	1.19%***	1.09%***	-0.05%	1.14%***	0.85%***	-0.22%	1.07%***
4	1.90%***	0.38%	1.52%***	2.02%***	0.26%	1.76%***	0.97%***	0.80%**	0.17%	0.54%**	0.08%	0.45%
5	1.35%***	0.43%	0.92%*	1.38%***	0.15%	1.24%***	0.70%**	-0.76%	1.46%**	1.10%***	0.45%	0.65%*
# 5-1	1.37%***	0.69%***	0.68%***	1.23%***	-0.01%	1.24%***	-0.37%	-0.65%***	0.28%	0.07%	0.77%***	-0.70%***
# 5-3	0.42%**	0.93%***	-0.51%**	0.49%**	0.44%**	0.05%	-0.38%*	-0.70%***	0.32%	0.25%	0.67%***	-0.42%*
# 1-3	-0.95%***	0.24%	-1.19%***	-0.74%***	0.45%**	-1.19%***	-0.01%	-0.05%	0.04%	0.18%	-0.10%	0.28%

Panel B	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**	**Man**	**Woman**	**M - W**
1	-0.10%	-0.41%**	0.30%	0.16%	0.18%	-0.02%	0.88%***	-0.19%	1.07%***	0.66%***	-0.19%	0.84%***
2	-0.09%	0.32%**	-0.40%***	-0.10%	0.12%	-0.22%*	0.65%***	0.65%***	0.00%	0.47%**	0.35%	0.11%
3	0.49%***	-0.62%***	1.11%***	0.41%**	-0.48%***	0.89%***	0.53%***	0.09%	0.44%**	0.34%**	-0.24%	0.57%***
4	1.22%***	0.93%**	0.29%	1.28%***	0.79%	0.48%	0.39%*	1.06%***	-0.67%**	0.11%	-0.05%	0.17%
5	0.94%***	1.66%***	-0.72%	1.06%***	0.40%	0.66%	0.17%	0.00%	0.17%	0.38%	0.70%*	-0.32%
# 5-1	1.04%***	2.06%***	-1.02%***	0.9%***	0.22%	0.68%***	-0.71%**	0.20%	-0.91%***	-0.28%	0.88%***	-1.16%***
# 5-3	0.45%**	2.28%***	-1.83%***	0.65%***	0.88%***	-0.23%	-0.36%**	-0.09%	-0.27%	0.04%	0.93%***	-0.89%***
# 1-3	-0.60%***	0.21%	-0.81%***	-0.25%	0.66%***	-0.91%***	0.35%**	-0.28%	0.64%***	0.32%*	0.05%	0.27%

Table A2.4 - Performance consequences of risk shifting in next quarter by level of specialization

This table reports the future performance of portfolios of mutual funds sorted according to their level of risk shifting and the type of responsibilities of fund managers. Managers are classified as generalist whether they run funds belonging to several investment objectives while they are classified as specialists whether they run funds on just one investment objective. Specifically, Panel A reports the CAPM alphas for the next quarter (period *t+3*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into specialist and generalist groups and then they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**
1	-0.09%	-0.06%	-0.03%	0.20%*	-0.04%	0.24%**	0.04%	0.47%	-0.43%	1.24%***	-0.24%	1.48%***
2	0.15%	0.07%	0.08%	0.10%	-0.12%	0.22%**	0.73%***	0.54%**	0.18%	0.44%*	0.67%**	-0.23%
3	0.40%**	0.72%***	-0.32%	0.50%**	0.73%***	-0.23%	0.51%***	0.95%***	-0.44%**	0.40%**	0.72%***	-0.32%
4	1.26%***	1.55%***	-0.29%	1.41%***	1.86%***	-0.46%	1.42%***	0.71%***	0.70%***	-0.09%	0.64%**	-0.73%***
5	1.28%***	1.06%***	0.22%	1.41%***	1.14%***	0.26%	0.68%*	0.19%	0.49%*	1.24%***	0.90%*	0.34%
# 5-1	1.37%***	1.12%***	0.24%***	1.21%***	1.18%***	0.03%	0.64%***	-0.28%	0.93%***	0.00%	1.14%***	-1.14%***
# 5-3	0.88%***	0.35%	0.54%***	0.91%***	0.42%*	0.49%**	0.17%	-0.77%***	0.94%***	0.84%***	0.19%	0.65%***
# 1-3	-0.49%***	-0.78%***	0.29%	-0.30%	-0.76%***	0.47%**	-0.47%***	-0.49%**	0.01%	0.84%***	-0.96%***	1.80%***

Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**	**Specialist**	**Generalist**	**S - G**
1	-0.19%*	0.00%	-0.19%	0.24%**	-0.04%	0.28%**	-0.10%	0.56%	-0.66%	1.16%***	-0.32%	1.49%***
2	0.13%	0.02%	0.11%	0.17%	-0.11%	0.28%***	0.85%***	0.53%**	0.32%	0.41%	0.14%	0.27%
3	0.23%	0.32%	-0.09%	0.28%	0.20%	0.08%	0.53%***	0.40%**	0.13%	0.29%*	0.17%	0.12%
4	1.06%***	0.98%***	0.08%	1.17%***	1.21%***	-0.05%	0.80%***	0.36%	0.44%*	-0.36%	0.28%	-0.64%***
5	1.17%***	0.81%***	0.37%	1.08%***	1.07%***	0.02%	0.01%	0.01%	0.00%	0.61%*	0.36%	0.24%
# 5-1	1.37%***	0.80%***	0.56%***	0.85%***	1.11%***	-0.26%**	0.11%	-0.55%	0.66%***	-0.56%**	0.69%***	-1.24%***
# 5-3	0.94%***	0.48%**	0.46%**	0.80%***	0.86%***	-0.06%	-0.52%***	-0.39%**	-0.13%	0.32%*	0.19%	0.12%
# 1-3	-0.42%**	-0.32%	-0.10%	-0.04%	-0.25%	0.21%	-0.62%***	0.17%	-0.79%***	0.88%***	-0.49%**	1.37%***

Table A2.5 - Performance consequences of risk shifting in next quarter by tenure

This table reports the future performance of the portfolios of mutual funds sorted according to their level of risk shifting and the level of tenure of fund managers. Managers are classified by high and low tenure to form two equal-sized groups according to whether the characteristic is above or below its median value. Specifically, Panel A reports the CAPM alphas for the next quarter (period *t+3*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into high and low tenure groups and then they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**
1	-0.05%	-0.36%	0.31%	0.06%	0.13%	-0.06%	-0.04%	0.59%**	-0.63%***	0.56%***	0.48%**	0.08%
2	0.02%	0.27%**	-0.25%**	0.10%	-0.12%	0.22%	0.56%***	0.40%	0.15%	0.72%***	0.39%	0.34%
3	0.84%***	0.26%	0.58%***	0.74%***	0.44%**	0.30%	1.05%***	0.43%**	0.62%***	0.76%***	0.28%	0.48%**
4	1.23%***	1.80%***	-0.57%*	1.47%***	1.86%***	-0.39%	0.67%***	1.17%***	-0.51%*	0.55%**	-0.03%	0.58%***
5	1.11%***	1.64%***	-0.53%	1.20%***	1.55%***	-0.35%	-0.25%	0.63%	-0.88%**	0.62%	1.46%***	-0.84%**
# 5-1	1.15%***	2.00%***	-0.84%***	1.14%***	1.42%***	-0.28%***	-0.20%	0.04%	-0.24%	0.06%	0.98%***	-0.92%***
# 5-3	0.27%	1.38%***	-1.11%***	0.46%**	1.10%***	-0.65%***	-1.30%***	0.20%	-1.50%***	-0.14%	1.18%***	-1.32%***
# 1-3	-0.88%***	-0.62%***	-0.26%	-0.68%***	-0.32%	-0.36%*	-1.10%***	0.15%	-1.25%***	-0.20%	0.21%	-0.40%*

Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**	**High**	**Low**	**H - L**
1	0.02%	-0.59%**	0.61%**	0.10%	0.10%	0.00%	-0.16%	0.85%***	-1.01%***	0.41%*	0.49%**	-0.07%
2	0.00%	0.23%*	-0.23%*	0.11%	-0.16%	0.27%	0.51%**	0.55%**	-0.04%	0.30%	0.42%	-0.13%
3	0.33%**	0.14%	0.19%	0.12%	0.33%*	-0.21%	0.41%**	0.49%***	-0.08%	0.13%	0.14%	-0.01%
4	0.41%	1.52%***	-1.11%***	0.51%	1.64%***	-1.13%***	0.32%	0.56%**	-0.24%	0.11%	-0.06%	0.16%
5	0.75%***	1.50%***	-0.76%***	1.02%***	1.20%***	-0.19%	-0.47%	0.21%	-0.68%**	0.07%	1.12%***	-1.05%***
# 5-1	0.73%***	2.09%***	-1.36%***	0.92%***	1.10%***	-0.18%*	-0.32%**	-0.65%**	0.33%**	-0.34%	0.63%***	-0.97%***
# 5-3	0.42%***	1.36%***	-0.94%***	0.90%***	0.87%***	0.02%	-0.88%***	-0.28%	-0.60%***	-0.06%	0.97%***	-1.04%***
# 1-3	-0.31%*	-0.73%***	0.42%***	-0.02%	-0.23%	0.21%	-0.56%***	0.36%**	-0.93%***	0.28%	0.34%*	-0.06%

Table A2.6 - Performance consequences of risk shifting in next quarter by manager age

This table reports the future performance of portfolios of mutual funds sorted according to their level of risk shifting and the age of fund managers. Managers are classified as young and old to form two equal-sized groups according to whether the characteristic is above or below its median value. Specifically, Panel A reports the CAPM alphas for the next quarter (period *t+3*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into young and old manager groups; then, they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**
1	-0.06%	-0.14%	0.08%	0.13%*	0.11%	0.02%	0.28%**	1.24%***	-0.97%**	0.34%	1.05%***	-0.71%**
2	0.03%	0.20%	-0.18%	-0.03%	0.18%	-0.21%	0.13%	1.62%***	-1.48%***	0.16%	0.93%**	-0.77%**
3	0.37%**	1.81%***	-1.44%***	0.53%***	1.75%***	-1.21%***	0.52%***	1.93%***	-1.40%***	0.35%**	1.63%***	-1.28%***
4	1.56%***	2.26%***	-0.70%	1.38%***	2.43%***	-1.04%**	1.01%***	0.93%**	0.07%	0.12%	0.85%**	-0.73%*
5	1.70%***	1.33%***	0.37%	1.71%***	1.20%***	0.51%	1.59%***	0.09%	1.50%***	1.92%***	1.11%***	0.80%**
# 5-1	1.76%***	1.48%***	0.29%	1.57%***	1.09%***	0.49%***	1.31%***	-1.15%***	2.46%***	1.57%***	0.06%	1.51%***
# 5-3	1.33%***	-0.47%	1.81%***	1.17%***	-0.55%	1.72%***	1.06%***	-1.84%***	2.90%***	1.57%***	-0.51%	2.08%***
# 1-3	-0.43%***	-1.95%***	1.52%***	-0.40%**	-1.63%***	1.23%***	-0.25%	-0.68%*	0.44%***	0.00%	-0.58%	0.57%***
Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**	**Young**	**Old**	**Y - O**
1	0.00%	-0.07%	0.06%	0.15%*	0.16%	-0.01%	0.23%	1.03%**	-0.80%*	-0.20%	0.67%**	-0.87%***
2	-0.05%	0.33%*	-0.38%**	-0.17%	0.30%	-0.47%**	0.12%	1.10%***	-0.99%***	0.15%	0.17%	-0.03%
3	0.13%	0.94%***	-0.81%**	0.30%*	0.71%**	-0.40%	0.21%	0.92%***	-0.70%**	0.14%	0.65%**	-0.51%*
4	1.09%***	1.09%***	0.00%	0.80%***	1.21%***	-0.42%	0.43%**	0.17%	0.26%	-0.19%	0.31%	-0.50%
5	1.33%***	0.91%***	0.42%	1.07%***	1.23%***	-0.16%	0.62%	-0.40%	1.02%***	0.83%	0.45%	0.38%
# 5-1	1.33%***	0.97%***	0.35%	0.93%***	1.08%***	-0.15%*	0.39%***	-1.43%***	1.82%***	1.03%***	-0.22%	1.25%***
# 5-3	1.19%***	-0.03%	1.23%***	0.77%***	0.52%	0.24%	0.40%***	-1.32%***	1.72%***	0.69%***	-0.20%	0.89%***
# 1-3	-0.13%	-1.01%***	0.88%***	-0.16%	-0.55%	0.40%**	0.01%	0.11%	-0.10%	-0.34%**	0.02%	-0.36%**

Table A2.7 - Performance consequences of risk shifting in next quarter by education

This table reports the future performance of the portfolios of mutual funds sorted according to their level of risk-shifting and the education of the fund managers. Managers are classified based on their education into two groups: managers with a master degree and managers without master degree. Specifically, Panel A reports the CAPM alphas for the next quarter (period *t+3*), while Panel B reports the Carhart alphas. Mutual funds are first sorted into Master and No Master groups; then, they are further divided into five groups according to their risk shifting level. The table reports the performance of the ten portfolios formed for each *RS* measure and the differences in the future performance between the selected portfolios. *; ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**
1	0.03%	-0.30%	0.33%	0.15%*	0.13%	0.02%	0.76%***	-0.17%	0.93%***	0.54%***	0.43%	0.11%
2	0.02%	0.22%	-0.20%	0.00%	-0.13%	0.13%	0.60%***	0.36%*	0.25%	0.70%***	0.64%***	0.06%
3	0.98%***	-0.10%	1.08%***	0.93%***	0.15%	0.78%***	1.03%***	0.28%	0.76%***	1.00%***	-0.07%	1.08%***
4	1.97%***	0.60%**	1.36%***	2.34%***	0.64%***	1.70%***	1.36%***	0.64%***	0.72%***	0.61%**	0.15%	0.46%**
5	2.19%***	0.68%***	1.51%***	1.86%***	0.73%***	1.14%***	0.69%	0.20%	0.49%**	0.95%***	0.64%*	0.31%
# 5-1	2.16%***	0.98%***	1.17%***	1.72%***	0.60%***	1.11%***	-0.07%	0.38%***	-0.45%	0.41%***	0.21%	0.20%
# 5-3	1.21%***	0.78%***	0.43%*	0.94%***	0.57%***	0.36%	-0.34%	-0.07%	-0.27%	-0.05%	0.71%***	-0.77%***
# 1-3	-0.95%***	-0.20%	-0.75%***	-0.78%***	-0.03%	-0.75%***	-0.27%	-0.45%***	0.18%	-0.47%*	0.51%***	-0.97%***

Panel B:	**RS measure**			**Systematic RS**			**Idiosyncratic RS**			**Equity-based RS**		
RS Portfolio	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**	**Master**	**No Master**	**M - NM**
1	0.08%	-0.79%*	0.87%**	0.20%**	0.03%	0.17%	0.86%***	-0.25%	1.11%***	0.39%**	0.43%	-0.05%
2	-0.05%	0.25%	-0.30%*	-0.05%	0.03%	-0.08%	0.56%**	0.68%***	-0.12%	0.23%	0.90%***	-0.67%***
3	0.52%**	-0.14%	0.66%***	0.36%*	0.03%	0.32%**	0.44%**	0.40%**	0.04%	0.42%**	-0.16%	0.58%***
4	1.09%***	0.80%***	0.28%	1.43%***	0.88%***	0.55%**	0.46%*	0.46%**	0.00%	0.18%	0.02%	0.15%
5	1.50%***	0.73%***	0.77%***	1.17%***	0.72%***	0.45%**	0.05%	0.05%	0.00%	0.19%	0.67%*	-0.48%
# 5-1	1.43%***	1.53%***	-0.10%	0.98%***	0.69%***	0.29%***	-0.81%***	0.30%*	-1.11%***	-0.19%	0.24%	-0.43%**
# 5-3	0.99%***	0.87%***	0.11%	0.82%***	0.69%***	0.13%	-0.39%**	-0.35%*	-0.04%	-0.23%	0.83%***	-1.06%***
# 1-3	-0.44%**	-0.65%***	0.21%	-0.16%	0.00%	-0.16%	0.42%**	-0.65%***	1.07%***	-0.03%	0.59%***	-0.63%***

Chapter 3:

Analysis of managers' efficiency: A sociodemographic approach.

Summary

This chapter analyzes the managers' efficiency through a model of Data Envelopment Analysis (DEA). This model is not only limited to examine the efficiency in financial terms but also consider the sociodemographic characteristics of managers. The study provides an innovative method to evaluate managers' efficiency: the Slacks-Based Measure (the SBM model). This chapter proposes an original set of inputs and outputs to evaluate managers' efficiency different from those conventionally used in the DEA literature to evaluate mutual funds' efficiency. After the analysis of managers' efficiency, managers are clustered by gender and level of specialization for a better identification of the real competitors for each manager based on similar sociodemographic characteristics.

3.1 Introduction and literature review

In recent decades, the financial sector has undergone major changes in its activities due to the internationalization and deregulation of financial markets, technological advances, etc. These changes have forced financial institutions to diversify their business to survive. These diversifications can imply changes in the efficiency and productivity of financial institutions. For this reason, in the last decades, several studies have investigated the productivity and efficiency in the different sectors and products of financial markets. One of the methods mostly used to evaluate the efficiency of the financial institutions has been Data Envelopment Analysis (DEA) models. Some of the papers that evaluate the efficiency of the financial institutions are the following, Berg *et al.* (1993) uses a DEA model to analyze competition in the banking sector in three Nordic countries; Schaffnit *et al.* (1997) analyze the efficiency of the staff of a large Canadian bank; Cummins *et al.* (2004) analyze the efficiency of the structure of Spanish insurance companies; Cummins and Xie (2008) analyze the impact of mergers between US insurance companies on productivity and efficiency; Cummins *et al.* (2010) investigate the economies of scope in the US insurance. More recently, Holod and Lewis (2011) propose a DEA model to measure bank efficiency through the double function of deposits in the production process of the bank.

These studies concentrate their attention on banks, saving banks, loan companies, and the insurance industry. In 1997, the DEA methodology was used, for the first time, to examine the efficiency of investment funds. Specifically, Murthi *et al.* (1997) evaluated the efficiency of 2,083 investment funds with a DEA Portfolio Efficiency Index model called DPEI. This model can be considered an extension of the well-known Sharpe ratio (Sharpe, 1966) by including the transactional costs as an

additional input to the standard deviation of the portfolio returns.[1] The interest in DEA models by mutual funds' literature may be largely explained because these frontier methods do not require any functional form between return and risk. In addition, the potential use of several inputs and outputs in the performance evaluation is an innovative way to explore the performance of financial portfolios. As a consequence of this work, the DEA models have been used to measure the performance of mutual funds as an alternative to the traditional measures such as Jensen (1968), Fama and French (1993) and Carhart (1997) alphas.

These traditional performance metrics do not use, explicitly, the information available in the decision making process of mutual managers while DEA models do. For example, the performance of mutual fund managers depends to a large extent on their efficiency at the time they buy and sell (the efficiency of their trading decisions), as indicated by Chen *et al.* (2000). Therefore, DEA models are an alternative approach for researchers and practitioners to traditional performance measures. DEA models can improve the results obtained by the traditional models using several inputs and outputs in the performance evaluation while the traditional models assume functional forms between risk and return.

Basso and Funari (2001), Choi and Murthi (2001), Basso and Funari (2003), Lozano and Gutiérrez (2008), Zhao and Yue (2010) and Lamb and Tee (2012) are examples of studies that analyze mutual fund efficiency through different models of DEA. More recently, Basso and Funari (2017) study the role of mutual fund size in the evaluation of fund performance with a DEA approach.

[1] The Sharpe ratio can be considered as a constant returns to scale (CRS) frontier model with the standard deviation of fund returns as a single input and the excess fund returns as a single output (Choi and Murthi, 2001).

On the other hand, Medeiros (2010) and Andreu *et al*. (2014) investigate the efficiency of pension funds through DEA models. Finally, some studies also apply DEA models to evaluate the hedge fund performance (see, e.g., Eling, 2006; Gregoriou, 2003; Gregoriou *et al*., 2005; and Kumar *et al*., 2010, among others).

Hence, many studies have analyzed the efficiency of the financial system (banks and insurance companies) and the efficiency of investment vehicles such as investment funds and hedge funds. However, as far as I know, the efficiency of portfolio managers has been scarcely analyzed through DEA models. Specifically, only the recent study by Banker *et al.* (2016) focuses on the efficiency of portfolio managers. These authors develop a trade-level measure to evaluate managers' efficiency in their buying and selling activities relative to the trades of other fund managers. They customize an additive DEA model to focus on risk-adjusted returns during different time periods. Unlike Banker *et al.* (2016), this chapter measures managers' efficiency depending on their characteristics through the SBM model and its variation III, using for this purpose a set of variables that are not only limited to profitability and risk. Therefore, this is the first empirical application of the SBM model to analyze managers' efficiency, filling this gap in the financial literature.

In this chapter of the Doctoral Thesis and after analyzing managers' behavior through parametric methodologies, I will analyze the efficiency of Spanish investment fund managers through a non-parametric methodology, specifically through a DEA model. The aim of this chapter is to analyze managers' efficiency through a model of DEA, which is not only limited to explore the financial efficiency but also consider the sociodemographic characteristics of portfolio managers. The sociodemographic variables examined in this chapter are the same than in Chapter 2; concretely, the gender, level of education, level of specialization and experience of fund managers.

Additionally, this chapter examines the determinants of the efficiency scores obtained by the portfolio managers.

This chapter carries out an empirical investigation on a set of 54 Spanish managers of European equity mutual funds from January 2009 to December 2014. The study focuses on those mutual funds that are single-managed to be able to consider properly the sociodemographic variables of the managers (as occurred in Chapter 2). This choice is justified because sociodemographic variables play an important role, and these variables can be very different between the members of a management team (a team can be formed by managers with varied experience; with managers of different gender, etc.).

Managers' efficiency is computed by using, for the first time, a suitable DEA technique. This model is the Slacks Based Measure (SBM) proposed by Tone (2001) and its further SBM variations (Tone, 2010). In particular, the study defines which variables are relevant to the efficiency of a portfolio manager. A manager will be classified as efficient whether he/she is able to maximize the gross return in a large number of assets under management assuming a low level of risk, minimizing the portfolio turnover and the cost that he/she represents for the management company. Once the model is defined, the chapter examines the efficiency of portfolio managers for each year of the sample through the application of the original SBM model.

Because the referent managers of the efficient frontier may be far from certain managers and therefore can be inappropriate as the reference set, managers are evaluated with respect to all the facets of the efficient frontier. It is important to determine those reference sets of efficient managers with similar characteristics than the target managers analyzed. Therefore, the second aim of the chapter is to analyze

managers' efficiency by clustering them depending on their sociodemographic characteristics.

Variation III of SBM model (Tone, 2010) evaluates the efficiency of each manager from all facets formed by efficient managers within each cluster. These results will be analyzed in detail because this variation identifies locally efficient managers in addition to those globally efficient detected in the previous analysis. The use of this type of methodology, will allow comparing the consequences in terms of efficiency of the sociodemographic variables of the managers without requiring any type of relationship between managers' efficiency and the gender and level of specialization of fund managers. Note that this is one of the great advantages of this type of methodology. Last, this analysis will allow a comparison of managers with similar characteristics, being able to develop a ranking of managers that will be of great interest to the different market members. First, it is relevant for investors to know which managers are more efficient than others. It is also relevant for managers themselves to know in which position of the ranking they are in comparison to their competitors and to try to improve their results. Finally, this chapter is also very important and interesting for management companies because it allows them to design and implement different policies of incentives and promotion depending on manager efficiency.

Finally, the analysis of the determinants that influence on the survival of a manager as individual manager show that the most relevant variable is the experience and education. On the other hand, the determinants of managers' efficiency score are her/his net assets under management, the level of risk and turnover.

The remainder of the chapter is organized as follows. Section 3.2 shows the evolution of the DEA models and the SBM .Section 3.3 describes the data and variables

used in the model. Section 3.4 provides a discussion of the empirical results. Section 3.5 provides a discussion about further questions about managers' efficiency. Section 3.6 concludes.

3.2 Evolution of the DEA models and the SBM

3.2.1 DEA Models

The aim of DEA is to evaluate the relative performance of a number of decision-making units (DMUs) comparable, which may be within a company or across different companies within an industry (see, e.g., Farrell, 1957 and Charnes *et al.*, 1978). In this chapter, the DMUs will be the different portfolio managers that individually are in charge of Spanish mutual fund that invest in European equities.[2]

The DEA method does not give preference to any factor; both outputs and inputs are incorporated in a single model independently of the units in which they are measured. On the other hand, the DEA models measure the relative efficiency with respect to the best observations obtained by the set of DMUs that are evaluated.

Given the outputs of the DMUs, which measure the production, and given the inputs, which are the resources consumed in the production of the outputs, the technical efficiency is calculated by the ratio of output/input. That is, the ratio of inputs consumed to produce a given quantity of outputs. To this end, all outputs and all inputs are added, and the conjunct ratio is studied.

The efficiency can be examined from a double perspective or orientation (input-oriented or output-oriented). A production system is efficient if for certain levels of

[2] Only single-managed funds are analyzed to consider the sociodemographic variables of portfolio managers. Therefore, team-managed funds are excluded in this chapter.

inputs it is able to produce the maximum amount of possible output or, alternatively, if the least amount of inputs is used to reach a certain level of output. Hence, the efficiency is calculated by a multidimensional ratio that considers weights on the different inputs and outputs used (see, e.g., Cooper *et al.*, 2001).

There are several types of DEA models, but the two models most extensively applied are the CCR model proposed by Charnes *et al*. (1978), which has an input orientation and assumes constant returns to scale (CRS), and the BCC model proposed by Banker *et al*. (1984), which considers variable returns to scale (VRS).

The input-oriented CCR model was the first to be widely applied in the DEA literature. Based on the explanations of Cook and Seiford (2009), the CCR model consider a set of *n* DMUs, with each DMU *j*, *(j = 1, 2, 3, ..., n)* using the same *m* inputs x_{ij} *(i = 1, 2, 3, ..., m)*, possibly in different amounts, and producing the same *s* outputs y_{rj} *(r = 1, 2, 3, ..., s)*, also possibly in different amounts. If the prices or multipliers $\bar{ur}$ and $\bar{vi}$ related to outputs *r* and inputs *i*, correspondingly, are known, then using the conventional benefit/cost concept, the efficiency of DMU*j* could be expressed as the ratio of weighted outputs to weighted inputs. If the multipliers are unknown, Charnes *et al.* (1978) proposed deriving appropriate multipliers for a given DMU by solving a particular non-linear programing problem. The objective of this problem is to minimize inputs while producing at least the given output levels, i.e., to obtain values (weights) for $\bar{ur}$ and $\bar{vi}$ that maximize the ratio. The constraints mean that this ratio should not exceed 1 for every DMU. By virtue of these constraints, the optimal objective value is at most 1.

The optimal solutions show the occurrence of both excess inputs and shortfalls in outputs, which are called slacks (s^-, s^+). If the ratio is less than 1, the objective DMU is inefficient. If the ratio is 1 with s^- and s^+ equal zero, it is called CCR-efficient.

The CCR model seems to be appropriate when the set of companies are operating at an optimal scale. However, imperfect competition, government regulations, funding constraints, etc., may cause that DMUs do not to operate on an optimal scale. For this reason, the BCC model suggests adjusting the CCR model to account for VRS. Banker *et al.* (1984) simply added a convexity constraint. That is, the BCC model has its production frontiers of its production possibility set P now spanned by the convex hull of all existing DMUs.[3]

On the other hand, Charnes *et al.* (1985) proposed the combination of both models and formulated the Pareto-Koopmans model (PK) or Additive model. In this approach, the inputs are reduced proportionally while the outputs are kept fixed, and the outputs increase proportionally while the inputs are maintained fixes. This model has no scalar measure or efficiency ratio, unlike the BCC and CCR models. The PK additive model can discriminate between efficient and inefficient DMUs due to the existence of gaps, but does not measure the depth of inefficiency.

Tone (2001) and Tone (2010) overcome the aforementioned limitation through the formulation of a new model, the SBM model. These studies are the methodological base of this third chapter of the Thesis.

[3] The standard BCC model is not appropriate in this study because the observations used are gross returns and some of them have negative values (see, e.g., Kerstens and Woestyne, 2014).

3.2.2 SBM and variations

3.2.2.1 Analysis of managers' efficiency through a slacks-based measure (SBM)

The first analysis carried out in this chapter is the analysis of managers' efficiency through a slacks-based measure (SBM). The SBM is invariant to the units of measurement and is monotonic increasing in each input and output slack. These complementary adjustments in the inputs (s^-) called input excesses or outputs (s^+) called output shortfalls are defined as slacks.

The SBM is a non-radial model that integrates the slacks of each input and output individually into an efficiency score (Tone, 2001). This approach overcomes the additive DEA models (Charnes *et al*., 1985) because it provides an efficiency measure based on slacks.

Let me consider a set of *n* DMUs[4], where each DMU_j (for j=1, 2, 3,…, n) has *m* inputs x_{ij} (for i=1, 2, 3,…,m) to produce *s* outputs y_{rj} (for r=1, 2, 3,…, s). This model assumes that $x_{ij} > 0$ and $y_{rj} > 0$. Under the hypothesis of constant returns to scale (CRS)[5], λ is a non-negative set of variables ($\lambda_{1,\ldots,} \lambda_n$), which represents the intensity vector; and s^+ and s^- are the slack vectors, which represent the non-negative sets of input excesses and output shortfalls. Therefore, the production possibility set P is defined as:

$$P = \{(x,y) \vdots x \geq \sum_j x_j \lambda_j, 0 \leq y \leq \sum_j y_j \lambda_j, \lambda_j \geq 0\} \qquad (3.1)$$

A DMU will be considered efficient in terms of Pareto–Koopmans when it has no input excesses and no output shortfalls for any optimal solution, that is, when $P_0^{min} = 1$ according to the following model:

[4] In this case, the DMUs are those managers that individually managed at least one Spanish mutual fund that invest in European equities during the whole year of analysis.
[5] Managers' efficiency has been contrasted with CRS and VRS, see section 3.4 for further details.

$$P_0^{\min} = \min \frac{1-(1/m)\sum_{i=1}^{m} s_i^- / x_{i0}}{1+(1/s)\sum_{r=1}^{s} s_i^+ / y_{r0}}$$

Subject to

$$\sum_{j=1}^{n} x_j \lambda_j + s^- = x_0$$

$$\sum_{j=1}^{n} y_j \lambda_j - s^+ = y_0$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \qquad (3.2)$$

The reference-set R_0 for the target DMU (x_0, y_0) is defined as the set of DMUs corresponding to positive λ_j^* in the solution of the previous model.[6] In other words, R_0 are DMUs on which the score for the DMU target is being calculated. These are best practice competitor that serves as reference for the target DMU.

$$R_0 = \{j : \lambda_j^* > 0, j = 1,....,n\} \qquad (3.3)$$

However, this measure has been questioned because there are other different approaches to determine the 'best-practice' reference set. According to Tone (2010), the SBM model fails to identify the 'best practice' competitors that can serve as a benchmark for the managers analyzed due to differences between the characteristics of the managers evaluated and those considered as 'best practice' competitors. These analyses will provide information about the efficiency of Spanish mutual fund managers, but it will not compare the "most efficient manager" with his/her competitors in a suitable way since there may be great differences in managers' characteristics.

This limitation may question the accuracy of SBM results. This problem is especially relevant in those industries where competitors show assorted characteristics,

[6] The consideration of VRS would require the convexity condition on the intensity vector λ. The restriction $\lambda_1 + \lambda_2 + \ldots + \lambda_n$ should be included in the SBM and the following variants. See section 7 of Tone (2010) for further details.

such as the Spanish fund industry. For example, a set of managers with a lot of experience may not be an adequate reference for a given manager that has little experience in the market although those experienced managers are in the efficient frontier of the SBM model. Therefore, SBM offers an efficiency ranking of managers that can be deceiving. For that reason, SBM Variation III (Tone, 2010) is carried out in the next section.

3.2.2.2 Analysis of managers' efficiency clustering depending on manager sociodemographic characteristics

The identification of adequate references according to homogeneous management characteristics is the main advantage of Variation III. However, the results obtained by this variant might be very sensitive to the clustering process in cases in which the management characteristics are not dramatically different. In those instances, reference sets and scores should be obtained according to different clusters to test the robustness of the rankings.

Specifically, managers' efficiency is examined through variation III of Tone (2010) by splitting the sample into groups of managers depending on manager characteristics. Similarly to Chapter 2, the characteristics of managers used here to cluster the sample are gender and level of specialization.

The management and therefore; the performance obtain by a masculine manager could not be appropriately compared with the management style of a female manager because the literature has extensively studied whether women behave differently from men and have revealed robust gender differences. Specifically, studies such as Bliss and Potter (2002), Schmidt and Traub (2002), Beckmann and Menkhoff (2008) and Welch

and Wang (2013) have predicted that female managers are more risk-averse, less overconfident and behave less competitively oriented than their male counterparts.

On the other hand, management companies can have incentives to assign portfolio managers depending on their abilities and level of specialization. Zambrana and Zapatero (2015) show that it is optimal to assign managers with market timing ability to generalist responsibilities and managers with stock-picking ability to specialist responsibilities. In accordance with these authors, the degree of manager specialization is measured by the difference between the overall number of funds managed by the manager and the number of funds managed in an investment vocation (in our case European equity mutual funds). When all mutual funds managed (or all expect one) belong to European equity funds, this manager is classified as a specialist; otherwise, the manager is classified as a generalist.

Due to the abovementioned evidence, this section considers both manager gender and level of specialization for an appropriate evaluation of managers' efficiency. That is, the SBM analysis allows observing the efficiency of Spanish fund managers but does not allow the comparison of the "most efficient manager" with its competitors in a suitable way because sociodemographic characteristics of fund managers can be very different. This limitation may question the accuracy of previous results.

Tone (2010) overcomes the aforementioned limitation through several variations on the original SBM (Tone, 2001). Tone (2010) provides appropriate tools to evaluate the efficiency records within consistent sets of competitors in the mutual fund management industry. This new approach aims to find locally efficient managers when they are compared to ‘best practice’ frontier portfolios with similar characteristics such as gender and level of specialization; otherwise the search for locally efficient portfolios would not be possible with other well-known DEA techniques.

Specifically, Tone (2010) proposes 4 variations to the SBM model. The original SBM evaluates efficiency based on the slacks-based measure to the efficient frontier. However, since its objective is to minimize this measure, the referent point can be far from the objective DMU. However, there are other approaches, for example, to find the nearest point on the frontier. For this purpose Tone (2010) first modifies the SBM to catch the minimum slacks-based measure point on the facet that the SBM found for the DMU. This first modification is called Variation I and evaluates each DMU by the nearest facet in the same border.

$$P_0^{\max} = \max \frac{1-(1/m)\sum_{i=1}^{m} s_i^- / x_{i0}}{1+(1/s)\sum_{r=1}^{s} s_i^+ / y_{r0}}$$

Subject to

$$x_0 = \sum_{j \in R_0} x_j \lambda_j + s^-$$

$$y_0 = \sum_{j \in R_0} y_j \lambda_j + s^+$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \qquad (3.4)$$

This variation is a first attempt to avoid the inappropriate reference problem potentially detected in the original SBM and requires only one easy-to-implement additional step for each inefficient DMU detected in the original SBM model. The new efficiency scores $P_0^{\max}$ will be at least similar to those obtained in the original SBM model because this variant works with the same facet than the original SBM model.

$$P_0^{\max} \geq P_0^{\min} \qquad (3.5)$$

However, there are other potential facets to evaluate the DMUs, which justify the introduction of Variation II that evaluates each DMU with all possible facets. That

is, the variations I and II are based on analyzing the consideration of VRS to evaluate the efficiency of the DMUs with different scale characteristics. These variations are based on the hyperplanes instead of the vertices of the border, which allows the new model to discover the most suitable facets with respect to each analyzed DMU.

After that, this first variant is extended to all facets of the efficient frontier. Therefore, SBM Variation II minimizes the SBM score from all facets through three steps. First, this variant finds the set of efficient DMUs by solving the original SBM model. Then, this variant enumerates all facets and only selects those *maximal friends*. A subset P_j of the CRS-efficient DMUs in the production possibility set P is defined as *friend* if a linear combination of the inputs and outputs of P_j is CRS-efficient.[7] Finally, for each inefficient DMU, Variation I is applied but only for the *maximal friends* facets (h) selected in the previous step.

$$P_0^h = \max \frac{1-(1/m)\sum_{i=1}^{m} s_i^- / x_{i0}}{1+(1/s)\sum_{r=1}^{s} s_i^+ / y_{r0}}$$

Subject to

$$x_0 = \sum_{j \in R(h)} x_j \lambda_j + s^-$$

$$y_0 = \sum_{j \in R(h)} y_j \lambda_j + s^+$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \qquad (3.6)$$

[7] A friend P_j is defined as *maximal friend* if any addition of the CRS-efficient DMUs (not in the *friends*) to P_j is not CRS-efficient. See Definitions 5, 6 and 7 (Tone, 2010) for further details of these subsets of DMUs. The identification of the *maximal friends* is programmed by Algorithm A (Tone, 2010), which first obtains those *friends* facets. After that, this algorithm deletes those *friends*, which are subsets of other *friends* (i.e., dominated *friends*).

Where $R(h)$ is the set of efficient DMUs that span each facet (h) obtained in the second step of this variant. The efficiency score P_0^{all} of each objective DMU is obtained as the maximum P_0^h obtained for all the *maximal friend* facets (h).

$$P_0^{all} = \max_h \{P_0^h\} \tag{3.7}$$

The following inequalities are found for the three SBM scores (Tone, 2010):

$$P_0^{all} \geq P_0^{\max} \geq P_0^{\min} \tag{3.8}$$

However, the enumeration of all genuine efficient frontiers of the production possibility set P required by Variation II may demand huge computational resources for large scale problems. On the basis of the idea of saving computation time and space, Variation III and Variation IV are proposed as approximate methods to find these *maximal friends* (Tone, 2010).

Variation IV is able to save computational resources but it is not going to solve the inappropriate reference problem addressed by extremely different managers' characteristics. Specifically, SBM Variation IV creates random directions around the centre of gravity of efficient DMUs, which is the average value of the inputs, X_G, and outputs, Y_G, of the set of K efficient DMUs obtained from the original SBM model.

$$X_G = \frac{X_1 + X_2 + \ldots + X_n}{K} \tag{3.9}$$

$$Y_G = \frac{Y_1 + Y_2 + \ldots + Y_n}{K} \tag{3.10}$$

The random directions (d_X, d_Y) are obtained for each efficient DMU j as a slight modification of the difference of the input and output values minus the centre of gravity (X_G, Y_G). The slight perturbations of these differences are obtained using random

numbers. After that, Variation IV finds a facet solving the following linear program in $t \in R$ and $\lambda \in R^k$.

$max\ t$

Subject to

$$X_G + d_X t \geq X_1\lambda_1 + X_2\lambda_2 + ... + X_k\lambda_k$$

$$Y_G + d_Y t \geq Y_1\lambda_1 + Y_2\lambda_2 + ... + Y_k\lambda_k$$

$$t, \lambda \geq 0 \qquad (3.11)$$

If the optimal solution t^* found by the previous lineal problem equals zero, then the centre of gravity (X_G, Y_G) is efficient and all K efficient DMUs are friends. If $t^* > 0$, then the reference DMUs obtained from $\lambda^* > 0$ form a facet of the production possibility set P. The previous program is repeated for different random directions around the K efficient DMUs until the method finds a sufficient number of facets.

However, the question raised with previous variations is whether these comparisons are applicable to problems that analyze heterogeneous sets of competitors such as Spanish mutual fund managers. The answer to this major concern is provided by the introduction of clusters (SBM Variation III) proposed by Tone (2010), which could be considered as a refinement of the general approach of Variation II. Variation III consists of the application of a clustering process and the application of variation II (Equation 3.8) to each cluster.

This variation is the relevant for this study because it will allow to analyze managers' efficiency according to their sociodemographic characteristics such as gender and level of specialization. Therefore, the hypothesis will be that managers with the same characteristics have the same opportunities to achieve efficiency, providing a ranking of managers more comparable and real than with other DEA models. The main advantage of this variant is the identification of more acceptable reference sets for the

target funds because the facets which are candidates for being maximal friends will be formed only by those managers belonging to the same cluster as the target manager.

The maximal friend facets (h0) of Variation III will only include those managers that may be considered real competitors of the target manager according to the clustering process, that is, managers with homogeneous characteristics.

In order to apply Variation III, all DMUs are first classified in L clusters. On the one hand, the sample is divided according to manager gender and on the other hand depending on managers' level of specialization. Therefore, there will be a total of 2x2 different clusters. After that, this variant obtains the original-SBM efficient DMUs.

Finally, SBM Variation III obtains the efficiency scores (Equation 3.8) for each inefficient DMU but in reference to the maximal friend facets (h') only composed by those efficient DMUs included in the same cluster than each target DMU. When this variant finds no feasible solution for the new set of facets (h'), the target DMU is considered to be globally inefficient but locally efficient in relation to the DMUs with common clustering characteristics.

Therefore, this analysis considers other existing facets of the production possibility than those obtained by the SBM model. As stated previously, the identification of the *maximal friends* facets (h) might demand huge computational resources for large scale problems. Therefore, SBM Variation III is quite convenient to appropriately identify locally efficient DMUs that might be misevaluated by the original SBM if the referent DMUs of the efficient frontier were not real competitors of the objective managers. Hence, this analysis will provide more accurate results of managers' efficiency according to their sociodemographic characteristics.

3.3 Data and variables of the model

The initial database of this chapter consists of 291 Spanish investment funds that invest in European equities funds. These funds are managed by 165 different managers. However, as the study focuses on the efficiency of single-managed funds, the final sample consists of 79 mutual funds that are managed by 54 individual managers from January 2009 to December 2014. This sample is representative of the heterogeneous characteristics of the rising Spanish investment mutual fund industry during this period.[8]

Spanish mutual fund information is obtained of the mutual fund database provided by the Spanish Securities Exchange Commission (CNMV). This database has information on returns and fund characteristics such as total net assets, number of investors, management fees and name of the management company for all Spanish mutual funds. Therefore, this database is free of survivorship bias.

On the other hand, mutual fund manager information is obtained from Morningstar Direct database. This database provides information on the managers' name, the date on which a manager assumed responsibility for the fund and in some cases a brief summary of managers' career and level of education. Both databases were matched by fund names and fund ISIN code (International Securities Identification Numbering).

The mutual fund manager information is complemented by websites such as Citywire or LinkedIn when available. These websites provide information on managers' education, career path, etc. Note that the search on these websites is done through the name of the manager, which also allows to know managers' gender.

[8] Note that managers are included in the sample whether they single-managed the fund during the whole year of analysis.

Once the database is described, it is important to define the input and output variables of the model proposed to measure managers' efficiency. The model proposed to evaluate managers' efficiency is an adaptation from the model proposed by Murthi *et al.* (1997) to evaluate mutual fund efficiency. These authors propose a relative measure of performance through a benefit/cost non-parametric analysis, where a relationship between return (benefit) and expense ratio, turnover, risk, and loads (cost) is established.

In portfolio management, performance is evaluated in terms of benefit to cost ratios. That is, investors should search for a fund that maximizes the benefit (return) and minimizes the cost (expense ratio, turnover and loads). This framework is consistent with the finance literature examining market efficiency regarding transaction costs in mutual fund industry.

Similarly to Murthi *et al.* (1997), a manager will be efficient, if she/he is able to maximize the return in the greatest amount of assets under management as possible assuming both the lowest risk and the lowest portfolio turnover because high turnover implies high transaction costs.

Additionally, the incorporation of both managers' education and industry experience could proxy the labor cost that managers' create for management companies. It is expected that the salary of a manager with a lower level of education and with low experience will not be the same as a manager with a high level of experience and education.

Lozano and Gutiérrez (2008) provide a complete review of the empirical studies that use DEA frontiers to assess the performance of mutual funds and hedge funds. The most common inputs in these studies are the standard deviation of fund returns and the expense ratio, while the fund return is the most common output. The latest studies fine-

tune these basic variables using subscription and redemption costs and fund size as new inputs (Basso and Funari, 2001; Daraio and Simar, 2006) and an ethical score as an output (Basso and Funari, 2003). Recently, Andreu *et al.* (2014) include some of these variables in a SBM model to evaluate the efficiency of the strategic asset allocation of a sample of pension funds.

Therefore, this chapter proposes an original set of inputs and outputs from those conventionally used in the DEA literature on portfolios, which are detailed below.

OUTPUT 1: Annual gross return

Annual gross return has been selected as output of the model, as in the majority of the applications of DEA techniques in financial portfolios (see, e.g., Choi and Murthi, 2001; Galagedera and Silvapulle, 2002; Chang, 2004; Daraio and Simar, 2006; Babalos *et al.*, 2012; Andreu *et al.*, 2014; Banker *et al*., 2014; Sánchez-González *et al.*, 2017; and Basso and Funari, 2017).

Mutual fund annual gross returns are TNA-weighted to calculate the gross return when the manager manages more than one fund in a given year. Then, the annual gross return of each manager is normalized between 0 and 1 each year, as proposed by Sánchez-González *et al.* (2017). This annual normalization could remove time effects from the analysis and it is really consistent to solve the potential problem of negative values of the variables included in the model.

OUTPUT 2: Total Net Assets

Grinblatt and Titman (1989) examine the effect of fund size on performance. They show that mutual funds with the smallest net asset values have the highest transaction costs and performance. Murthi *et al*. (1997) find some evidence that larger

funds may be more efficient. This may be due to the fact that they have lower transactions costs. Basso and Funari (2017) conclude that does not exist a linear relationship between size and performance, but the large funds tend, on average, to exhibit a slightly higher performance score than the smaller ones, thus indicating the presence of scale economies. Therefore, another variable that efficient managers should maximize is the assets under management for the management company. Specifically, the assets under management by each fund manager at the end of each year are calculated.

INPUT 1: Annual level risk

Mutual fund investors try to chase good performers, i.e., those fund managers who are able to provide high returns assuming a low level of risk. The use of the risk level as input is frequently used in DEA techniques to evaluate the efficiency of mutual funds (see, e.g., Basso and Funari, 2001; Choi and Murthi, 2001; Galagedera and Silvapulle, 2002; Basso and Funari, 2003; Chang, 2004; Gregoriou *et al*, 2005; Daraio and Simar, 2006; Babalos *et al.*, 2012 and Andreu *et al.,* 2014). For that reason, one of the inputs of the model is the annual level of risk assumed by the manager each year. Specifically, the annual risk of a manager is calculated as the weighted sum of the cross products of the annual variances and covariances of the daily gross returns of the mutual funds managed by a given manager.

INPUT 2: Annual turnover

The performance of managers of actively managed funds depends largely on their efficiency in timing their buy and sell trades (see, e.g., Chen *et al*., 2000). The portfolio turnover allows to observe the decision making process of the manager in their

transactions. Portfolio turnover has been included as input in the DEA literature because it is the main proxy to capture the transaction cost structure in the evaluation of financial portfolios (see, e.g., Murthi, 1997, Choi and Murthi, 2001; Daraio and Simar, 2006 and Andreu *et al*., 2017). Previous literature shows that managers who rotate more their portfolios incur higher transaction costs. Specifically, Babalos *et al.* (2012) conclude that the turnover rate is the main source of inefficiency for their sample funds. Therefore, an efficient manager should incur in the lowest possible costs.

Similarly to other variables, turnover is TNA-weighted to calculate the manager turnover in case the manager manages more than one fund in a given year. Annual mutual fund turnover is calculated as the lesser of purchases or sales divided by the average monthly net asset value of the fund (see, e.g., Elton *et al*., 2010).

INPUT 3: Education and experience

There are very few papers that studies the relation between portfolio manager compensation and mutual fund performance (see, e.g, Elton *et al.*, 2003; Golec and Starks, 2004; Agarwal *et al.*, 2009; Ma *et al.*, 2016). These authors found that managers with performance-based compensation exhibit superior fund performance. These studies are focused on the US mutual fund industry. However, there is no information on managers' remuneration for other less developed markets and therefore this model use a proxy on the remuneration of managers based in education and experience.

To determine manager efficiency both education and experience play an important role. It is expected that the salary of a manager with a lower level of education and with low experience will not be the same as a manager with a high level of experience and education. Therefore, this study uses education and experience as proxy of managers' remuneration. The variable education-experience is created through

a Sigmoid function because this mathematical function has an "S" shaped curve.[9] This function is suitable for variables such as education and experience because they will not be infinitely growing; there is a point where that growth is paralyzed.

The variable education-experience of manager *i* denoted as S_i is calculated as follows:

$$S_i = \exp_i \frac{1}{\frac{1}{1+e^{-edu_i}}} \tag{3.12}$$

where $\exp_i$ is the experience of manager *i*. Manager experience in the industry is calculated from the first year that Morningstar reports for a manager in the database; edu_i is the level of education of the manager. Specifically, the study discriminates between those managers with a master degree and those without a master. Therefore, if a manager does not have a master, the variable S_i will take the value of the experience of the manager.

Table 3.1 summarizes manager characteristics and the variables employed as inputs and outputs in the sample from January 2009 to December 2014 in Panels A and B, respectively. Specifically, Panel A reports the number of managers and funds analyzed each year and the distribution of these managers according to their gender and their level of specialization. On average, there are 36 managers for which, on average, there are 25 men and 10 women. These figures represent 71% and 29% of the sample, respectively. On the other hand, there are on average 11 specialist managers and 24 generalist managers which represent 32% and 68% of the sample, respectively.

[9] The sigmoid function is widely used in the finance literature (see, e.g., Wang and Huang, 2010 and Zhao and Yue, 2010). Appendix 3.1 shows the “S” shaped curve provided by the sigmoid function.

Panel B reports summary statistics of the inputs-outputs used in the model. Specifically, it reports the mean, the median and the standard deviation over the time of the normalized value of the annual gross return (output 1), the annual assets under management (output 2), the normalized value of the annual risk level assumed by the manager (input 1), the annual manager turnover (input 2) and the education-experience variable (input 3).

Table 3.1 - Description of the sample and variables of model

This table summarizes the characteristics of managers and variables employed in the sample from January 2009 to December 2014. Panel A reports the number of managers and funds analyzed each year and the distribution of these managers according to their gender and their level of specialization. Panel B reports summary statistics of the inputs-outputs used in the model. Specifically, it reports the mean, the median and the standard deviation over the time of the normalized annual gross return (output 1), the annual assets under management (output 2), the annual risk level assumed by the manager (input 1), the annual manager turnover (input 2) and the education-experience variable (input 3).

Panel A	**2009**		**2010**		**2011**		**2012**		**2013**		**2014**	
Mutual Funds	37		56		56		40		43		47	
Managers	30		41		40		32		34		36	
Men	22	*(73.33%)*	28	*(68.29%)*	29	*(72.50%)*	22	*(68.75%)*	25	*(73.53%)*	26	*(72.22%)*
Women	8	*(26.67%)*	13	*(31.71%)*	11	*(27.50%)*	10	*(31.25%)*	9	*(26.47%)*	10	*(27.78%)*
Specialists	10	*(33.33%)*	12	*(29.27%)*	13	*(32.50%)*	10	*(31.25%)*	11	*(32.35%)*	12	*(33.33%)*
Generalists	20	*(66.67%)*	29	*(70.73%)*	27	*(67.50%)*	22	*(68.75%)*	23	*(67.65%)*	24	*(66.67%)*
Total managers	54		**Mean Manager:** 36		**Mean Men:** 25 *(71.44%)*		**Mean Women**: 10 (*28.56%)*		**Mean Spec.:** 11 *(32.00%)*		**Mean Gen.:** 24 *(68.00%)*	
Total M. Funds	79		**St.Dev:** 4.3704		**St.Dev:** 2.9439		**St.Dev:** 1.7224		**St.Dev:** 1.2111		**St.Dev:** 3.3116	

Panel B	**Mean**	**Median**	**St.Dev**	**Mean**	**Median**	**St. Dev**	**Mean**	**Median**	**St. Dev**	**Mean**	**Median**	**St. Dev**	**Mean**	**Median**	**St. Dev**	**Mean**	**Median**	**St. Dev**
OUTPUTS																		
Gross return (%)	0.5768	0.6021	0.2027	0.4252	0.357	0.2885	0.6095	0.6745	0.2172	0.4607	0.3758	0.2445	0.3053	0.2665	0.1639	0.6364	0.6714	0.2205
TNA (thousand €)	54,267	36,952	71,410	47,061	21,138	70,876	40,631	18,239	61,228	36,192	20,927	51,792	95,876	48,219	128,111	111,113	70,007	111,091
INPUTS																		
Risk (%)	0.5966	0.7011	0.3513	0.3971	0.4749	0.2688	0.4357	0.5499	0.288	0.501	0.5805	0.304	0.4234	0.5211	0.267	0.4517	0.5638	0.3036
Turnover (%)	0.4641	0.4071	0.2828	0.4595	0.3896	0.3302	0.4509	0.4081	0.2618	0.46	0.4361	0.3178	0.3762	0.3472	0.2703	0.1118	0.0901	0.094
Education-experience	6.9916	6.2035	5.4161	5.9031	4.0027	5.6537	6.99	5.2243	5.6974	7.3666	5.035	6.0334	8.3159	6.5129	5.9531	8.676	7.0105	6.1617

3.4 Empirical results

3.4.1 Managers' efficiency through a slacks-based measure (SBM)

First, the initial SBM model defined in equation (3.4) is applied to obtain the minimum score P^{min} associated with the relative maximum slacks of any input and output from the efficient frontier.[10] Table 3.2 shows the distribution of managers' efficiency scores P^{min} in the sample period analyzed (2009-2014). The first column of the table shows a manager code in order to keep the anonymity of portfolio managers. Then, for each year, the table shows the managers' efficiency scores, the reference set of each manager obtained in the model and the efficiency ranking.

Table 3.2 shows that years with higher levels of efficiency are 2009 and 2013 with 0.437 and 0.4344 mean score P^{min}, respectively. On the other hand, the year with the lowest efficiency deviation is 2011 with a value of 0.293. Note that managers' efficiency decreased during the period 2009-2011. In the following years, there was an improvement of the efficiency.

Table 3.2 also displays the reference set for any objective manager. Note that all of the members of these sets are efficient. The most observed reference facets, for 2009, are those formed by managers *#39, #39-42* and *#4-39-42* which compose the reference sets for 8 out of 21 inefficient managers. For 2010, 2011, 2012 and 2014, manager *#7* is the reference set for 26 out of 35 inefficient managers**,** 35 out of 36 inefficient managers, 20 out of 26 inefficient managers and 18 out of 27 inefficient managers, respectively. The most observed reference facets, for 2013, are those formed by managers *#35, #7-35*, and *#7-19* which compose the reference sets for 20 out of 23 inefficient managers.

[10] Managers' efficiency has been calculated with CRS and VRS, obtaining a correlation superior to 90% in the majority of the years of the sample period. Therefore, the model to examine managers' efficiency assumes CRS in line with the original DPEI (Murthi *et al.,* 1997). The use of CRS allows interpreting the findings as an extended application of the traditional Sharpe ratio (Choi and Murthi, 2001).

Additionally, Table 3.2 shows that manager #7 is efficient all the years that is analyzed (2010-2014). Note that this manager is a woman and she manages several funds of different investment vocations at the same time; therefore, she is classified as a generalist manager.

On other hand, Table 3.3 shows summary statistics about efficient managers resulting from the original SBM Model. Specifically, Table 3.2 and Table 3.3 exhibit a total of 9 (30%) efficient managers for year 2009, 6 (15%) managers for year 2010, 4 (10%) managers for year 2011, 6 (19%) managers for year 2012, 11 (32%) managers for year 2013 and 9 (25%) efficient managers for year 2014, respectively.[11]

[11] Note that the number of managers in all sample years is not the same. Remember that the sample consists of single-managed funds that invest in European equities and that are managed by the same manager during the whole year analyzed.

Table 3.2 Managers' efficiency through the application of the SBM model

This table shows the distribution of managers' efficiency scores P^{min} in the sample period analyzed 2009-2014. The first column of the table shows a manager code in order to keep the anonymity of portfolio managers. Then, for each year, the table shows the managers' efficiency scores, the facets of each manager obtained in the model and the efficiency ranking.

	2009			2010			2011			2012			2013			2014		
Managers	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**
1	0.430	*2,4*	12	**1**	*1*	1	**1**	*1*	1	**1**	*1*	1	**1**	*1*	1	**1**	*1*	1
2	**1**	*2*	1	**1**	*2*	1	**1**	*2*	1	-	-	-	-	-	-	-	-	-
3	0.128	*39*	19	0.021	*7*	32	0.029	*7*	27	-	-	-	0.124	*7,35*	18	0.145	*7*	22
4	**1**	*4*	1	0.184	*7*	8	0.074	*7*	17	0.076	*7*	14	0.146	*7,35*	17	0.231	*7*	20
5	**1**	*5*	1	0.117	*7,39*	13	0.079	*7*	15	-	-	-	-	-	-	-	-	-
6	-	-	-	-	-	-	-	-	-	0.027	*7*	26	0.053	*7,35*	27	0.542	*7*	10
7	-	-	-	**1**	*7,39*	1	**1**	*7*	1	**1**	*7*	1	**1**	*7*	1	**1**	*7*	1
8	0.077	*39*	24	0.035	*7*	25	0.030	*7*	25	0.033	*7*	23	0.000	*7,27*	34	0.000	*7,27*	36
9	-	-	-	0.025	*7,49*	28	0.028	*7*	28	0.035	*7,46*	21	0.031	*7,35*	31	0.033	*7*	33
10	0.420	*2,4,39*	13	0.139	*7*	11	0.203	*7*	8	0.064	*7*	16	0.074	*7,35*	23	0.253	*7*	19
11	**1**	*11*	1	0.025	*7,48*	29	0.323	*7,48*	6	-	-	-	-	-	-	-	-	-
12	0.128	*2,4,42*	20	0.075	*7*	16	0.108	*7*	12	0.100	*7*	12	0.109	*35*	19	0.299	*7,31*	16
13	0.128	*4,39,42*	21	0.043	*7*	23	0.034	*7*	24	0.043	*7*	19	0.039	*35*	29	0.096	*7*	27
14	**1**	*14*	1	0.172	*7,48*	9	0.152	*7*	9	0.168	*7*	8	**1**	*14*	1	0.361	*1,23,29*	14
15	0.553	*2,14*	11	0.067	*7*	18	0.053	*7*	21	0.027	*7*	27	0.047	*29,35*	28	0.020	*7*	34
16	-	-	-	0.006	*7*	38	0.007	*7*	38	0.007	*7*	31	0.063	*7,35*	26	0.272	*7*	18
17	-	-	-	0.053	*7*	22	0.056	*7*	20	0.045	*7*	18	-	-	-	-	-	-
18	0.063	*2*	25	0.018	*7*	34	0.021	*7*	33	0.010	*7*	30	0.015	*35*	33	0.051	*29*	31
19	0.613	*4,5,39*	10	0.000	*39*	41	0.095	*7*	13	0.059	*7*	17	0.372	*7,35*	13	0.385	*7*	13
20	0.044	*2,4,14,42*	27	0.005	*7*	39	0.005	*7*	39	-	-	-	-	-	-	-	-	-
21	0.237	*11,42*	15	0.036	*7*	24	-	-	-	-	-	-	-	-	-	-	-	-
22	-	-	-	0.156	*7*	10	0.224	*7*	7	0.133	*7*	10	**1**	*22*	1	0.446	*7,27*	11
23	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	**1**	*23*	1
24	-	-	-	0.066	*7*	20	-	-	-	-	-	-	-	-	-	-	-	-
25	**1**	*25*	1	0.017	*7,49*	35	0.023	*7*	31	-	-	-	-	-	-	-	-	-
26	0.031	*39*	28	0.008	*7*	37	0.011	*7*	37	-	-	-	-	-	-	-	-	-
27	-	-	-	0.115	*7*	14	0.114	*7*	11	0.107	*7*	11	**1**	*27*	1	**1**	*27*	1

Table 3.2 Continued

	2009			2010			2011			2012			2013			
Managers	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P^{min}	**Ref.**	**Rank**	P
28	0.046	*39,42*	26	0.004	*7*	40	0.011	*7*	36	0.014	*7*	28	0.076	*7,35*	22	0.1
29	0.079	*39*	23	0.022	*7*	30	0.028	*7*	29	0.034	*7*	22	**1**	*29*	1	
30	-	-	-	-	-	-	-	-	-	-	-	-	**1**	*30*	1	
31	0.010	*39,42*	29	0.009	*7*	36	0.022	*7*	32	0.027	*7*	25	0.161	*35*	16	
32	0.362	*4,11,14,42*	14	0.069	*7*	17	0.088	*7*	14	0.087	*7*	13	0.071	*35*	24	0.0
33	0.127	*11,25,39,54*	22	-	-	-	-	-	-	-	-	-	-	-	-	
34	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.1
35	0.229	*4,39,42*	17	0.066	*7*	19	0.070	*7*	18	-	-	-	**1**	*35*	1	
36	-	-	-	0.100	*7,48,49*	15	0.000	*7*	40	**1**	*36*	1	-	-	-	
37	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
38	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.3
39	**1**	*39*	1	**1**	*39*	1	0.412	*7*	5	**1**	*39*	1	**1**	*39*	1	
40	0.000	*4*	30	-	-	-	-	-	-	-	-	-	-	-	-	
41	-	-	-	-	-	-	-	-	-	**1**	*41*	1	**1**	*41*	1	0.2
42	**1**	*42*	1	0.196	*7*	7	0.141	*7*	10	-	-	-	-	-	-	
43	-	-	-	-	-	-	-	-	-	-	-	-	0.102	*7,19*	20	0.0
44	-	-	-	0.124	*7,49*	12	0.039	*7*	22	0.169	*7,36,46*	7	-	-	-	
45	-	-	-	-	-	-	0.029	*7*	26	0.072	*7,46*	15	0.258	*7,19*	14	0.3
46	-	-	-	-	-	-	-	-	-	**1**	*46*	1	0.241	*7,30,52*	15	0.1
47	-	-	-	0.022	*7,49*	31	0.011	*7*	35	0.012	*7*	29	0.021	*7,19*	32	0.0
48	-	-	-	**1**	*48*	1	**1**	*48*	1	-	-	-	-	-	-	
49	-	-	-	**1**	*49*	1	0.035	*7*	23	0.037	*7,46*	20	0.033	*35*	30	0.0
50	-	-	-	0.059	*7*	21	0.067	*7*	19	0.158	*7*	9	0.743	*7,19*	12	
51	0.163	*14,42*	18	0.027	*7*	27	0.079	*7*	16	-	-	-	-	-	-	
52	-	-	-	-	-	-	-	-	-	-	-	-	**1**	*52*	1	0.2
53	0.230	*4,11,39,42*	16	0.032	*7*	26	0.025	*7*	30	0.000	*7,46*	32	0.070	*7,35*	25	0.1
54	**1**	*54*	1	0.019	*7*	33	0.020	*7*	34	0.028	*7,46*	24	0.090	*7,19*	21	0.0
Mean	0.437			0.198			0.169			0.237			0.410			0.3
St. Dev	*0.404*			*0.340*			*0.293*			*0.375*			*0.434*			*0.3*

Table 3.3 – Summary statistics about managers' efficiency

This table shows summary statistics about efficient managers resulting from the original SBM Model.

	2009	2010	2011	2012	2013	2014	Mean
# of efficient managers	9	6	4	6	11	9	8
# total managers	30	41	40	32	34	36	36
% efficient managers	30.00%	14.63%	10.00%	18.75%	32.35%	25.00%	21.13%

3.4.2 Managers' efficiency clustering depending on manager sociodemographic characteristics

Before creating the clusters according to different sociodemographic variables, Table 3.4 reports summary statistics about efficient managers according to the manager gender and level of specialization; the variables used to make the cluster subsequently.

Specifically, the distribution of the 9 efficient managers of 2009 according to the manager gender leads to a total number of 7 efficient men while only 2 women were efficient. Note that this is not an exception, in all the years analyzed, the number of efficient managers that are men is higher than the number of efficient women. Note, however, that the number of women is also much more reduced than men in the database.

Similarly to gender, the number of efficient managers that are generalists is higher than the number of efficient specialists for years (2010-2014). Note, however, that the number of specialists is also much more reduced than generalist in the database. In this case, there is an exception. The distribution of the 9 efficient managers of 2009 according to the manager specialty leads to a total number of 5 specialists efficient while only 4 generalists were efficient.

Table 3.4 - Sociodemographic variables of efficient managers

This table shows summary statistics about efficient managers according to the manager gender and level of specialization. The total number of managers in each cluster is denoted in parenthesis.

	2009	**2010**	**2011**	**2012**	**2013**	**2014**
# Total managers	30	41	40	32	34	36
# of efficient men	**7** (22)	**5** (28)	**3** (29)	**4** (22)	**7** (25)	**6** (26)
# of efficient women	**2** (8)	**1** (13)	**1** (11)	**2** (10)	**4** (9)	**3** (10)
# of efficient specialists	**5** (10)	**2** (12)	**1** (13)	**3** (10)	**5** (11)	**3** (12)
# of efficient generalists	**4** (20)	**4** (29)	**3** (27)	**3** (22)	**6** (23)	**6** (24)

To carry out Variation III of SBM model, manager gender is firstly used to split the sample into males and females to compare the efficiency scores within a given group of managers. The cluster denoted by *M* is constituted by men managers and the cluster denoted by *W* is constituted by women managers.

First, all the combinations of efficient male managers for each year of analysis should be enumerated. Tone (2010) considers supporting hyperplanes such as the facets of production possibility set *P*. Let $P_0=(\xi_j,\ \eta_j)$ (j=1,…,k) be k DMUs in *P*. Tone (2010) makes a linear combination of these k DMUs with positive coefficients as

$$\xi_0 = w_1\xi_1 + .. + w_k\xi_k$$

$$\eta_0 = w_1\eta_1 + .. + w_k\eta_k$$

where $w_j > 0$ (j=1,…,k)

Tone (2010) shows that if (ξ_0, η_0) defined above is CRS-efficient, then (ξ_j, η_j) (j=1,…,k) must be CRS-efficient, and that there exists a supporting hyperplane to P at (ξ_0, η_0) that also supports P at (ξ_j, η_j) (j=1,…,k).[12]

Table A3.1 in Appendix 3.2 shows the number of facets, friends and maximal friends for the four clusters in the sample from January 2009 to December 2014. Note that the cluster with the greatest number of facets is that of men managers in 2013 with 127 total facets. This set of facets enables to enumerate 22 friends to finally obtain 8 maximal friends facets (h), which are not dominated by any other set of friends.

Although Variation III is highlighted as a relevant contribution to reduce the computational resources needed for large-scale problems involving a massive enumeration of facets (Tone, 2010), this advantage is not so relevant for this study. Note that the computational load to determine these maximal friends has not been a real problem for current technologies because in this study have been to enumerate 120 combinations in the worst case.

Results of the clustering process carried out to analyze managers' efficiency according to their gender are reported in Table 3.5. Specifically, Panel A shows the distribution of managers' efficiency scores ($P^{cluster}$) in the sample period 2009-2014 when the sample is focused on women and Panel B when the sample is focused on men. The first column of the table shows a manager code in order to keep the anonymity of portfolio managers. Then, for each year, the table shows the managers' efficiency scores for each manager and cluster obtained in the model. When this model finds no feasible solution for the new set of facets (h'), the target DMU is considered to be globally

[12] See section 2.3 of Tone (2010) for further details about the facets of the production possibility set.

inefficient but locally efficient in relation to the DMUs with common clustering characteristics, men and women in this case.

Table 3.5 - Managers' Efficiency depending on manager gender

This table shows the distribution of variation III of SMB model efficiency scores ($P^{cluster}$) in the sample period 2009-2014. Panel A shows the distribution of managers' efficiency scores ($P^{clusterW}$) when the sample is based on women. Panel B shows the distribution of managers' efficiency scores ($P^{clusterM}$) when the sample is based on men. When this model finds no feasible solution for the new set of facets *(h')*, the target DMU is considered to be globally inefficient but locally efficient in relation to the DMUs with common clustering characteristics, men and women in this case.

Panel A: Women Managers						
	2009	2010	2011	2012	2013	2014
7		**1**	**1**	**1**	**1**	**1**
8	*1 Loc. Effic*	0.035	0.030	0.148	0.000	0.000
9		*1 Loc. Effic*	0.028	0.501	0.232	0.166
10	*1 Loc. Effic*	0.139	0.203	0.204	*1 Loc. Effic*	0.261
14	**1**	0.218	0.152	0.280	**1**	*1 Loc. Effic*
19	*1 Loc. Effic*	0.000	0.095	0.286	0.565	0.476
21	*1 Loc. Effic*	0.036				
22		0.156	0.224	0.228	**1**	*1 Loc. Effic*
23						**1**
24		0.066				
29	*1 Loc. Effic*	0.022	0.028	0.401	**1**	**1**
36		*1 Loc. Effic*	0.000	**1**		
51	*1 Loc. Effic*	0.027	0.079			
54	**1**	0.019	0.020	0.096	*1 Loc. Effic*	0.391
Mean cluster	1.000	0.286	0.169	0.414	0.755	0.629
St. Dev. cluster	*0.000*	*0.412*	*0.286*	*0.330*	*0.394*	*0.410*

(Continued)

Panel B: Men Managers						
	2009	**2010**	**2011**	**2012**	**2013**	**2014**
1	0.597	**1**	**1**	**1**	**1**	**1**
2	**1**	**1**	**1**			
3	0.516	0.156	*1 Loc. Effic*		0.609	0.511
4	**1**	0.468	*1 Loc. Effic*	0.493	0.721	*1 Loc. Effic*
5	**1**	0.235	*1 Loc. Effic*			
6	-			0.290	0.489	*1 Loc. Effic*
11	**1**	0.146	*1 Loc. Effic*			
12	0.315	0.312	*1 Loc. Effic*	0.464	0.626	0.534
13	0.476	0.491	*1 Loc. Effic*	0.503	0.554	0.648
15	*1 Loc. Effic*	0.445	*1 Loc. Effic*	0.309	0.394	0.382
16		0.504	*1 Loc. Effic*	0.055	0.093	0.696
17		0.226	*1 Loc. Effic*	0.278		
18	0.274	0.213	*1 Loc. Effic*	0.269	0.505	0.083
20	*1 Loc. Effic*	0.164	*1 Loc. Effic*			
25	**1**	0.615	*1 Loc. Effic*			
26	0.219	0.311	*1 Loc. Effic*			
27		*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*	**1**	**1**
28	0.264	0.237	*1 Loc. Effic*	0.435	0.712	0.448
30					**1**	**1**
31	0.106	*1 Loc. Effic*	*1 Loc. Effic*	0.485	0.478	1
32	0.695	0.402	*1 Loc. Effic*	0.414	0.419	0.332
33	*1 Loc. Effic*					
34						0.805
35	0.613	*1 Loc. Effic*	*1 Loc. Effic*		**1**	
37						**1**
38						0.470
39	**1**	**1**	*1 Loc. Effic*	**1**	**1**	**1**
40	0.000					
41				**1**	**1**	0.487
42	**1**	*1 Loc. Effic*	*1 Loc. Effic*			
43					0.523	0.400
44		*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*		
45			*1 Loc. Effic*	0.542	0.704	*1 Loc. Effic*
46				1	0.687	0.530
47		0.511	*1 Loc. Effic*	0.144	0.175	0.088
48		**1**	**1**			
49		**1**	1 Loc. Effic	0.203	0.432	0.461
50		0.227	1 Loc. Effic	0.390	*1 Loc. Effic*	
52					**1**	0.578
53	0.690	0.251	*1 Loc. Effic*	0.000	0.434	0.437
Mean cluster	0.671	0.568	1.000	0.512	0.662	0.650
St. Dev. cluster	*0.350*	*0.347*	*0.000*	*0.336*	*0.277*	*0.299*

Panel A of Table 3.5 shows that the years in which there are more efficiency for the cluster that includes women are years 2009 and 2013 with 1.000 and 0.755 mean score $P^{clusterW}$, respectively. As in the SBM analysis, the efficiency scores decrease in years 2009-2011 and improve the following years. On the other hand, Panel B shows that the years in which there are more efficiency for the cluster that includes men are years 2009, 2011 and 2013 with 0.671, 1.000 and 0.434 mean score $P^{clusterM}$, respectively.

As indicated by Tone (2010), an improvement in managers' efficiency scores is observed when comparing the original SBM scores (P^{min}) with the cluster scores ($P^{cluster}$). Therefore, Table 3.5 exhibits the maximum efficiency scores $P^{clusterM}$ and $P^{clusterW}$ for each inefficient manager, as a consequence, equation 3.10 is confirmed.

Table 3.6 reports summary statistics about global efficient managers and locally efficient managers according to manager gender. Comparing Table 3.3 with Table 3.6 it is observed that there are efficiency improvements when comparing managers with managers of the same gender. Specifically, SBM model reported 7 efficient male managers in 2009. Now, when the efficiency of male managers is compared with the rest of the male managers, a total of 10 men are considered efficient.

Table 3.6 – Distribution of efficient managers by gender

This table shows summary statistics about globally efficient and locally efficient managers according to manager gender.

	2009	2010	2011	2012	2013	2014
# Total efficient men	10	10	29	6	8	9
# of global efficient men	7	5	3	4	7	6
# of local efficient men	3	5	26	2	1	3
# Total efficient women	8	3	1	2	6	5
# of global efficient women	2	1	1	2	4	3
# of local efficient women	6	2	-	-	2	2

The cluster analysis reports a 100% efficiency level for men in year 2011. All men in that year (29) are now efficient as opposed to the 3 efficient managers obtained in the SBM analysis. This peculiar fact is due to the fact that the most efficient manager of 2011 is a woman (manager number 7). Therefore, comparing men only with men have left a greater number of locally efficient managers. This finding can be seen as a weakness of Variation III proposed by Tone (2010) because in real life excluding one of the most efficient managers due to a certain characteristic (the gender in this case) could overestimate the efficiency of other managers with different characteristics.

Observing with more details the efficiency scores P^{cluster} of the SBM gender cluster, it can be seen that for year 2009, 8 out of 21 reference sets of the initial SBM are inappropriate because certain funds included in these reference sets do not belong to the same cluster as the objective manager. Similar figures are shown for the remaining years.[13]

On the other hand, the level of manager specialization is also used to split the sample into generalist and specialist managers. The cluster denoted by *S* consists of specialist managers while cluster denoted by *G* consists of generalist managers.

Results of the clustering process carried out to analyze managers' efficiency according to their level of specialization are reported in Table 3.7. Specifically, Panel A shows the distribution of managers' efficiency scores ($P^{cluster}$) in the sample period 2009-2014 when the sample is split into specialist managers and Panel B when the sample is split into generalist managers. The first column of the table shows a manager code in order to keep the anonymity of portfolio managers. Then, for each year, the

[13] 27 out of 35 reference sets for the year 2010, 26 out of 36 reference sets for the year 2011, 20 out of 26 reference sets for the year 2012, 16 out of 23 reference sets for year 2013 and 18 out of 27 reference sets for year 2014, respectively.

table shows the managers' efficiency scores for each manager and cluster obtained in the model.

Table 3.7 - Managers' Efficiency depending on manager level of specialization

This table shows the distribution of variation III of SMB model efficiency manager's scores ($P^{cluster}$) in the sample period 2009-2014. Managers are classified as generalist whether they run funds belonging to several investment objectives while they are classified as specialists whether they run funds on just one investment objective. Panel A shows the distribution of managers' efficiency scores ($P^{clusterS}$) when the sample is based on specialist managers while Panel B shows the distribution of managers' efficiency scores ($P^{clusterG}$) when the sample is based on generalist managers. This model picks up the efficient DMUs in the adjacent clusters to form the maximal friend facets. When this model finds no feasible solution for the new set of facets *(h')*, the target DMU is considered to be globally inefficient but locally efficient in relation to the DMUs with common clustering characteristics, specialists and generalists in this case.

Panel A: Specialist managers						
	2009	2010	2011	2012	2013	2014
1	*1 Loc. Effic*	1	1	1	1	1
6				0.272	0.116	*1 Loc. Effic*
8	0.640	0.283	*1 Loc. Effic*	0.255	0.000	0.000
9		*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*	0.217	*1 Loc. Effic*
10	*1 Loc. Effic*	0.397	*1 Loc. Effic*	0.317	*1 Loc. Effic*	*1 Loc. Effic*
11	1	0.109	*1 Loc. Effic*			
14	1	*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*	1	*1 Loc. Effic*
17		0.226	*1 Loc. Effic*	0.278		
20	0.092	0.106	*1 Loc. Effic*			
25	1	*1 Loc. Effic*	*1 Loc. Effic*			
34						*1 Loc. Effic*
35	*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*		1	
37						1
39	1	1	*1 Loc. Effic*	1	1	1
41				1	1	0.337
42	1	*1 Loc. Effic*	*1 Loc. Effic*			
43					0.420	0.183
45			*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*	*1 Loc. Effic*
Mean Cluster	0.873	0.677	1.0000	0.712	0.705	0.793
St. Dev. Cluster	0.297	0.406	0.000	0.372	0.421	0.381

(Continued)

Panel B: Generalist managers						
	2009	2010	2011	2012	2013	2014
2	1	1	1			
3	0.386	0.320	0.316		0.593	0.537
4	1	0.420	0.404	0.447	0.646	0.595
5	1	*1 Loc. Effic*	0.132			
7		1	1	1	1	1
12	0.225	0.098	0.130	0.129	*1 Loc. Effic*	0.534
13	0.368	0.298	0.413	0.360	0.525	0.702
15	*1 Loc. Effic*	0.303	0.431	0.276	0.453	0.382
16		0.504	0.290	0.041	*1 Loc. Effic*	0.696
18	0.193	0.292	0.507	0.246	0.505	0.286
19	*1 Loc. Effic*	0.000	0.145	0.310	0.716	0.476
21	*1 Loc. Effic*	0.670				
22		0.448	0.333	0.229	1	0.923
23						1
24		0.291				
26	0.509	0.333	0.115			
27		0.133	0.120	0.129	1	1
28	0.247	0.240	0.201	0.433	0.684	0.482
29	0.353	0.664	0.398	0.517	1	1
30					1	1
31	0.070	0.050	0.124	0.373	0.736	1
32	*1 Loc. Effic*	0.362	0.557	0.388	0.339	0.427
33	*1 Loc. Effic*					
36		0.659	0.000	1		
38						*1 Loc. Effic*
40	0.000					
44		0.732	0.617	0.321		
46				1	0.687	0.530
47		0.510	0.457	0.223	0.175	0.088
48		1	1			
49		1	0.081	0.161	0.432	0.461
50		0.268	0.516	0.415	0.822	
51	0.277	0.558	0.155			
52					1	0.563
53	*1 Loc. Effic*	0.246	0.490	0.000	0.434	0.518
54	1	0.602	0.411	0.109	0.637	0.509
Mean Cluster	0.631	0.483	0.383	0.369	0.712	0.655
St. Dev. Cluster	0.392	0.304	0.278	0.290	0.255	0.271

Panel A of Table 3.7 shows that 2009 and 2011 are the years with higher levels of efficiency for specialist managers with 0.873 and 1.000 mean score $P^{clusterS}$, respectively. On the other hand, Panel B shows that 2011 and 2012 are the years with more efficiency for generalist managers with 1.000 and 0.755 mean score $P^{clusterG}$, respectively.

Table 3.7 exhibits the maximum efficiency scores P^{clusterS} and P^{clusterG} for each inefficient manager, hence improving the efficiency results obtained by the SBM model applied in the previous section.

Table 3.8 reports summary statistics about globally efficient and locally efficient managers according to the manager level of specialization. Specifically, for the specialist manager cluster, Tables 3.7 and 3.8 show that years 2011 and 2014 are those with a greater number of locally efficient managers. In year 2011, the original SBM obtained one efficient manager of a total of 13 specialist managers while Variation III shows 13 efficient managers (1 global and 12 locally efficient managers). The justification for this finding is similar to that commented in the men cluster for the same year. In this case, manager #7 is a generalist manager and is mostly included in the reference sets of the original SBM analysis. Therefore, specialist managers were referenced to an efficient generalist manager in the original model and once specialist managers are compared with managers that assume the same level of responsibilities, all of them can be considered locally efficient.

Similarly, Table 3.8 shows that 2009 is the year in which more locally efficient generalist managers are obtained. Originally, 4 generalist managers were efficient (see Table 3.3); however, this figure increases till 10 when Variation III was applied (6 generalists managers where defined as locally efficient when they were compared with

managers that assume the same level of responsibility). The analysis has have only detected 1 locally efficient for the years 2010 and 2014, 2 for the year 2013 and none for the year 2011. Note that this is due to the fact that there are more generalist managers than specialists in the database and therefore, the probability that generalist managers are compared with them is higher than for the case of specialist managers.

Table 3.8 - Distribution of efficient managers by level of specialization

This table shows summary statistics about globally efficient and locally efficient managers according to manager level of specialization.

	2009	2010	2011	2012	2013	2014
# Total efficient specialists	8	7	13	6	7	9
# of global efficient specialists	5	2	1	3	5	3
# of local efficient specialists	3	5	12	3	2	6
# Total efficient generalists	10	5	3	3	8	7
# of global efficient generalists	4	4	3	3	6	6
# of local efficient generalists	6	1	-	-	2	1

Variation III of SBM model provides more appropriate results in terms of ranking the efficiency of managers with similar characteristics. However, a limitation has been detected. When the sample is small, the fact that a manager of some specific characteristic is efficient can provoke the appearance of many locally efficient managers.

3.5 Further questions about managers' efficiency

Once managers' efficiency have been analyzed through the SBM model and its Variation III, the chapter further analyzes mean differences between those whole-period managers (those managers included in the database all years of the period 2009-2014)

and the remaining managers and between top and bottom managers in terms of efficiency scores. Specifically, this section examines the following questions:

Question 1: Are whole-period managers more efficient?

The research on the performance persistence evaluation of individual mutual funds is vast (see, e.g., Grinblatt and Titman, 1992; Goetzmann and Ibbotson, 1994; Elton *et al*., 1996; and Bollen and Busse, 2005). Additionally, several studies have found that portfolio past performance is very important when it comes to making investment decisions (see, e.g., Sharpe, 1966; Brown *et al.,* 1992; Hendricks *et al.*, 1993; Carhart, 1997; Capocci and Hübner, 2004; Kosowski *et al.*, 2006; and Andreu *et al.*, 2007). However, little attention has been given to the persistence of managers' performance or efficiency.

The aim of this section is to compare the efficiency scores of those managers that are analyzed during the whole sample period with the remaining managers. To carry out the analysis, the sample of 54 managers is divided into two subsamples. On the one hand, the 17 whole-period managers and, on the other hand, the remaining 37 managers who in some year have stopped being in the sample. Then, a mean difference test is applied to the efficiency scores P^{min} obtained by each manager in the original SBM analysis (see section 3.4.1 of the chapter).

Table 3.9 shows the results of the comparison of the efficiency scores P^{min} obtained in the original SBM model for the different groups of managers. This table shows that managers included in the sample as individual managers of at least one Spanish mutual fund in European equity funds during all the years of the sample 2009-2014 are slightly less efficient than the remaining managers. However, there is no

statistical significance. Therefore, management performance does not appear as a relevant variable to determine the management as individual manager.

Table 3.9 –Efficiency scores split by level of managers' persistence

This table shows the results of the comparison of the efficiency scores P^{min} obtained in the original SBM model for the whole-period managers (those who are in all the years of the sample) and the remaining managers. ***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

	Score P^{min}
Whole-period Managers	0.260
Remaining Managers	0.334
Difference	-0.074

Question 2: Which variables influence on the survival of a manager as individual manager?

Similarly to question 1, financial variables and manager sociodemographic characteristics used as inputs and outputs in previous sections are used to study whether they are determinant or not to explain a long tenure as individual manager in the sample examined in this chapter.

Table 3.10 shows the results of the comparison of the variables employed in the original SBM model for the whole-period managers and the remaining managers. Specifically, the variables analyzed are annual gross returns, annual total net assets, annual risk level, annual turnover, and manager experience and education.

With regard to the output variables of the model, both gross return and total net assets are higher in managers who individually manage European equity funds all the years of the sample compared to the remaining. However, these differences are not statistically significant; therefore, they are not relevant factors to explain the persistence as individual managers.

Table 3.10 - Variables that influence the persistence of a manager as individual manager

This table shows the results of the comparison of the variables employed in the original SBM model for whole-period managers and the remaining managers. Specifically, the variables analyzed are annual gross returns, annual total net assets, annual risk level, annual turnover, and manager experience and education. ***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

	Return	Asset	Risk	Turnover	Exp-Edu
Whole-period Managers	0.084	72389.988	0.010	0.391	10.816
Remaining Managers	0.054	56008.438	0.010	0.380	4.134
Difference	0.030	16381.549	-0.001	0.011	**6.682*** **

With respect to the input variables, it seems that there are not great differences in the level of risk of whole-period managers and the remaining managers. Similarly, the turnover ratio is not statistically different between both subsamples of managers. This result suggests that being more or less active in portfolio management is not determinant for a manager to continue to work individually in the investment fund industry.

Note that the only variable that is statistically different between both subsamples of managers is experience and education, the variable used as proxy of managers' remuneration. Table 3.10 seems to suggest that managers acting as individual managers during the entire sample period have a higher tenure in the industry and they have a high level of education (a master degree).

In summary, from the five variables used in the managers' efficiency model, only the integrated variable for both experience and education of managers is a statistically significant indicator that differentiates managers who are individually managing during the sample period (2009-2014) and the remaining managers.

Question 3: Which variables influence on managers' efficiency?

After analyzing the differences between the efficiency of the whole-period managers and the remaining managers and once I have determined which are the relevant variables to remain in the management industry as individual manager, the next question is to determine which variables are determinant to the efficiency level obtained by managers.

The majority of studies that measure managers' efficiency through DEA methodology perform an analysis of the variables used to determine the degree of influence of each one on the efficiency of the managers. (See, e.g, Basso and Funari, 2001; Choi and Murthi, 2001; Basso and Funari, 2003; Lozano and Gutierrez, 2008; Zhao and Yue, 2010; Lamb and Tee, 2012 and Basso and Funari, 2017).

To carry out the analysis, managers are divided into quartiles ordered by the efficiency score P^{min} obtained in the original SBM model each year being the first quartile the most efficient managers and the fourth quartile the least efficient managers for each year. Therefore, this study compares the variables of the first quartile managers (Top efficient managers) with the managers of the fourth quartile (Bottom managers).

Table 3.11 shows the difference in the variables used to measure managers' efficiency. As previously, these variables are annual gross returns, annual total net assets, annual risk level, annual turnover, and manager experience and education.

Table 3.11 shows statistically significant differences for the variables assets under management, level of risk and portfolio turnover. As can be seen, the most efficient managers manage more assets than less efficient managers. This fact is consistent with Basso and Funari (2017), who conclude the large funds tend, on average, to exhibit a slightly higher performance score than the smaller ones.

Table 3.11 – Determinants of managers' efficiency

This table shows the difference in the variables used to measure managers' efficiency. Specifically, the variables analyzed are annual gross returns, annual total net assets, annual risk level, annual turnover, and manager experience and education. ***, ** and * denote significance at the 1%; 5% and 10% levels, respectively.

	Return	**Asset**	**Risk**	**Turnover**	**Exp-Edu**
Top efficient manager	0.106066	132260.42	0.006803	0.265283	7.17
Bottom efficient manager	0.051082	20183.63	0.012658	0.495474	8.59
Difference	0.054984	**112076.79*** **	**-0.005855*** **	**-0.230191*** **	-1.42

Top managers in terms of efficiency also show a statistically lower level of risk. On the other hand, the turnover ratio is much lower in top efficient managers than in bottom efficient managers. This result supports the fact that portfolio rotation entails transaction costs for the management company that makes the managers not to be efficient if they do not reduce those costs. This fact supports the works that use this measure as output of the efficiency model (see, e.g., Sengupta, 2003; Zhao and Yue, 2010; Babalos *et al*., 2012; Andreu *et al.,* 2017; and Basso and Funari, 2017).

3.6 Conclusions

This chapter provides an alternative method to evaluate the efficiency of managers of European equity mutual funds taking into account a financial point of view but also the sociodemographic characteristics of portfolio managers. This chapter proposes an original set of inputs and outputs from those conventionally used in the DEA literature on portfolios, which may be useful for measuring managers' efficiency. The variables analyzed are annual gross returns, annual total net assets, annual risk level, annual turnover, and manager experience and education variable. Specifically, the SBM model

and their variants are applied to a sample of 54 Spanish managers in the period January 2009 to December 2014.

The first analysis carried out in this chapter is the analysis of managers' efficiency through a slacks-based measure (SBM). This analysis reports a ranking of efficient managers. The efficient manager that is mostly observed in all the years is a woman that manages several funds of different investment vocations at the same time; hence she is a generalist manager. Aditionally, this analysis shows that years 2009 and 2013 are the years with higher levels of efficiency.

Secondly, this chapter provides a measure of managers' efficiency according to their characteristics, specifically, according to gender and level of specialization, through the consideration of variation III of SBM model proposed by Tone (2010). The consideration of all facets clustered by gender and level of specialization allows for a better identification of the reference competitors for each manager based on similar management resources. The results obtained in this second analysis report that there are efficiency improvements when comparing managers with managers of the same gender and managers with the same specialization. The results support the use of this SBM variant in those managers with very assorted characteristics. Therefore, the model proposed in this chapter is of great interest for financial markets and shows key information about manager behavior. In particular, management companies could apply it as a measure to evaluate and promote the most efficient managers.

Last, this chapter examines both persistence patterns and determinants of the efficiency scores obtained by portfolio managers. The chapter concludes that performance does not appear to be a relevant element to determine the management as an individual manager. Additionally, from the 5 variables used in the managers'

efficiency model, only the integrated variable for both experience and education of managers is a statistically significant indicator that differentiates managers who serve as individual managers the whole sample period. Last, the variables that statistically influence on managers' efficiency are the annual assets under management, annual level of risk and portfolio turnover.

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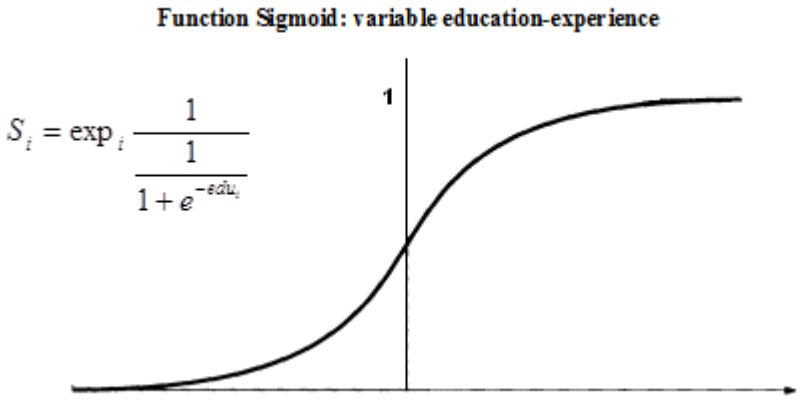
Appendix 3.1: Description of the Sigmoid Function

Figure A3.1 - Sigmoid function

This graph shows the "S" shaped curve provided by the sigmoid function.



Appendix 3.2: Managers' efficiency clustering depending on manager characteristics

Table A3.1 - Facets, Friends and Maximal Friends per cluster and year

This table summarizes the number of facets, friends and *maximal friends* obtained in the analysis of managers' efficiency by clustering depending on manager characteristics (gender and level of specialization) in the sample from January 2009 to December 2014.

Men Managers	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
# of Facets	127	31	7	15	127	63
# of Friends	39	8	3	7	22	15
# of Maximal friends	4	3	3	3	8	3
Women Managers						
# of Facets	3	1	1	3	15	7
# of Friends	2	1	1	3	7	7
# of Maximal friends	2	1	1	1	3	1
Specialist Managers						
# of Facets	31	3	1	7	31	7
# of Friends	19	3	1	4	9	4
# of Maximal friends	2	1	1	2	4	2
Generalist Managers						
# of Facets	15	15	7	7	63	63
# of Friends	6	9	4	7	27	23
# of Maximal friends	3	2	2	1	3	3

FINAL CONCLUSIONS

Through these lines, I summarize the main conclusions and contributions of the thesis. It is important to note that two of the main reasons that has led me to investigate the behavior of mutual fund managers have been, on the one hand, the lack of empirical studies that study the consequences and implications of manager replacement, the performance consequences of the risk shifting behavior and the managers' efficiency through a model DEA in less developed markets with a culture different from the US market. On the other hand, my motivation is based on the interest shown by the financial literature to understand mutual fund manager behavior.

The aim of first chapter is to analyze the consequences of manager replacement in the Spanish mutual fund industry. The chapter firstly examines the performance consequences, that is, whether underperforming funds in the pre-replacement period are able to turn around their performance. This chapter documents that those manager replacements carried out in underperforming funds lead to significant improvements in the performance that lasts over time in the case of domestic equity funds. Hence, the monitoring mechanism of managerial replacement is effective for those funds with bad records. On the contrary, those funds with positive performance in the pre-replacement period tend to suffer deterioration in the performance that last over time in case of European equity funds but that is only observed in the short-term for domestic equity funds. Therefore, it seems that it takes some time for new managers to improve their results.

Secondly, the chapter examines whether there are shifts in the risk profile of mutual funds across the pre- and post-replacement periods. The results show that funds

suffering a manager replacement do not report risk levels significantly different from those reported by funds without manager replacement in the pre-replacement period. However, as a consequence of the manager change, the total risk level tends to increase in the long-term probably in an attempt to achieve higher levels of performance.

Finally, the chapter analyzes the effectiveness of manager replacements by examining the relationship between these changes and the investment flows into the funds. This analysis shows that manager changes, in general, have a negative impact on subsequent investment flows when considering the entire time period of each mutual fund. However, taking into account not only those funds with manager replacement but all the mutual funds in the investment category, an improvement in the money flows attracted by mutual funds with negative performance in the pre-replacement period is observed. Hence, the results of this investigation are of great interest for investment advisors and mutual fund unit-holders because they demonstrate that the control mechanism of manager replacement have positive consequences for underperforming funds not only in a developed market like US but also in growing markets like Spain.

The results obtained in chapter 1 about the impact of manager replacement on the level of risk assumed by mutual funds and the fact that financial literature has only focused on the analysis of the causes and incentives of mutual fund managers to change risk, lead me to investigate the performance consequences of the risk shifting behavior shown by domestic equity mutual funds through the analysis of monthly portfolio holdings. Therefore, the objective of chapter 2 is to assess the implications of risk shifting for mutual fund investors.

The first aim this chapter is to examine the performance consequences of the risk shifting behavior shown by Spanish domestic equity mutual funds through the analysis

of monthly portfolio holdings to assess the implications to fund investors. The second aim is to detect whether performance consequences are the same or different depending on the mechanisms of risk shifting used, because the portfolio risk level can shift due to the change in the composition between equity and cash holdings or by changing the systematic or idiosyncratic risk within the equity positions. The results documents that funds that increase risk obtain a positive and statistically significant outperformance compared to funds that maintain stable risk levels and funds that reduce their risk in subsequent periods. This finding, in contrast to previous evidence in the US mutual fund industry, provides evidence that risk shifting is not harmful to investors in less developed markets; instead, it is the opposite. This finding is very robust regardless of the mechanism of risk shifting used by managers (mainly changes in asset allocation and changes in the systematic risk). The findings obtained when using the idiosyncratic risk are slightly different. Increasing the idiosyncratic risk, which occurs when funds increase their portfolio concentration, leads to underperformance. This finding suggests that the driver of poor performance for increasing idiosyncratic risk is poor stock-picking abilities.

Finally, this chapter analyze the performance consequences of risk shifting depending on fund manager characteristics such as age, gender, tenure, and education. The chapter documents that the positive performance consequences of increasing risk are robust to manager sociodemographic variables However, there are statistically significant differences depending on manager characteristics. Specifically, the decision of increasing risk is better when it is made by a female, a specialist or a more educated manager.

After analyzing managers' behavior through parametric methodologies, I will examine the efficiency of Spanish investment fund managers through a non-parametric

methodology, specifically through a DEA model. As opposed to previous DEA models that measure the performance of mutual funds, the aim of chapter 3 is to examine managers' efficiency through a DEA model, which is not only limited to explore the financial efficiency but also consider the sociodemographic characteristics of portfolio managers. The sociodemographic variables examined in this chapter are the same than in Chapter 2; concretely, the gender, level of education, level of specialization and experience of fund managers.

This chapter defines which variables are relevant to the efficiency of a portfolio manager. A manager will be classified as efficient whether he/she is able to maximize the gross return in a large number of assets under management assuming a low level of risk, minimizing the portfolio turnover and the cost that he/she represents for the management company. Once the model is defined, the chapter examines the efficiency of portfolio managers for each year of the sample through the application of the original SBM model. This analysis reports a ranking of managers' efficiency and shows that years 2009 and 2013 are those with higher levels of efficiency.

However, the SBM model has been questioned because there are other different approaches to determine the 'best-practice' reference set. Therefore, the second aim of this chapter is to analyze managers' efficiency clustering managers depending on sociodemographic characteristics. The results obtained in this second analysis report that there are efficiency improvements when comparing managers with managers of the same gender and managers with the same level of specialization. Therefore, this analysis provides more appropriate results in terms of efficiency. The model proposed in this chapter is of great interest for financial markets; in particular, management companies can use this methodology to evaluate and promote the most efficient managers.

Last, this chapter examines certain patterns and the determinants of the efficiency scores obtained by managers. Performance does not appear as a significant variable to determine the survival of a manager as an individual manager. Additionally, from the 5 variables used in the managers' efficiency model, only the integrated variable for both experience and education of managers is a statistically significant indicator that differentiates managers who work as individual managers during the sample period from the remaining managers. Last, the variables that determine the efficiency score of a manager are the assets under management, the level of risk and the portfolio turnover.

With all of the aforementioned, this thesis, composed of three essays about mutual fund manager behavior, contributes to different gaps found in the financial literature.

RESUMEN Y CONCLUSIONES (SUMMARY IN SPANISH)

Dado que la Tesis Doctoral estará íntegramente escrita en inglés, a continuación se presenta un resumen en español, tal y como se indica en el artículo 2 Título I del Acuerdo de 17/12/2008, del Consejo de Gobierno de la Universidad de Zaragoza, relativo al "Reglamento sobre Tesis Doctorales".

MOTIVACIÓN

El desarrollo de esta Tesis Doctoral está justificado dado que, en los últimos años, los investigadores han analizado varias cuestiones sobre el comportamiento de los gestores de fondos de inversión debido a los problemas de agencia que pueden existir entre los gestores y los inversores de estos productos de ahorro. Como consecuencia, la literatura financiera ha mostrado cada vez más interés en la comprensión de los incentivos que explican las acciones de los gestores, las consecuencias que éstas provocan en las carteras de inversión colectiva, así como la eficacia de los diferentes mecanismos de control de las gestoras y reguladores sobre el comportamiento de los gestores.

La presente Tesis Doctoral se compone de 3 capítulos empíricos. En el primer capítulo, analizamos las consecuencias financieras que produce un cambio de gestor en los fondos de inversión.

En el segundo capítulo, estudiamos las consecuencias de los cambios de riesgo en los fondos de inversión mediante distintas medidas de cambio de riesgo así como en función de las características sociodemográficas del gestor.

Por último, el tercer capítulo analiza la eficiencia de los gestores a través de un modelo de Análisis Envolvente de Datos (DEA) que se centra en analizar la eficiencia de los gestores no sólo desde el punto de vista puramente financiero (capacidad para maximizar la rentabilidad obtenida en la mayor cantidad de fondos y patrimonio gestionado asumiendo para ello el menor riesgo posible) sino también teniendo en cuenta variables sociodemográficas del gestor como son su experiencia, su sexo, edad y educación.

Para finalizar con este apartado, destacar que la falta de estudios empíricos que estudian las consecuencias e implicaciones del cambio del gestor, las consecuencias del cambio del nivel de riesgo y la eficiencia con la que gestionan sus carteras los gestores de fondos de inversión en mercados menos desarrollados y con una cultura diferente a Estados Unidos nos lleva a analizar estos temas en la industria española de fondos de inversión. Otro de los motivos por el que hemos elegido la industria española de fondos de inversión es debido a que ha sido uno de los mercados financieros más dinámicos de Europa en las últimas décadas. Además, este mercado tiene unas características peculiares que merecen atención. El elevado número de fondos de inversión provoca que el tamaño medio de los fondos españoles sea mucho más pequeño que el fondo promedio de Reino Unido o Estados Unidos. Este aspecto es el resultado de un exceso de oferta de fondos de inversión, probablemente debido a la fuerza de ventas de los bancos y cajas de ahorros en España. Otra peculiaridad es el alto grado de concentración, ya que pocas compañías gestoras son capaces de gestionar un alto porcentaje de la industria. Concretamente, las dos mayores gestoras representan casi el 50% de los activos gestionados por el total de la industria.[1]

[1] Véase, por ejemplo, Cambon y Losada (2014) y Golez y Marin (2015).

CAPÍTULO 1:

Implicaciones financieras del cambio del gestor: Evidencia en la industria de fondos de inversión españoles.

El primer capítulo de la tesis, se centra en analizar las consecuencias económicas de un cambio de gestor en la industria de fondos de inversión españoles. Es un tema reseñable dada la falta de estudios empíricos que examinan las consecuencias e implicaciones del cambio de gestor en mercados fuera de los EE.UU. Este análisis nos puede ayudar a comprender la eficacia de algunos mecanismos de control por parte de las gestoras de fondos de inversión, como el cambio de gestor en otros mercados menos desarrollados. Por lo tanto, este estudio nos permite llenar este vacío detectado en la literatura financiera internacional.

En los últimos años, los investigadores han analizado varias cuestiones sobre el comportamiento de los gestores de fondos de inversión debido a los problemas de agencia que pueden existir entre los gestores y los inversores. Como consecuencia, la literatura financiera ha mostrado cada vez más interés en la comprensión de los incentivos que explican las acciones de los gestores, las consecuencias en las carteras de

inversión colectiva que estas acciones provocan, así como la eficacia de los diferentes mecanismos de control sobre su comportamiento.

Brown *et al.* (1996), Kempf y Ruenzi (2008) y Elton *et al.* (2010) centran su atención en el comportamiento del gestor, que se ve sometido a una especie de Tournament o "Competición" para conseguir una buena posición en los rankings de performance. Estos autores argumentan que los gestores analizan la performance de sus carteras en relación a sus competidores en ciertos períodos de tiempo y cambian su nivel de riesgo en función de sus propios intereses, siempre con el interés de terminar en los primeros puestos del ranking dada la relación existente entre performance pasada y nuevos flujos de inversión.

A pesar del intenso debate acerca de la existencia de este tipo de comportamientos denominado "tournament behavior", recientemente, sólo el estudio de Huang *et al.* (2011) analiza las consecuencias de los cambios en el nivel de riesgo asumido por las carteras. Dichos autores encuentran que los fondos que cambian su nivel de riesgo de forma regular obtienen peor performance que los fondos que mantienen los niveles de riesgo estables en el tiempo, lo que sugiere que el cambio de riesgo es un indicador de una escasa habilidad o bien, está motivado por los problemas de agencia entre gestores e inversores. Se observa, por tanto, la existencia de un problema de agencia entre el interés de los gestores que tratan de estar en la cima de los rankings de performance y el interés de los inversores, que quieren alcanzar altas rentabilidades, dado el nivel de riesgo que están dispuestos a asumir.

Otra rama de la literatura de fondos de inversión se ha centrado en el análisis de cómo las características personales de los gestores de fondos influyen en su comportamiento. En concreto, Chevalier y Ellison (1999a, 1999b) estudian la relación

entre la performance y el cambio del gestor con la edad y la educación del mismo. Dwyer *et al.* (2002), Gottesman y Morey (2006) y Watson y McNaughton (2007) también examinan la relación entre las características del gestor como la educación y el género y la performance de los fondos de inversión.

Por último, algunos estudios han investigado la organización de las industrias de fondos de inversión y de pensiones y la eficacia de algún mecanismo de control como el cambio del gestor. Denis y Denis (1995) estudian los efectos del cambio del gestor de los fondos de inversión de Estados Unidos.

Del mismo modo, Khorana (1996) también examina la relación entre el cambio del gestor y su performance anterior. Más tarde, Khorana (2001) analiza los cambios en la performance alrededor de la fecha del cambio del gestor.

Un problema de los estudios que analizan el cambio del gestor está relacionado con el hecho de que la sustitución del gestor puede ser debida a diferentes razones. Por un lado, la sustitución puede deberse al despido de dicho gestor si sus resultados no eran los deseados por la compañía gestora. Por otro lado, el cambio de gestor puede deberse a la jubilación del gestor o su marcha voluntaria a otra gestora. A pesar de que las diferentes circunstancias se reflejan en la información de que se dispone (observamos que hay un cambio de gestor), los factores que causan el cambio del gestor pueden ser muy diferentes y no son conocidos por los investigadores y los inversores. Por ello, Khorana (2001) sugiere que una aproximación razonable de la razón que hay detrás del cambio de gestor puede ser la performance pasada de los fondos de inversión que gestionaba dicho gestor.

Es por ello, que para llevar a cabo el objetivo de este primer capítulo, la base de datos se divide en dos submuestras, los fondos que tienen performance negativa previa

al cambio del gestor que serán incluidos en la submuestra de performance negativa (NP) y aquellos que muestran una evolución de performance positiva antes del cambio y que serán incluidos en la submuestra de performance positiva (PP). Destacar que los análisis se llevarán a cabo, en un primer momento, para toda la muestra, que está constituida por 104 fondos que sufren un cambio de gestor durante el período 1999-2009 (57 fondos de inversión en Renta Variable Española y 47 fondos de Renta Variable Europea). Luego, se separará en dos subgrupos para examinar las consecuencias del cambio del gestor de acuerdo con la performance anterior a la sustitución.

En primer lugar, se analiza el impacto del cambio del gestor en la performance obtenida por los fondos de inversión que han sufrido un cambio de gestor. Por lo tanto, si los malos resultados en el período previo a la sustitución son atribuibles a la capacidad de gestión, cabría esperar una mejora en la performance después del cambio de gestor en el grupo de NP. Por otro lado, en el grupo de PP, la capacidad de mantener o mejorar la performance depende de las habilidades de gestión e inversión del nuevo gestor. Si el nuevo gestor tiene éxito, él/ella va a generar persistencia en la performance de los fondos, mientras que si la performance disminuye después de la sustitución, se debe a las escasas capacidades de gestión del nuevo gestor.

El análisis empírico sobre las consecuencias del cambio del gestor en la industria de fondos de inversión españoles se basa principalmente en dos fuentes de datos. En primer lugar se utiliza la información sobre la rentabilidad de los fondos, patrimonio gestionado, objetivos de inversión y otras características de los fondos de inversión españoles proporcionada por el supervisor oficial del mercado español, la Comisión Nacional del Mercado de Valores (CNMV). Este capítulo de la Tesis Doctoral se centra en los fondos de inversión en Renta Variable Española y Renta Variable Europea entre junio de 1999 y diciembre de 2009. En concreto, se analizan los cambios del gestor que

se producen desde septiembre de 1999 porque se necesita un mínimo de información para el período previo a la sustitución. Nótese que para definir el segmento de mercado en el que operan los fondos se utiliza la vocación inversora de la CNMV.

En segundo lugar, se recopila manualmente la información sobre los fondos de inversión en los que el gestor ha sido sustituido de la página web de Morningstar. Dicha institución proporciona información del nombre del gestor y de la fecha en que un gestor asume la responsabilidad de gestionar el fondo. Una vez recogida esta información, se unifica la información obtenida de ambas bases de datos utilizando para ello el código ISIN del fondo y el nombre del fondo. La muestra está formada por 354 fondos de inversión españoles, 173 fondos de inversión en Renta Variable Española y 181 fondos de Renta Variable Europea, donde 104 fondos sufren un cambio de gestor durante el período 1999-2009 (57 fondos de inversión en Renta Variable Española y 47 fondos de Renta Variable Europea).

La base de datos está libre de sesgo de supervivencia ya que el conjunto de datos proporcionado por la CNMV contiene información de todos los fondos de inversión comercializados en España con independencia de que hayan desaparecido a lo largo del tiempo. Por lo tanto, se incluye información tanto de los fondos que sobreviven como de los fondos que no sobreviven durante todo el periodo temporal analizado. No obstante, es importante indicar que la página web de Morningstar sólo proporciona información sobre el último cambio del gestor que se ha producido en cada fondo.

Concretamente, las consecuencias del cambio de gestor en la performance se analizan a través del uso de las siguientes medidas de performance:

- Exceso de rentabilidad bruta sobre el mercado: se utiliza el índice MSCI España o MSCI Emu como punto de referencia de mercado en función de la categoría de inversión estudiada (fondos de renta variable nacional o renta variable euro).
- Exceso de rentabilidad neta sobre el mercado: se utiliza el índice MSCI España o MSCI Emu igual que en el caso anterior.
- Alfa del modelo de un factor, alfa de Jensen (1968).
- Alfa del modelo de tres factores, modelo de Fama y French (1993).

Una vez que se han analizado las consecuencias en la performance, se analiza el impacto del cambio del gestor sobre el nivel de riesgo asumido por los fondos de inversión. En este sentido, la teoría sobre "tournament behavior" (ver, por ejemplo, Brown *et al*., 1996) sugiere que, en un intento de maximizar su compensación, es de esperar que los gestores que obtienen baja performance tiendan a aumentar la volatilidad general de sus carteras (el riesgo de sus carteras) en un intento de tener suerte y terminar el año con buena performance. Por el contrario, Busse (2001) y Taylor (2003) también justifican que los fondos que están clasificados por encima de la mediana de performance de los fondos de su categoría aumentan más el riesgo total que los fondos que están por debajo, concretamente cuando las acciones ofrecen un alto rendimiento y baja volatilidad.

De acuerdo con estudios previos, el nivel de riesgo de los fondos de inversión es medido a través del cálculo del riesgo total y el riesgo sistemático. En concreto, se emplean las siguientes medidas de riesgo:

- Riesgo total: se calcula como la desviación típica de las rentabilidades brutas de un fondo de inversión.

- El riesgo sistemático: se calculará a través del modelo de un factor de Jensen (1968) y el modelo de tres factores de Fama y French (1993).

Por último, también se analizan los flujos de los fondos de inversión en los períodos pre y post al cambio del gestor. Este análisis es interesante por varias razones. En primer lugar, permite detectar si el nuevo gestor es capaz de captar más flujos de inversión que antes y, por lo tanto, si es capaz de mejorar la cuota de mercado de los fondos de inversión. Se espera que los fondos con mala performance en el periodo previo al cambio vayan a tener dificultades para atraer más flujos que los fondos restantes y, por tanto, aumentar su cuota de mercado. En segundo lugar, el análisis de la relación entre los flujos de inversión y la performance alrededor de la fecha del cambio de gestor proporciona evidencia a los participantes del mercado con respecto a la capacidad de los fondos de exhibir persistencia en su performance.

A diferencia de los estudios anteriores, la magnitud de los flujos de inversión en los períodos pre y post al cambio se medirá utilizando datos tanto del patrimonio gestionado por los fondos como del número de inversores. Por otra parte, las gestoras no sólo están interesadas en la atracción de flujos de dinero, sino también de flujos de inversores debido a los efectos secundarios y los beneficios que los nuevos inversores pueden ofrecer al grupo financiero ("spillover effects"). Por lo tanto, el análisis de los flujos de los inversores puede añadir información relevante para examinar el comportamiento de los inversores individuales. En consecuencia, este trabajo es uno de los pocos estudios que trabajan con flujos de dinero, así como con flujos inversores (véase, por ejemplo Guercio y Tkac de 2002 y Vicente *et al.*, 2011).

Las diferentes medidas que se emplean en los tres análisis (performance, riesgo y flujos), se calcularán para períodos de 3, 12 y 24 meses en torno a la fecha del cambio del gestor.

Los resultados que se han obtenido en este primer capítulo de la tesis son que los fondos que cambian de gestor debido a su mala performance muestran una mejora significativa en su performance tras el cambio, mejora que perdura en el tiempo. Por lo tanto, se observa que el mecanismo de control de cambio del gestor es eficaz para aquellos fondos con mala performance. Por el contrario, los fondos con performance positiva en el período previo al cambio tienden a sufrir una disminución en la performance tras el cambio del gestor, aunque esta disminución sólo es significativa en los fondos de Renta Variable Europea. Este hecho, apoya la idea de que la capacidad de mantener y mejorar la performance depende de las habilidades del nuevo gestor. Si el nuevo gestor tiene éxito, va a generar persistencia en la performance de los fondos, mientras que si la performance disminuye después de la sustitución es debido a una menor capacidad del nuevo gestor en comparación con el antiguo.

Los resultados que se obtienen al analizar el riesgo no son concluyentes, aunque sí que se observa que los fondos con una baja performance en el período previo al cambio del gestor tienden a aumentar su nivel de riesgo posteriormente. Estos resultados son consistentes con la idea de que los gestores con una mala performance en el período previo al cambio tienden a asumir un mayor nivel de riesgo en su cartera posteriormente, en un intento de mejorar su posición en los rankings de performance.

Por último, se observa que el cambio de gestor, en general, tiene un impacto negativo sobre los flujos de inversión de los fondos de inversión tras el cambio del gestor. Este resultado es robusto en las dos metodologías aplicadas en este análisis.

La contribución principal de este capítulo es ayudar a la comprensión de la eficacia del cambio del gestor como mecanismo de control en los mercados menos desarrollados, ya que este conocimiento es útil para los diferentes agentes que intervienen en los mercados financieros. Los asesores financieros pueden estar interesados en saber si un cambio de gestor altera el patrón de los flujos de inversión en el período posterior al cambio. Del mismo modo, los inversores también pueden querer saber si el cambio de gestor altera los resultados futuros. Por último, los reguladores del mercado pueden querer examinar la performance antes y después del cambio para comprender mejor la eficiencia de la industria.

CAPÍTULO 2:

Consecuencias del cambio de riesgo en función de las características del gestor.

El objetivo del segundo capítulo de la tesis es doble. En primer lugar, el objetivo es estudiar las consecuencias que tiene el cambio de riesgo sobre la performance de los fondos de inversión españoles a través del análisis de la composición de carteras mensuales. Dicho estudio es interesante para los inversores dado que les interesa saber si el cambio de riesgo perjudica las rentabilidades de los fondos de inversión.

En este sentido, es importante indicar que la literatura previa sólo se ha centrado en el análisis del cambio de riesgo o del "tournament behavior" a través de medidas de riesgo basadas principalmente en las rentabilidades de los fondos de inversión (véase, por ejemplo, Daniel y Wermers, 2000). Por ello, es necesario ampliar y contribuir a los resultados obtenidos sobre las consecuencias que el cambio de riesgo tiene sobre la performance obtenida empleando medidas de cambio de riesgo basadas en la composición de las carteras. Actualmente, sólo el trabajo de Huang *et al.* (2011) aborda esta cuestión.

Para llevar a cabo este capítulo se mide el cambio de riesgo (RS) como en el trabajo de Huang, *et al.* (2011); dichos autores analizan la composición de las carteras utilizando períodos de tiempo idénticos para estimar la volatilidad observada en las carteras y la volatilidad realmente soportada por las carteras.

La volatilidad observada de acuerdo con la composición de las carteras sería idéntica a la volatilidad real soportada por el fondo de inversión sólo si dicho fondo de inversión mantiene la misma composición durante el periodo de tiempo establecido. En este caso, no hay cambio de riesgo. Por el contrario, si la medida del cambio de riesgo $RS_{p,t}$ es positiva, esto se debe a que la volatilidad de la última cartera reportada es más alta que la volatilidad real que ha sufrido dicho fondo de inversión durante el tiempo establecido, de lo contrario dicha medida es negativa. Por lo tanto, una medida del cambio de riesgo que es positiva indica que un fondo de inversión ha aumentado el riesgo de la cartera durante el período de tiempo analizado.

El segundo objetivo es detectar si las consecuencias en la performance son las mismas o diferentes, según los mecanismos de cambio de riesgo empleados por los gestores. Esto es debido a que la variación del nivel de riesgo de las carteras puede ser causado por el cambio en la composición de las carteras entre renta variable y tenencia de efectivo o "cash" o al cambio del riesgo sistemático o idiosincrático dentro de las posiciones de renta variable.

La literatura financiera ha analizado en profundidad las causas y los incentivos de los cambios de riesgo realizados por los gestores en los fondos de inversión. Brown, et al. (1996) y Taylor (2003) sugieren que la respuesta óptima de un gestor de fondos de inversión sobre su performance provisional es un ajuste en la asunción de riesgos debido a que esto maximiza la probabilidad de que el fondo alcance una posición superior en la parte final del año.

Más tarde, otros estudios también ponen de manifiesto la importancia de los incentivos que tienen los gestores para variar la asunción de riesgo de sus carteras, ya sea por compensaciones personales o inquietudes profesionales. En concreto, Kempf et

al. (2009) centran su atención en el análisis de la competencia existente entre las carteras para conseguir una buena posición en los rankings de performance dependiendo del estatus de los mercados financieros (mercados alcistas y bajistas). Estos autores argumentan que, en contexto de mercados bajistas, cuando los gestores de fondos obtienen una mala performance a mitad de año tienden a disminuir el riesgo de sus carteras en comparación al resto de gestores para prevenir la posible pérdida del puesto de trabajo (employment incentives). Sin embargo, en contextos de mercados alcistas, los incentivos salariales se hacen más relevante que el riesgo de perder el empleo (compensation incentives), y los gestores de los fondos de inversión con una baja performance a mitad de año, incrementan el riesgo para ponerse al día con el resto de gestores que tiene una mejor performance a mitad de año. Del mismo modo, Massa y Patgiri (2009) también demuestran cómo los incentivos de los gestores afectan a la performance y al cambio de riesgo en la industria de fondos de inversión de Estados Unidos.

Estudios más recientes, como Lee *et al.* (2015), concluyen que analizar los incentivos que tienen los gestores de carteras pueden ser tan importante como analizar la relación de flujos futuros de inversión en función de la performance pasada para determinar el cambio de riesgo en los fondos de inversión. Esto es debido a que la gran mayoría de los gestores de los Estados Unidos tienen un contrato ligado a incentivos variables basados en la performance obtenida por los fondos de inversión que gestionan. Sin embargo, estos contratos no son simétricos debido a que el gestor no es penalizado si el fondo obtiene una performance inferior al objetivo marcado. Por lo tanto, los gestores de cartera tienen incentivos para cambiar el nivel de riesgo de los fondos de inversión y así obtener un mayor incentivo personal. Además, los gestores de los fondos de inversión pueden cambiar el riesgo para impresionar a los inversores (véase, por

ejemplo, Chevalier y Ellison, 1997; Sias, 2007; y Huang *et al.*, 2011) o por motivos fiscales.

En general, los estudios anteriores tienden a plantear la hipótesis de que el cambio de riesgo es perjudicial para los inversores, sin centrarse en las consecuencias que el cambio del nivel de riesgo tiene en la performance de los fondos de inversión. Sin embargo, el cambio de riesgo puede ser impulsado por razones muy diferentes y, por tanto, las consecuencias también pueden ser diferentes. Obviamente, el cambio de riesgo no es recomendable para los inversores financieros si este comportamiento lo realizan gestores no cualificados o gestores que operan para aumentar su remuneración personal. Sin embargo, si el cambio de riesgo lo realizan gestores cualificados que tienen habilidades de inversión, el cambio del nivel de riesgo sí que es deseable para los inversores de los fondos de inversión, ya que se beneficiarían de una performance superior. De hecho, existe evidencia de que los gestores de fondos de inversión más activos tienen una mayor habilidad para invertir que el resto de gestores (véase, por ejemplo Kacperczyk *et al*, 2005; Cremers y Petajisto, 2009 y Fama y French, 2010).

Para llevar a cabo este capítulo de la Tesis Doctoral se emplea una muestra inicial que incluye 173 fondos que poseen al menos información de un año de rentabilidades diarias y 11 carteras reportadas. De esta muestra se eliminan los fondos que no cumplen con los requisitos de inversión de esta vocación inversora para asegurar que todas las carteras analizadas hayan sido clasificadas apropiadamente como fondos de inversión de renta variable española. La muestra final consta de 144 fondos de inversión de renta variable nacional. La eliminación de algunos fondos mal clasificados no implica ningún sesgo en la muestra. La información para constituir la base de datos se ha obtenido de la Comisión Nacional de Valores (CNMV) y de la base de datos

Morningstar Direct, lo cual ha permitido analizar un total de 10.730 carteras desde marzo de 2000 a diciembre de 2011.

Para analizar las consecuencias del cambio de riesgo en la performance de los fondos de inversión se compara la performance de los fondos que aumentan o disminuyen su riesgo con la performance de los fondos de inversión que tiene un nivel de riesgo más estable. Para ello, se utilizan seis medidas diferentes de performance. En primer lugar, se calculan las rentabilidades brutas y las rentabilidades netas (las primeras son relevantes para evaluar la performance de los gestores, mientras que las segundas son relevantes desde el punto de vista del inversor) y el exceso de rentabilidad del mercado para evaluar la performance frente a la cartera de mercado. Además, para ajustar los efectos del riesgo, se emplean el alfa del modelo CAPM, el alfa del modelo de Fama y French (1993) y el alfa de Carhart (1997).

Por otro lado, los fondos de inversión pueden cambiar el nivel de riesgo de sus carteras a través de varios mecanismos. En primer lugar, pueden cambiar la composición entre renta variable y liquidez. En segundo lugar, dentro de la renta variable, los fondos pueden cambiar su exposición al riesgo sistemático invirtiendo en acciones con beta alta o baja y sus exposiciones a riesgos idiosincráticos desviándose de su benchmark o cambiando la concentración de la cartera.

Por tanto, en este capítulo de la tesis se construyen medidas de cambio de riesgo o "*Risk Shifting"* alternativas basadas en algunos de estos mecanismos de cambio de riesgo con el objetivo de investigar si las consecuencias que tienen cada una de ellas en la performance de los fondos son idénticas o por el contrario difieren. Estas medidas alternativas de *RS* utilizadas son el ratio del cambio de riesgo, el cambio de riesgo

sistemático, el cambio de riesgo idiosincrático y el cambio de riesgo basado en renta variable.

Por último, se analizan las consecuencias del cambio del nivel de riesgo en función de las características de los gestores de los fondos de inversión, tales como el género (hombres vs. mujeres), el nivel de especialización (gestores generalistas vs. gestores especialistas), la experiencia, la edad y la educación (gestores con master vs. gestores sin master).

En esta línea de investigación, autores como Chevalier y Ellison (1999b), Prather y Middleton (2002), y Bliss *et al*. (2008) indican que las características del gestor como la edad, el género y la experiencia pueden afectar a los perfiles de riesgo de las carteras gestionadas.

Chevalier y Ellison (1999b) encuentran que los gestores más jóvenes asumen un menor riesgo no sistemático que los gerentes que tiene una edad mayor. Chevalier y Ellison (1999a) también encuentran que los gestores de los fondos de inversión que cursaron sus estudios en instituciones de mayor prestigio tienen una performance mayor que los gestores de fondos de inversión que asistieron a instituciones de menos prestigio, o incluso que tienen un nivel de estudios inferior. Menkhoff *et al.* (2006) sostienen que los gestores de fondos que son menos experimentados tienen menos confianza y asumen menos riesgos que los gestores que tienen una larga trayectoria profesional.

Como se puede ver, hay una gran variedad de estudios que analizan el impacto de las características del gestor en la performance y en la asunción de riesgos. En este sentido, este capítulo contribuye a la literatura por ir un paso más allá a través del análisis de las consecuencias que el cambio del nivel de riesgo de las carteras tiene en la

performance en función de algunas características sociodemográficas de los gestores de fondos.

Para llevar a cabo este último análisis, es necesario seleccionar aquellos fondos de inversión de la muestra que estén gestionados por un gestor individual, y no por un equipo de gestores, ya que el objetivo es analizar las consecuencias del cambio de riesgo en función de las características del gestor y no de un equipo.

Los resultados que se obtienen en este capítulo son que los fondos que aumentan el riesgo obtienen una performance positiva y estadísticamente significativa en comparación a los fondos que mantienen niveles de riesgo más estables y a los fondos que reducen su riesgo en períodos posteriores. Este hallazgo, en contraste con la evidencia previa en la industria de fondos de inversión de Estados Unidos, proporciona evidencia de que el cambio de riesgo no es perjudicial para los inversores en los mercados menos desarrollados, sino todo lo contrario. También se observa que este resultado es bastante robusto, el resultado es el mismo independientemente del mecanismo de cambio del nivel de riesgo usado por los gestores (principalmente cambios en la asignación de activos y cambios en el riesgo sistemático). Sin embargo, los resultados obtenidos al utilizar el riesgo idiosincrásico son ligeramente diferentes. Se obtiene que el aumento del riesgo idiosincrásico, que se produce cuando los fondos aumentan su concentración de cartera, conduce a una performance inferior. Este resultado sugiere que el obtener una mala performance por haber aumentado el riesgo idiosincrásico es propiciado por la escasa capacidad de selección de valores que poseen los gestores analizados.

Finalmente, también se constata que las consecuencias positivas que sobre la performance generan los aumentos de riesgo son robustas cuando se analizan las

variables sociodemográficas de los gestores, tales como la edad, el género, la experiencia, el nivel de especialización y la educación. Sin embargo, hay algunas diferencias estadísticamente significativas dependiendo de las características del gestor. Concretamente, la decisión de aumentar el riesgo es aún mejor cuando es tomada por una mujer, un gestor especialista o un gestor con un nivel de educación superior.

Por tanto, este segundo capítulo de la tesis, contribuye a la literatura financiera de varias maneras. En primer lugar, el estudio refuerza estudios previos que estudian las consecuencias del cambio de riesgo sobre la performance a través de medidas del cambio de riesgo basadas en la composición de las carteras. Proporciona un análisis más potente de las consecuencias del cambio del nivel de riesgo mediante dado que se utilizan carteras mensuales así como rentabilidades diarias a diferencia del trabajo de Huang *et al.* (2011), el cual emplea carteras semestrales o trimestrales, así como rentabilidades mensuales. En segundo lugar, dado lo que me es conocido, este es el primer trabajo que analiza las consecuencias del cambio del nivel de riesgo en un mercado fuera de EEUU. Por otra parte, es el primer trabajo que analiza las consecuencias del cambio del nivel de riesgo en función de las características sociodemográficas de los gestores de fondos.

CAPÍTULO 3:

Análisis de la eficiencia de los gestores: un enfoque sociodemográfico.

El objetivo del tercer capítulo es analizar la eficiencia de los gestores a través de un modelo de Análisis Envolvente de Datos (DEA) que no sólo se limita a analizar la eficiencia desde un punto de vista financiero (maximizar rentabilidad-minimizar riesgo) sino que pretende también analizar la eficiencia de los mismos en función de sus características sociodemográficas. Dichas características fueron también analizadas en el capítulo 2 de la Tesis (experiencia, sexo, educación, etc.).

Este análisis nos permitirá realizar una comparación de gestores con similares características pudiendo desarrollar un ranking de gestores que será de gran interés para los distintos miembros del mercado financiero (gestoras, inversores, etc.). Además, el uso de este tipo de metodología, nos permitirá contrastar la importancia que en términos de eficiencia tienen las variables sociodemográficas de los gestores sin exigir ningún tipo de relación funcional entre las variables utilizadas para definir que un gestor puede ser considerado eficiente. Nótese que esta es una de las grandes ventajas de este tipo de metodología.

En las últimas décadas, el sector financiero ha experimentado grandes cambios en sus actividades debido a la internacionalización y la desregularización de los mercados, a los avances tecnológicos, etc. Dichos cambios han obligado a que las entidades financieras hayan diversificado su negocio para permanecer en el mercado. Estas diversificaciones podrían suponer cambios en la eficiencia y la productividad de las entidades financieras. Es por ello, que en las últimas décadas, se han realizado diversos estudios en los que se han investigado la productividad y la eficiencia en los distintos sectores y productos del mercado financiero. Para ello, uno de los métodos más empleados a la hora de evaluar la eficiencia de las instituciones del sistema financiero han sido los modelos DEA, véase por ejemplo, Berg *et al.* (1993) que emplean un modelo DEA para analizar la competencia existente entre el sector bancario de tres países nórdicos; Schaffnit *et al.* (1997) analizan la eficiencia del personal de un gran banco canadiense; Cummins *et al.* (2004) analizan la eficiencia de la estructura de las compañías de seguros españolas; Cummins and Xie (2008) analizan las consecuencias que tienen las fusiones entre compañías de seguros estadounidenses en su productividad y eficiencia; Cummins *et al.* (2010) investigan las economías de alcance en la industria de seguros de Estados Unidos durante el período 1993-2006 a través de modelos DEA; Holod and Lewis (2011) proponen un DEA para medir la eficiencia bancaria a través de los depósitos bancarios tratándolos como producto intermedio, enfatizando así, la doble función de depósitos en el proceso de producción del banco, etc.

Como se puede observar, hay muchos estudios que se centran en la eficiencia de las instituciones financieras. Estos estudios concentran su atención en bancos, cajas de ahorro, compañías de seguros, etc. Es en 1997, cuando la metodología DEA se utilizó por primera vez, para analizar la eficiencia de los fondos de inversión. Concretamente,

Murthi *et al.* (1997) evaluaron la eficiencia de 2.083 fondos de inversión con un modelo de índice de eficiencia de cartera DEA llamado DPEI. Este modelo puede considerarse una extensión del bien conocido ratio de Sharpe (Sharpe, 1966) al incluir los costes de transacción como una entrada adicional a la desviación estándar de las rentabilidades de la cartera. El interés en los modelos de DEA se explica, en gran medida, debido a que estos métodos de frontera no requieren ninguna forma funcional entre rentabilidad y riesgo. Además, el uso potencial de varios inputs y outputs en la evaluación de la performance es una forma innovadora de explorar la performance de las carteras financieras. Como consecuencia de este trabajo, los modelos DEA comenzaron a ser utilizados para medir la performance de los fondos de inversión de una manera alternativa a las medidas tradicionales como Jensen (1968), Fama y French (1993) y Carhart (1997).

Estas últimas medidas no utilizan, de manera explícita, la información disponible en la toma de decisiones de los gestores mientras que los distintos modelos de DEA sí que la tienen en cuenta. Por ejemplo, la actuación de los gestores de fondos de inversión, es decir, sus decisiones de trading dependen, en gran medida, de la eficiencia/habilidad del gestor a la hora de decidir el momento de la compra y la venta (véase, Chen *et al.*; 2000). Por lo tanto, los modelos DEA pueden mejorar los resultados obtenidos por los modelos tradicionales dado que utilizan varios inputs y outputs en la evaluación de la performance además de no asumir ninguna relación funcional entre la rentabilidad y el riesgo.

Basso y Funari (2001), Choi y Murthi (2001), Basso y Funari (2003), Lozano y Gutiérrez (2008), Zhao y Yue (2010) y Lamb y Tee (2012) son ejemplos de estudios que analizan la eficiencia de los fondos de inversión a través de diferentes modelos

DEA. Recientemente, Basso y Funari (2017) estudian el papel del tamaño de los fondos de inversión en el análisis de la performance del fondo con un modelo DEA.

Por otro lado, Medeiros (2010) y Andreu *et al.* (2014) también investigan la eficiencia de los planes de pensiones a través de los modelos DEA. Por último, algunos trabajos también aplican modelos DEA para evaluar la performance de los hedge funds (véase, por ejemplo, Eling, 2006; Gregoriou, 2003; Gregoriou *et al.*, 2005 y Kumar *et al.*, 2010, entre otros).

Como ha quedado constatado anteriormente, son muchos los estudios que han analizado la eficiencia del sistema financiero, del sistema de seguros, e incluso cada vez hay más trabajos que analizan la eficiencia de los fondos de inversión y de los hedge funds. Sin embargo, dado lo que me es conocido, los estudios de la eficiencia de los gestores a través de un modelo DEA han sido escasos. Concretamente, sólo el reciente estudio de Banker *et al.* (2016) centra su análisis, no en la eficiencia de los fondos, sino en la eficiencia de los gestores (de las personas que se dedican a gestionarlos). Estos autores analizan la eficiencia de los gestores en sus operaciones de compra y venta a través de un modelo aditivo DEA. Sin embargo, este capítulo analiza la eficiencia de los gestores dependiendo de sus características sociodemográficas (género y nivel de especialización) a través de la medida SBM y su Variación III. Por lo que con nuestro trabajo de investigación en este campo, trataremos de rellenar este vacío en la literatura financiera.

Por último, se realiza un análisis en el que permite comparar si existen diferencias entre los gestores que persisten en el tiempo en la base de datos y los gestores restantes, así como variables que podrían explicar las diferencias de eficiencia entre los gestores con mayor y menor eficiencia.

La base de datos utilizada en este capítulo de la Tesis Doctoral incluye un conjunto de 54 gestores españoles de fondos de inversión de renta variable europea durante el periodo que va de enero de 2009 a diciembre de 2014. El estudio se centra, concretamente, en aquellos fondos de inversión que son gestionados de forma individual para así, poder considerar las variables sociodemográficas de los gestores (como ha ocurrido en el Capítulo 2). La justificación de analizar únicamente los fondos gestionados de forma individual se debe a que las variables sociodemográficas pueden ser muy diferentes entre los miembros de un equipo de gestores (un equipo puede estar formado por gestores con experiencia variada, con gestores de diferente género, etc.).

La eficiencia de los gestores se calcula utilizando la medida basada en slacks (SBM) propuesta por Tone (2001, 2010). En concreto, el estudio define qué variables son relevantes para determinar la eficiencia de un gestor. La hipótesis utilizada es que un gestor se clasificará como eficiente si puede maximizar la rentabilidad bruta y el patrimonio gestionado, asumiendo un bajo nivel de riesgo, minimizando el ratio de rotación de la cartera y el coste que representa para la gestora. Una vez definido el modelo, el capítulo examina la eficiencia de los gestores de fondos de inversión para cada año de la muestra a través de la aplicación del modelo SBM original propuesto por Tone (2001).

Dicho autor muestra que para que una unidad de producción (DMU) alcance la eficiencia, no basta con la reducción proporcional de inputs, o incremento de outputs, lograda con los factores de eficiencia que emplean los anteriores modelos DEA si no que es necesario una reducción adicional de inputs, o incremento adicional de outputs, que ya no es proporcional. Estos ajustes complementarios en los inputs (s^-) denominados exceso de input o en los outputs (s^+) denominados como déficit de output son los conocidos slacks. Este análisis proporciona información sobre la eficiencia de

los gestores de fondos de inversión españoles (proporciona un ranking de eficiencia), sin embargo, puede ocurrir que los gestores que se estén comparando entre sí tenga características diferentes.

Esta limitación puede cuestionar la exactitud de los resultados del modelo SBM. Este problema es especialmente relevante en aquellas industrias donde los competidores muestran características variadas, como ocurre en la industria de fondos de inversión española. Por ejemplo, un grupo de gestores con mucha experiencia puede no ser una referencia adecuada para un gestor con poca experiencia en el mercado, aunque esos gestores experimentados estén en la frontera eficiente del modelo SBM. Por lo tanto, la medida SBM puede ofrecer una clasificación de eficiencia de los gestores que puede ser engañosa. Por esta razón, en este capítulo la eficiencia de los gerentes también se analiza dividiendo la muestra en grupos de gestores dependiendo de las características de los mismos. Al igual que en el Capítulo 2, las características de los gestores que se utilizan aquí para agrupar a los gerentes son el género (hombres versus mujeres) y el nivel de especialización (gestores especialistas versus gestores generalistas). Por tanto, el segundo análisis desarrollado en este capítulo analiza la eficiencia de los gestores en función de las características sociodemográficas de los mismos, teniendo en cuenta la Variación III propuesta por Tone (2010).

Tone (2010) evalúa la eficiencia de cada gestor con todos los facets formados por gestores eficientes dentro de cada grupo. Por tanto, este análisis permite comparar a cada gestor con gestores con características similares (hombres, mujeres, especialistas y generalistas), obteniendo así un ranking de eficiencia no sólo global sino también un ranking de eficiencia local (dentro de cada grupo de gestores).

El primer análisis, en el que se aplica la medida SBM, muestra un ranking de la eficiencia de los gestores, destacando que los años con mayores niveles de eficiencia son los de 2009 y 2013. Por otro lado, el gestor eficiente que más se observa en todos los años analizados (2010-2014) es una mujer, la cual gestiona varios fondos de diferentes vocaciones de inversión al mismo tiempo (es una gestora generalista).

Con respecto al segundo análisis realizado, en el que se aplica la Variación III del modelo SBM, proporciona resultados más apropiados en términos de clasificación de la eficiencia de los gestores con características similares. Los resultados apoyan el uso de esta variante SBM en aquellos sectores/industrias con características muy variadas. Por lo tanto, el modelo propuesto en este capítulo es de gran interés para los mercados financieros y muestra información clave sobre el comportamiento del gestor. En particular, las compañías gestoras podrían aplicarlo como una medida para evaluar y promocionar a los gestores más eficientes.

A continuación, se realiza un análisis para determinar si existen o no diferencias significativas entre los gestores que persisten en el tiempo en la base de datos (gestores que persisten como gestores individuales) y el resto de gestores. Los resultados obtenidos indican que aquellos gestores que han gestionado, al menos un fondo de renta variable europea de forma individual, durante todos los años de estudio (2009-2014) son ligeramente menos eficientes que el resto de gestores. No obstante, dicha diferencia no es estadísticamente significativa.

Posteriormente, se ha realizado un análisis de los posibles determinantes que aseguran una larga vida laboral del gestor como gestor individual (gestores que están en la muestra durante todo el horizonte temporal analizado versus el resto de gestores). Los resultados obtenidos indican que de las cinco variables utilizadas en el modelo de

eficiencia (rentabilidad bruta, riesgo, patrimonio gestionado, ratio de rotación y coste que el gestor supone a la gestora), sólo la variable que sirve de proxy para saber el coste/remuneración de los gerentes es estadísticamente significativa.

Finalmente, se analizan las diferencias en términos de rentabilidad bruta, riesgo, nivel de educación, etc de los gestores en función de la eficiencia alcanzada por los gestores (gestores con altos niveles de eficiencia versus gestores con bajos niveles de eficiencia). Los resultados de este análisis muestran que el patrimonio gestionado, el riesgo y el ratio de rotación son identificativas de eficiencia. Es decir, para que un gestor sea eficiente debe maximizar el patrimonio de sus carteras minimizando tanto el riesgo como la rotación de las mismas.

Por tanto, este tercer capítulo de la tesis, contribuye a la literatura financiera de varias maneras. En primer lugar, es el primer trabajo que analiza la eficiencia de los gestores a través de un modelo DEA en mercados fuera de EEUU, que sepa sólo está el trabajo de Banker *et al.* (2016) en EEUU. Dichos autores analizan la eficiencia a través de un modelo aditivo DEA, mientras que este capítulo proporciona un método innovador para evaluar la eficiencia de los gestores, el modelo SBM. Por último, dado lo que me es conocido, este es el primer trabajo que analiza la eficiencia de los gestores en función de sus características sociodemográficas.

CONCLUSIONES FINALES

A continuación se resumen las principales conclusiones de la tesis. En este sentido, es importante tener en cuenta que las dos razones principales que me han llevado a investigar el comportamiento de los gestores de fondos de inversión españoles han sido, por un lado, la falta de estudios empíricos que estudian las consecuencias e implicaciones del cambio del gestor, las consecuencias del cambio del nivel de riesgo y la eficiencia con la que gestionan sus carteras los gestores de fondos de inversión en mercados menos desarrollados y con una cultura diferente a Estados Unidos. Por otro lado, ha sido el interés que muestra la literatura financiera por comprender el comportamiento de los gestores de fondos de inversión.

El objetivo del primer capítulo es analizar las consecuencias del cambio de gestor en la industria española de fondos de inversión. El estudio examina en primer lugar las consecuencias en la performance, es decir, si los fondos con malos resultados en el período previo al cambio de gestor son capaces de cambiar sus resultados. Los resultados obtenidos son que los cambios de gestor llevados a cabo en fondos con malos resultados llevan a mejoras significativas en la performance que perdura en el tiempo en el caso de los fondos de inversión nacionales. Por lo tanto, el mecanismo de control del cambio de gestor es efectivo para los fondos con resultados negativos. Por el contrario, aquellos fondos con unos resultados positivos en el periodo previo al cambio tienden a sufrir deterioro en la performance que perdura en el tiempo en el caso de los fondos de inversión de renta variable europea, pero que sólo se observa a corto plazo para los

fondos de inversión nacionales. Por lo tanto, parece que debe de pasar el tiempo para que los nuevos gestores que obtenían resultados positivos antes del cambio mejoren sus resultados tras el cambio.

En segundo lugar, el capítulo examina si hay cambios en el nivel de riesgo de los fondos de inversión durante los períodos previos y posteriores al cambio. Los resultados muestran que estos fondos no reportan niveles de riesgo significativamente diferentes a los reportados por los fondos que no han sufrido cambio de gestor en el período previo al cambio. Sin embargo, como consecuencia del cambio del gestor, el nivel de riesgo total tiende a aumentar a largo plazo, probablemente en un intento de alcanzar mayores niveles de performance.

Finalmente, el capítulo analiza la efectividad de los cambios de gestor examinando la relación entre estos cambios y los flujos de inversión en los fondos. Este análisis muestra que los cambios del gestor, en general, tienen un impacto negativo en los flujos de inversión posteriores al cambio al considerar el período de tiempo completo de cada fondo de inversión. Sin embargo, teniendo en cuenta no sólo los fondos con cambios de gestor sino todos los fondos de inversión en la categoría de inversión, se observa una mejora en los flujos de dinero atraídos por los fondos de inversión con performance negativa en el período previo al cambio. Por lo tanto, los resultados de esta investigación son de gran interés para los asesores financieros y para los partícipes de fondos de inversión porque demuestran que el mecanismo de control de cambio del gestor tiene consecuencias positivas para los fondos con malos resultados no sólo en un mercado desarrollado como EE.UU., sino también en España.

La contribución principal de este capítulo es ayudar a la comprensión de la eficacia del cambio del gestor como mecanismo de control en los mercados menos

desarrollados, ya que este conocimiento es útil para los diferentes agentes que intervienen en los mercados financieros. Los asesores financieros pueden estar interesados en saber si un cambio de gestor altera el patrón de los flujos de inversión en el período posterior al cambio. Del mismo modo, los inversores también pueden querer saber si el cambio de gestor altera los resultados futuros. Por último, los reguladores del mercado pueden querer examinar la performance antes y después del cambio para comprender mejor la eficiencia de la industria.

Debido a los resultados obtenidos en el capítulo 1 sobre las consecuencias del cambio de gestor en el nivel de riesgo asumido por los fondos y a que la literatura financiera sólo se ha centrado en el análisis de las causas y los incentivos de los gestores de fondos de inversión para cambiar el riesgo, he decido investigar las consecuencias que tiene el cambio de riesgo sobre la performance de los fondos de inversión españoles a través del análisis de la composición de carteras mensuales. Por lo tanto, el objetivo del capítulo 2 es evaluar las implicaciones del cambio de riesgo que tiene sobre los inversores de los fondos inversión.

El primer objetivo de este segundo capítulo es examinar las consecuencias que tiene el cambio de riesgo sobre la performance de los fondos de inversión españoles a través del análisis de la composición de carteras mensuales. El segundo objetivo es detectar si las consecuencias en la performance son las mismas o diferentes, según los mecanismos de cambio de riesgo empleados por los gestores, ya que la variación del nivel de riesgo de las carteras puede ser causado por el cambio en la composición de las carteras entre renta variable y tenencia de efectivo o "cash" o al cambio del riesgo sistemático o idiosincrático dentro de las posiciones de renta variable. Los resultados que se obtiene son que los fondos que aumentan el riesgo obtienen una performance superior (estadísticamente significativa), en comparación con los fondos que mantienen

niveles de riesgo estables y fondos que reducen su riesgo en períodos posteriores. Este hallazgo, en contraste con la literatura financiera previa en el sector de fondos de inversión de los Estados Unidos, proporciona evidencia de que el cambio de riesgo no es perjudicial para los inversores en mercados menos desarrollados. Este resultado es muy sólido, independientemente del mecanismo de cambio de riesgo utilizado por los gestores.

Por último, en este capítulo se analizan las consecuencias del cambio del nivel de riesgo en función de las características de los gestores de los fondos de inversión, tales como el género (hombres vs. mujeres), el nivel de especialización (gestores generalistas vs. gestores especialistas), la experiencia, la edad y la educación (gestores con master vs. gestores sin master). El capítulo documenta que la performance positiva obtenida como consecuencia de un aumento de riesgo es robusta para las variables sociodemográficas del gestor. Sin embargo, existen diferencias estadísticamente significativas dependiendo de las características del gestor. Concretamente, la decisión de aumentar el riesgo es mejor cuando está tomada por una mujer, un especialista o un gestor con nivel de educación superior.

Por tanto, este segundo capítulo de la tesis, contribuye a la literatura financiera de varias maneras. En primer lugar, el estudio refuerza estudios previos que estudian las consecuencias del cambio de riesgo sobre la performance a través de medidas del cambio de riesgo basadas en la composición de las carteras. Proporciona un análisis más potente de este tópico de investigación dado que se utilizan carteras mensuales así como rentabilidades diarias a diferencia del trabajo de Huang *et al.* (2011), el cual emplea carteras semestrales o trimestrales, así como rentabilidades mensuales. En segundo lugar, dado lo que me es conocido, este es el primer trabajo que analiza las consecuencias del cambio del nivel de riesgo en un mercado fuera de EEUU. Por otra

parte, es el primer trabajo que analiza las consecuencias del cambio del nivel de riesgo en función de las características sociodemográficas de los gestores de fondos.

Después de analizar el comportamiento de los gestores a través de metodologías paramétricas, se analizará la eficiencia de los gestores de fondos de inversión españoles a través de una metodología no paramétrica, concretamente, a través de un modelo DEA. Los modelos DEA se han utilizado como medidas alternativas a las medidas de performance tradicionales. Por lo tanto, el objetivo del capítulo 3 es analizar la eficiencia de los gestores a través de un modelo DEA, que no sólo se limita a explorar la eficiencia financiera, sino también teniendo en cuenta las características sociodemográficas de los gestores. Las variables sociodemográficas examinadas en este capítulo son las mismas que en el Capítulo 2. Concretamente, el género, nivel de educación, nivel de especialización y experiencia de los gestores de fondos.

El primer objetivo del capítulo 3 es analizar la eficiencia de los gestores, que se calcula utilizando por primera vez una técnica adecuada de DEA, el modelo SBM. En particular, el estudio define qué variables son relevantes para la eficiencia de un gestor de cartera. Un gestor será clasificado como eficiente si puede maximizar la rentabilidad bruta en un gran número de activos gestionados asumiendo un bajo nivel de riesgo, minimizando la rotación de la cartera y el coste que representa para la sociedad gestora. Este análisis reporta un ranking de eficiencia de los gestores, destacando que los años con mayores niveles de eficiencia de la muestra son 2009 y 2013. Por otro lado, el gestor eficiente más observado en todos los años analizados (2010-2014) es una mujer que gestiona varios fondos de diferentes vocaciones de inversión al mismo tiempo (se le clasifica como gestora generalista).

Sin embargo, el modelo SBM ha sido cuestionado porque hay otros enfoques diferentes para determinar el conjunto de referencia de "mejores prácticas". Por tanto, el segundo objetivo de este capítulo es analizar la eficiencia de los gestores dependiendo de sus características sociodemográficas utilizando para ello clusters. Los resultados obtenidos en este segundo análisis indican que hay mejoras en la eficiencia al comparar los gestores con gestores del mismo género y con gestores con la misma especialización. Por lo tanto, la variación III del modelo SBM proporciona resultados más apropiados en términos de clasificación de la eficiencia de los gestores con características similares. Nótese que el modelo propuesto en este capítulo es de gran interés para los mercados financieros y muestra información clave sobre el comportamiento del gestor. En particular, las compañías gestoras podrían aplicarlo como una medida para evaluar y promocionar a los gestores más eficientes.

Por último, este capítulo analiza tanto los patrones de persistencia como los determinantes de la eficiencia obtenida por los gestores de cartera. El capítulo concluye que la performance no parece un elemento importante para determinar la continuidad de un gestor como gestor individual. Además, de las 5 variables utilizadas en el modelo de eficiencia de los gestores, sólo la variable que integrada tanto la experiencia como la educación de los gestores es un indicador estadísticamente significativo que diferencia a gestores que gestionan individualmente en el período de la muestra con respecto al resto de gestores. Por último, las variables que más influyen en la eficiencia de un gestor son el patrimonio gestionado, el nivel de riesgo y la rotación de la cartera.

Por lo tanto, este capítulo contribuye a la literatura financiera de varias maneras. En primer lugar, es el primer trabajo que analiza la eficiencia del gestor a través de un modelo DEA en mercados fuera de los Estados Unidos. Además, proporciona un

método innovador para evaluar la eficiencia de los gestores dado que aplica un el modelo SBM y tiene en cuenta las características sociodemográficas de los gestores.

Con todo lo mencionado anteriormente, esta tesis, compuesta por tres ensayos sobre el comportamiento de los gestores de fondos de inversión, contribuye a la literatura financiera sobre el comportamiento de los gestores analizando un mercado menos desarrollado.

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