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Ruth Gimeno Losilla

Three essays on fund managers' abilities: learning, autonomy and divergent trading.

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THREE ESSAYS ON FUND MANAGERS' ABILITIES: LEARNING, AUTONOMY AND DIVERGENT TRADING.

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THREE ESSAYS ON FUND MANAGERS' ABILITIES: LEARNING, AUTONOMY AND DIVERGENT TRADING

RUTH GIMENO

THREE ESSAYS ON FUND MANAGERS' ABILITIES: LEARNING, AUTONOMY AND DIVERGENT TRADING

By

Ruth Gimeno

Supervisor: José Luis Sarto

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, June 2021

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ABBREVIATIONS

AUM	Assets Under Management
CAPM	Capital Asset Pricing Model
CNMV	Spanish Securities and Exchange Commission (*Comisión Nacional de Mercado de Valores*)
EFAMA	European Fund and Asset Management Association
FE	Fixed Effect
FMSI	Financial Market Stress Indicator
GFC	Global Financial Crisis
GLS	Generalised Least Squares
GMM	Generalized Method of Moments
INVERCO	Spanish Collective Investment and Pension Fund Association (*Asociación de Instituciones de Inversión Colectiva y Fondos de Pensiones*)
ICB	Industry Classification Benchmark
NAV	Net Asset Value
RE	Random Effect
TNA	Total Net Assets
UCITS	Undertakings for Collective Investment in Transferable Securities
UK	United Kingdom
US	United States
VIF	Variance Inflation Factors

MOTIVATION

The development of this doctoral thesis is justified by the growing general importance of collective investment and especially that of mutual funds. The Spanish mutual fund industry reached €260 trillion by the end of June 2020 with more than 11 million shareholders across 1,419 mutual funds (Spanish Collective Investment and Pension Fund Association, INVERCO and Spanish Securities and Exchange Commission, CNMV). The persistent low interest rates of banking deposits has led to the growth of the mutual fund industry because of its advantages to individual investors, such as professional management and portfolio diversification.

Most individual investors trust their savings to mutual funds. Fund managers are responsible for managing funds and ensuring portfolio diversification; therefore, their role is crucial. They attempt to buy or hold stocks that they expect will make a positive contribution to fund performance and to sell stocks that they expect will not. Fund managers' trading decisions are based on the information that they collect from several sources such as social interaction, experience, the learning process, and individual research. Furthermore, their decisions may be influenced by top management and financial analysts within the family to which they belong.

A mutual fund offers the advantage of diversification to individual investors regardless of the amount that they invest. Furthermore, shareholders could seek greater diversification by allocating their money to different funds; however, different is not always the same thing as diverse. Therefore, the similarity level among portfolios is an important aspect within the fund industry as well as the autonomy of fund managers within the portfolio allocations and their ability to add value through their distinct trading decisions.

This doctoral thesis consists of three empirical chapters on fund managers' abilities; learning, autonomy, and divergent trading, and first includes an introduction to the Spanish mutual fund industry that provides some statistics about its evolution and summarises its specific characteristics.

Chapter 1 examines the learning process in the Spanish equity mutual fund industry through the evolution of important trading errors. We define important trading errors as trading decisions with a significantly higher negative influence on fund performance with respect to other decisions both within a fund and across other funds. This chapter is based on the hypothesis that you learn when it hurts and thus, fund managers learn from errors, especially when these errors have severe negative consequences on fund performance. This chapter is motivated by the lack of research on learning process in portfolio management compared to research on this topic in corporate management. The latter could be explained by the more drastic consequences that a management error might have on a corporation while from the mutual fund's perspective an error is less costly due to their higher diversification. However, the learning process in the mutual fund industry deserves research attention because the efficiency of this market has important social and economic implications.

Chapter 2 examines the correlation among portfolio holdings in the Spanish equity mutual fund industry and its implications on individual investors in terms of diversification and performance. In accordance with the literature, individual investors will concentrate their investment funds in a single fund family (e.g., fund management company) due to the economic and time costs. This tendency of investors motivates the interest in studying the similarity level among portfolios, particularly when mutual funds belong to the same family. In addition, this preference of concentrating fund investments in a single family is especially important in the Spanish mutual fund industry due to its high concentration and dependence on banking and insurance groups. Consequently, we also study the characteristics of those fund families with a higher similarity level among their funds in Chapter 2. Finally, this chapter also examines the autonomy of fund managers in selecting stocks in a certain industry and its implications on an investor's return.

Chapter 3 focuses on the level of divergence in fund managers' trading decisions when controlling for the influence of the previous portfolio holdings. This chapter is motivated by the aim to link the research on the ability of managers to add value to the mutual fund's management and the relationship among their trading decisions. In particular, we study to what extent the trading decisions of funds differ among them and how this divergence contributes to fund performance. Our hypothesis is that the distinct decisions of fund managers may be an important source of added value.

INTRODUCTION: THE SPANISH MUTUAL FUND INDUSTRY

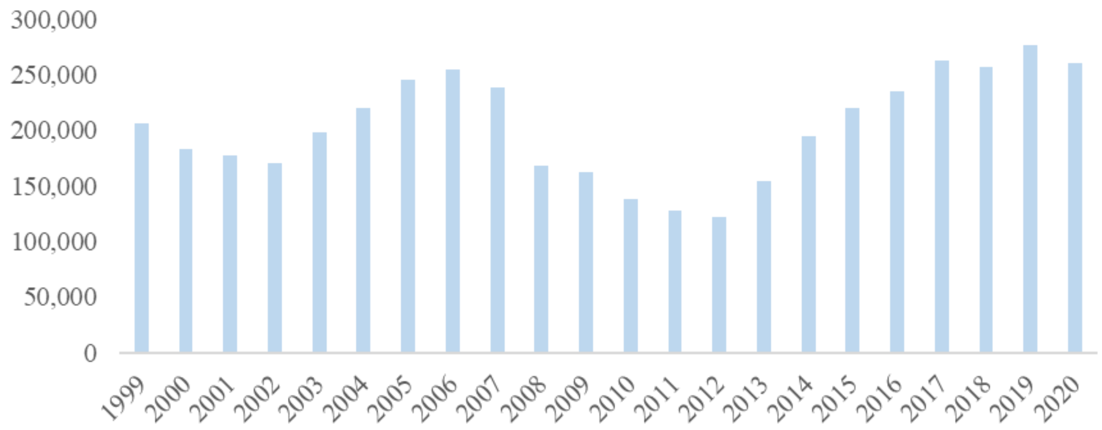
Collective investment has an important role in the financial system because it attracts investors' savings to a portfolio managed by professional managers. Therefore, individual investors can invest in several stocks through these financial products that thus provides diversification advantages and reduces fees.

Over the last decades, collective investment has undergone extraordinary growth worldwide, especially in the mutual fund industry. According to the European Fund and Asset Management Association (EFAMA), total net assets of the European mutual fund industry at the end of June of 2020 had reached €17 trillion across 63,291 funds. The Spanish mutual fund industry was among the top 10 in that industry.

This introduction to the thesis provides a closer look at the evolution of the Spanish mutual fund industry both through the demand perspective (magnitudes related to the assets under management (AUM) and the number of shareholders) and the supply perspective (magnitudes related to the number of funds and the number of mutual fund families).

Figure I.1 shows the notable evolution of the Spanish mutual fund industry in terms of the assets under management (AUM). This industry amounted to €206,166 million in December 1999; while in June 2020, this amount was approximately €55,000 million higher at a total of €260,895 million. Despite the positive evolution observed, Figure I.1 also shows the strongly negative impact of the Global Financial Crisis (GFC) of 2008 and the European debt crisis of 2011 on the mutual fund industry and its subsequent recovery. The negative impact of both crises caused a decrease in AUM of 49% from December 2007 to December 2012. The industry began to recover in 2013, and by 2017 had achieved a similar level as before the GFC. The important pace of growth of the mutual fund industry over the past few years has been due in part to the low interest rates on banking deposits and the recovery of investors' confidence in professional investment advice. Nevertheless, the COVID-19 crisis has also caused a slight decrease in this industry. In particular, the AUM of mutual funds decreased by about 6% between December 2019 and June 2020. Therefore, the evolution of this industry provides evidence as to the important vulnerability of the demand in the mutual fund industry to the economic climate.

Figure I. 1: AUM by Spanish mutual funds: December 1999-June 2020
(EUR million)

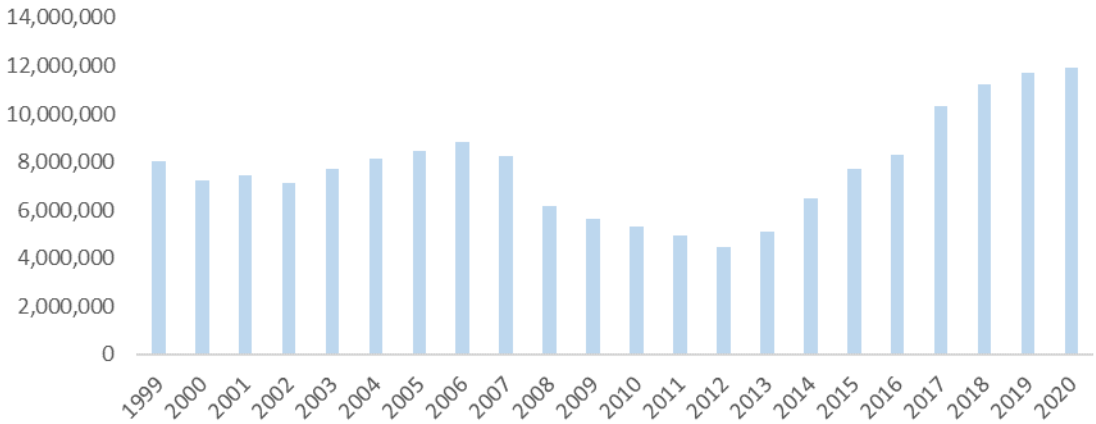


Source: INVERCO

The number of shareholders reflects the great economic and social impact that the fund industry has as the savings of a large proportion of the Spanish population depend on it. Therefore, high efficiency in the management of mutual funds is of the great importance.

In terms of the number of shareholders, Figure I.2 presents a similar evolution to the AUM. However, the evolution of this magnitude also shows a decline of approximately 46% from December 2007 to December 2012. However, we observe an increase of 2% between December 2019 and June 2020 in contrast to the slight decrease in the AUM.

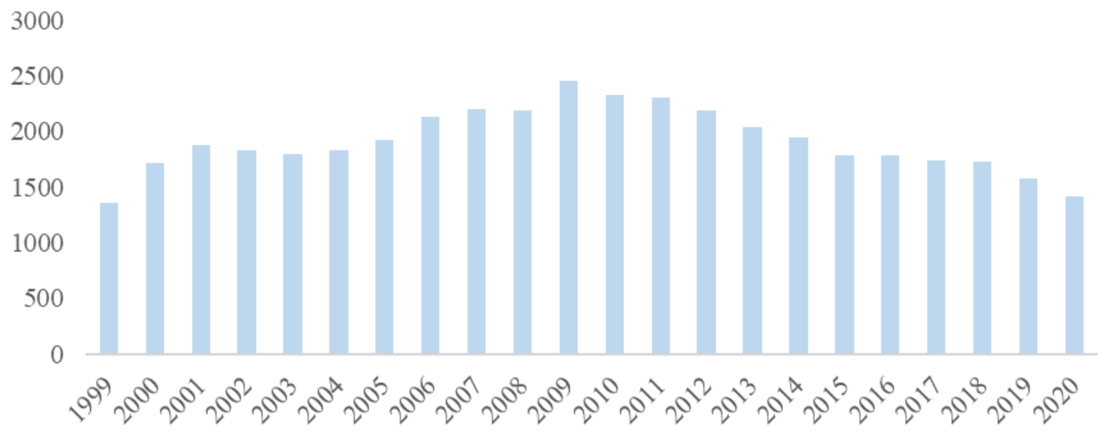
Figure I. 2: Number of shareholders in the Spanish mutual fund industry from December 1999 to June 2020



Source: INVERCO

The previous magnitudes reflect the evolution of the mutual fund industry from the demand perspective. The number of listed funds and the number of fund families provide evidence about the evolution of the industry's supply. Figure I.3 presents the evolution of the number of funds over the last two decades. We observe an extraordinary growth in that number for funds domiciled in Spain from 1999 to 2009. However, the trend has been negative since then, which is related to the huge restructuring process of the Spanish financial system over the last decade. This process aimed to improve the efficiency of the market and has resulted in mutual fund mergers.

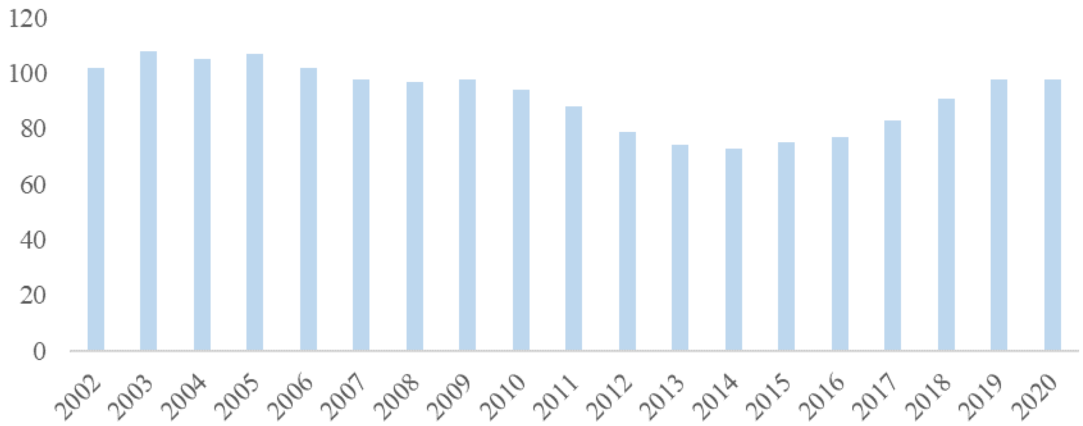
Figure I. 3: Number of mutual funds domiciled in Spain
from December 1999 to June 2020



Source: INVERCO

Similarly, Figure I.4 also shows a negative trend in the number of fund families, although that number has started to grow slightly over the last few years.

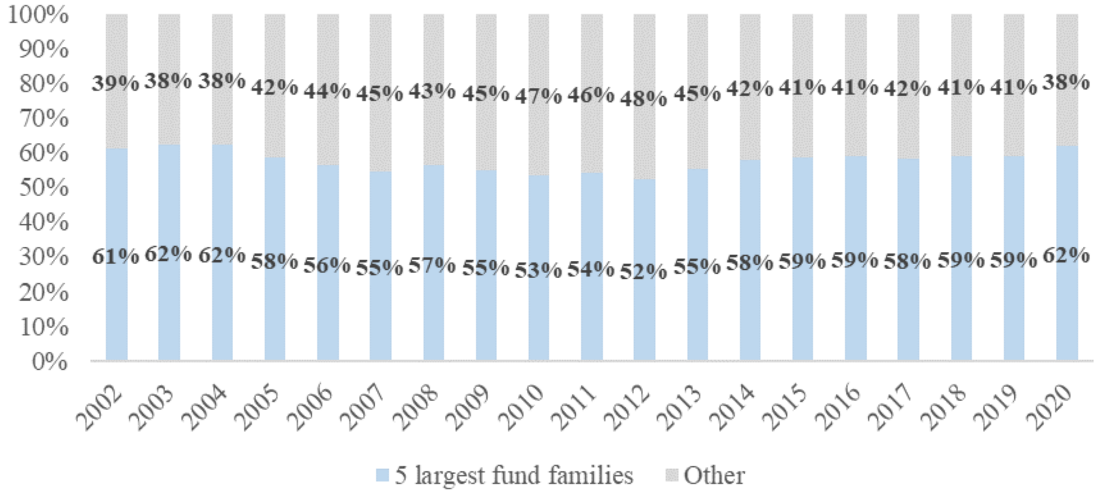
Figure I. 4: Number of Spanish mutual fund families
from December 1999 to June 2020



Source: CNMV

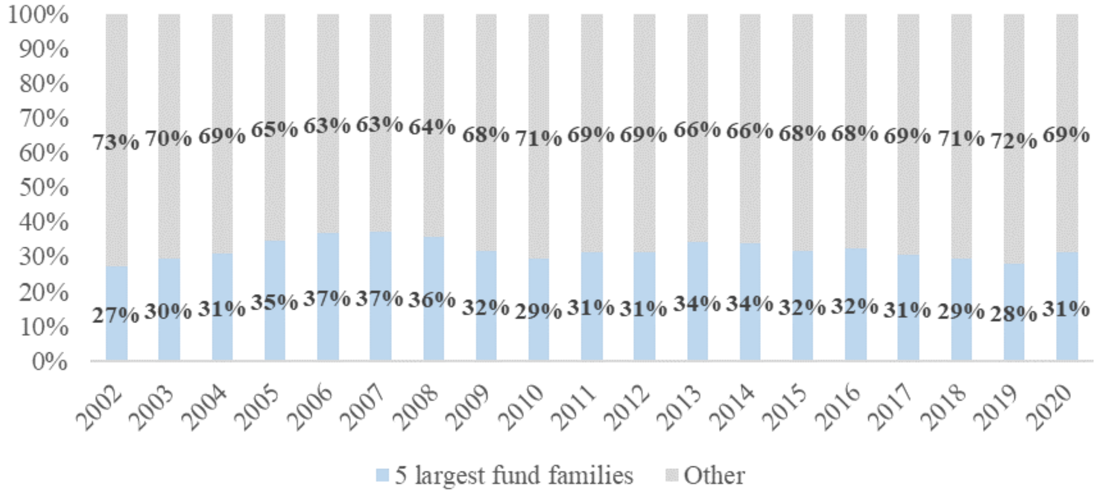
Although the evolution and growth of the Spanish mutual fund industry are notable and the shareholders can select among a wide range of funds and families, this industry has a high degree of concentration that may distort the competition level and could have implications for individual investors in terms of the diversification and efficiency of funds. Further, the five largest fund families managed approximately 62% of the total assets and 71% of the shareholders were invested in this industry in June of 2020. Figures I.5, I.6, and I.7 show the market share of the five largest fund families in terms of the AUM, the number of funds managed, and the number of shareholders, respectively.

Figure I. 5: The evolution of market share of the five largest fund families in terms of the AUM from December 2002 to June 2020



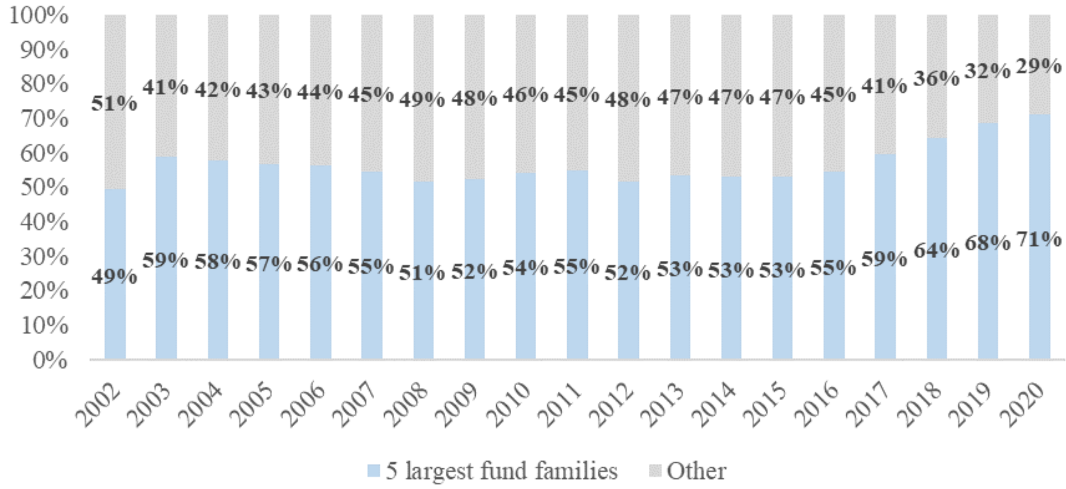
Source: CNMV

Figure I. 6: The evolution of market share of the five largest fund families in terms of the number of funds from December 2002 to June 2020



Source: CNMV

Figure I. 7: The evolution of market share of the five largest fund families in terms of the number of shareholders from December 2002 to June 2020

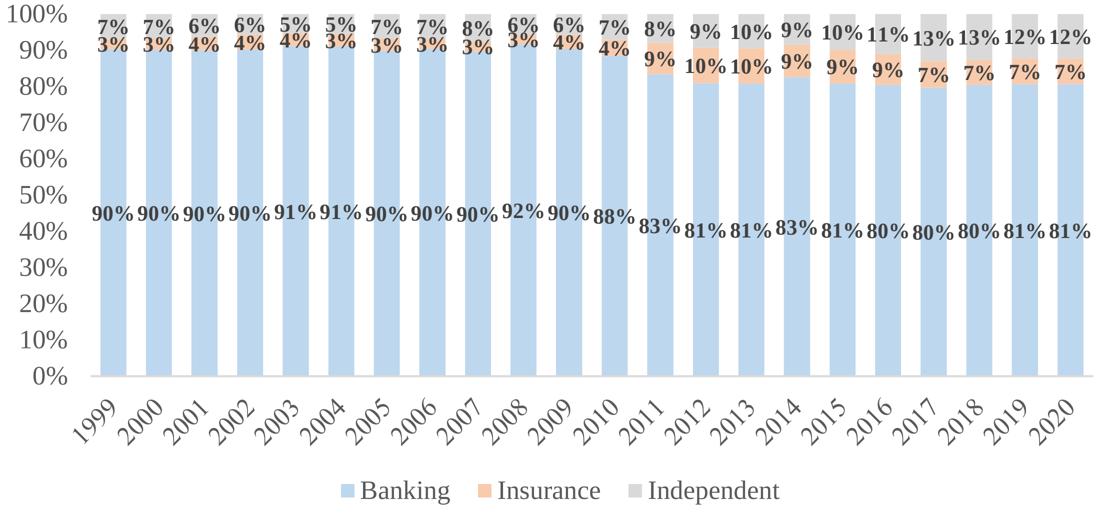


Source: CNMV

In addition, the high concentration is even more dramatic when we consider the two largest fund families. They controlled approximately 34% of the total AUM in June of 2020. The magnitude of the concentration level shows that this industry is far from a perfect competition paradigm. Along this vein, Losada (2015) states that individual investors do not enjoy the perfect information about the funds offered in the market. Consequently, they face high search and switching costs for suppliers that then lead to investors focusing their fund investments on a single family.

Another important issue in the Spanish mutual fund industry is the scarce number of families that do not belong to financial groups. Although a slightly positive trend exists for independent fund families, Figure I.8 illustrates that the Spanish mutual fund industry is still characterised by a high dependence on the banking and insurance groups that may have implications for individual investors, and for the overall efficiency of the industry.

Figure I. 8: Relative importance of mutual fund families by group categories from December 1999 to June 2020



Source: CNMV

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CHAPTER 1:

YOU LEARN WHEN IT HURTS: EVIDENCE IN THE MUTUAL FUND INDUSTRY

-*"Mistakes are the growing pains of wisdom."*-

William Jordan

Synopsis

This chapter aims to fill the gap in the research on the learning process by mutual fund industry. The empirical design is focused on the ability of the Spanish equity mutual fund industry to learn from its important errors in important trading decisions. The choice of this industry is justified by both its relevance to the European mutual fund markets and some specific characteristics, such as its concentration and banking control that may affect the learning process. We use a model with dynamic panel data and find an overall significant decrease in the percentage of important trading errors over time that provides evidence of the global learning process by the industry. In addition, we find that a large number of fund families drives this evidence. Finally, in general terms, we show that the size of the fund family and its dependence on financial groups do not play significant roles in explaining the learning process of Spanish equity mutual funds.

1.1 Introduction

The main objective of this chapter is to test the ability of the mutual fund industry to learn from its important trading errors. We define an important trading decision as a buy or sell decision for a stock *k* made by fund *f* in month *t* that simultaneously represents a high relative importance with respect to: 1) the total net assets of fund *f* in month *t*; 2) the other trading decisions made by fund *f* for other stocks in month *t*, and 3) the other trading decisions for the same stock *k* made by other funds in month *t*. This important trading decision on stock *k* could be an important trading error if it has a significantly negative effect on the subsequent performance of fund *f*.

The literature on corporate management has widely analysed the learning from errors (Finkelstein and Sanford, 2000; Tjosvold et al., 2004), while there is a lack of research regarding mutual fund management. One possible explanation is that an important error in corporate management may have critical consequences, such as the termination of the management company (Cardon et al., 2011). In contrast, the consequences of an important trading error in mutual funds may be less severe due to the diversification rules that regulators generally require, such as the current European Union Directive 2009/65/CE[1] in the European mutual fund industry. However, this lack of research and the important social and economic implications of the better management of mutual funds motivate our interest in shedding light on the learning process in the mutual fund industry.

The findings of this study have several implications for the constituents of this industry. First, mutual fund managers have incentives to avoid making errors and to learn

[1] Directive 2009/65/EC on the coordination of laws, regulations, and administrative provisions relating to the Undertakings for Collective Investment in Transferable Securities (UCITS). This Directive has been implemented in all member countries of the European Union.

from them because their positions, reputations, and salaries may depend on their performance records (Mason et al., 2016). Agarwal et al. (2009) also find that managerial incentives are associated with better performance. In the same line, Khorana (1996) finds an inverse relationship between the probability of managerial replacement and past fund performance. Second, our study is also of interest due to the relationship between past performance and future fund flows (Sirri and Tufano, 1998). Berk and Green (2004) and Dangl et al. (2008) find a consistent flow-performance relationship with high average levels of management skills. Thus, the learning process should improve both the performance records of and the subsequent flows into mutual funds. Third, supervisors could be interested in the evolution of important trading errors of mutual funds to guide their supervision with the aim of insuring investor protection and good practices in this market. Fourth, the learning process in the mutual fund industry could mean superior levels of financial efficiency and an improvement in the socioeconomic aspects of a country (King and Levine, 1993; Rousseau and Wachtel, 2002) because this industry has experienced a significant worldwide growth in recent years and consequently, it manages a significant amount of money. This growth is particularly evident in Europe where €15.6 billion of net assets are managed by almost 60,000 mutual funds, making it the second biggest mutual fund industry in the world (European Fund and Asset Management Association, EFAMA, 2018).

This study differs from others as it analyses the learning process of professional management in contrast to the widely studied behaviour of retail investors in the mutual fund industry. We mainly contribute to the literature by analysing this learning process, and assuming that not all trading decisions have the same importance and, thus, do not have the same influence on the learning experience. We measure the learning process through the evolution of the percentage of important errors in important trading decisions over time. The underlying rationale is that mutual funds are more sensitive to the learning process when the performance consequences of their trading errors are severe. This approach is consistent with the hypothesis that learning is mainly motivated by past errors (Singh et al., 2007; Zhao, 2011). Therefore, we consider the learning process at the industry and family levels that is based on the hypothesis that the decision-making, and consequently learning abilities, are not only specific to individual managers.

We use the generalised method of moments (GMM) to control for any endogeneity bias to provide evidence that important trading errors follow a decreasing trend in overall terms; therefore, over time, management makes fewer decisions that have significantly negative effects on subsequent performance, which offers evidence of the learning process in the mutual fund industry. In addition, we find that this learning process is present in most of the fund families.

The rest of the chapter is structured as follows: Section 2 presents the background of our study. Section 3 presents the database. Section 4 describes the methodology. Section 5 provides the results of the empirical analysis. Finally, Section 6 concludes.

1.2 Background

Decision-making is one of the basic cognitive processes of human behaviour through which agents choose a preferred alternative based on the given criteria or strategies (Wang and Ruhe, 2007). This process is associated with other mental processes involved in the capturing, synthesising, and memorising of information as well as with other factors. Several studies provide evidence of factors which influence decision-making such as knowledge and experience (Calvet et al., 2009), uncertainty, environment, and context (McDevitt et al., 2007), ability to predict the future (Kahneman, 1994), difficulty of decisions (Tversky and Shafir, 1992), and the necessary time to make decisions (Ariely and Zakay, 2001) as well as feelings, moods, and emotions (Lucey and Dowling, 2005), and the influence of past errors (Gervais and Odean, 2001; Zhao, 2011). The influence of these factors may depend on both the kind of decision and the context in which the decision-making takes place.

Focusing on mutual funds, the manager selects the assets to include in the portfolio of the mutual fund and the period that these assets are being held. Following Campbell (2006), Fischer and Gerhardt (2007) identify six different decisions: evaluation of initial situation, selection of risk level and time horizon, allocation of assets, selection of stocks, open and close positions; and tracking positions. This decision-making is difficult due to uncertainty, a dynamic environment, and other external factors (Wang and Lee, 2011). Portfolio holdings disclosed by mutual funds are the final output of this decision process, thereby providing useful information to measure performance (Daniel et al., 1997; Wermers, 2000; Kacperczyk et al., 2006; Wermers et al., 2012).

In the research about decision-making on portfolios, there are two main trends: rational and behavioural models. On the one hand, most classical models and theories are based mainly on the seminal assumptions of rational agents and efficient markets (Markowitz, 1952; Sharpe, 1964; Lintner, 1965; Fama, 1968). On the other hand, behavioural finance considers that agents systematically violate the axioms considered by the rational choice theory (De Bondt and Thaler, 1985; Tversky and Kahneman, 1986; Hirshleifer, 2001; Shiller, 2003). Koestner et al. (2017) find that numerous empirical studies have shown that these behavioural biases lead to costly errors (Goetzmann and Kumar, 2005; Bailey et al., 2011; Barber and Odean, 2013; Cuthbertson et al., 2016). Between both main trends, there are authors who suggest combining rational and efficient markets with behavioural models (Tseng, 2006; Subrahmanyam, 2008; Statman, 2014). In the same vain, Sargent (1993) defends a non-rigid rationality which is based on the idea that agents affected by cognitive biases may make errors but that these wrong decisions are not persistent over time that thereby indicates the agents learn from their errors. Additionally, List (2003) finds that market experience plays a significant role in eliminating the behavioural effect on investment decisions.

Closely related to the practice of decision-making, learning is the process by which information becomes knowledge. This knowledge can incorporate techniques and progressively develops the capacity for judgment that is based on experience. This judgment leads to future decisions that help to improve efficiency (Schön and Argyris, 1996; Stanovich and West, 2000). This statement is consistent with the learning-by-doing concept, which was initially studied by Arrow (1962).

Crossan et al. (1999) consider a multilevel learning perspective: individual, group, and organizational. The process of organizational learning has generated interest from practitioners and academics in the economic environment because they consider learning to be a strategic asset on which sustainable competitive advantages are based over time (March, 1991; Adams and Lamont, 2003; Hatch and Dyer, 2004). According to Levitt and March (1988), organizational learning is routine-based and history-dependent. Marsick and Watkins (2015) show that errors are a key tool for organizational learning.

Alongside this organizational learning approach in economics and business, academics have also shown interest in the mutual fund industry. Tindale and Winget (2019) argue that decision-making and its quality are often group-oriented rather than individual-oriented. Chen et al. (2004), Nanda et al. (2004) and Cici et al. (2018) also support the idea of the influence of the fund family on mutual funds' management, and Brown and Wu (2016) find that membership in a fund family creates rich possibilities that are not available when fund managers manage alone. In the same vein, Sevcenko and Ethiraj (2018) argue that learning generates positive externalities at the fund company level. Jones and Shanken (2005) also reject the learning independence across funds. These studies support the hypothesis that the decision-making, and consequently learning abilities, of mutual funds are not specific only to individual managers.

Regarding the measure of learning, there are several authors who have computed this process as the reduction of the cognitive biases identified in the behavioural finance literature (Dhar and Zhu, 2006; Campbell, 2006; Nicolosi et al., 2009; Seru et al., 2009; Koestner et al., 2017). These authors identify experience as the source of this dynamic process, and they measure it by both the number of years of experience and the number of operations accumulated in the financial markets. Focusing on the learning abilities of institutions rather than individuals, Ayoubi et al. (2017) consider that the knowledge flow within a team is a source of learning. Crossan and Bapuji (2003) defend that the traditional measurement of learning is related to the so-called curves of learning and experience in which the ability of institutions to learn is a function of time and call it internal learning. Similarly, Offerman and Sonnemans (1998) and Kempf et al. (2017) focus on the importance of the concept of learning-by-doing in professional investors and show that experience is associated with better management abilities.

Weick and Ashford (2001) find that learning from errors is an important activity for individuals, groups, and organizations within the theoretical framework of learning from experience (Agyris, 1993; Argote, 1999). Errors can be costly to organizations and involve negative consequences such as economic costs, damaged reputations, stress, and dissatisfaction (Zhao and Olivera, 2006). However, Zhao (2011) finds a positive relationship between a negative feeling caused by making errors and the motivation to learn from those errors. Marsick and Watkins (2015) also find that errors are a key tool for organizational learning. In the same vein, Reason (1999) argues that when we acquire insight and knowledge about our past errors, we can prevent future errors. Focusing on portfolio holdings, Gervais and Odean (2001) also show that traders learn about their own abilities that they infer from their success and failures by observing the consequences of their actions.

1.3 Data

This chapter examines whether the Spanish equity mutual fund industry learns from its trading errors between January 2000 and March 2014. Mutual funds have grown and been consolidated into the collective investment industry of Europe over the last twenty years. We focus on the Spanish fund industry because it represents a unique setting for our research objectives. First, Spain is one of the most important Euro mutual fund industries. In fact, the Spanish mutual fund industry is ranked 5th in the Euro area in terms of number of registered mutual funds (EFAMA, 2018), so the economic implications of our research are important. Second, the high concentration in the Spanish mutual fund market, where the top 10 fund management companies (fund families) manage more than 75% of the total fund assets (Inverco, 2018), allows an appropriate identification of the role of the assorted characteristics of the competitors in this industry in the learning process. According to Cambon and Losada (2014), the strong degree of market concentration and the model of universal banking are distinguishing characteristics of the Spanish mutual fund industry. Ferreira and Ramos (2009) study the mutual fund industry concentration in different countries and find that both the market share of the ten largest fund families and the Herfindahl-Hirschman Index are significantly higher in the Spanish market than in other important mutual fund markets. Third, the Spanish mutual fund industry is a more recent industry than the U.S. industry or other important European markets, such as France, Germany and the U.K. The great boom of Spanish mutual funds occurred during the 1990s. Therefore, our sample period coincides with the maturity stage of the Spanish mutual fund industry, avoiding possible effects of expansion and growth stages that may affect the learning process (Penrose, 1959; Autio et al., 2000).

Our data includes 292 equity mutual funds registered in Spain which are managed by 101 fund families. Specifically, the sample consists of 145 Euro domestic equity mutual funds and 147 Euro non-domestic equity mutual funds[2] which are managed by 83 and 77 fund families, respectively. We include both surviving and terminated mutual funds from January 2000 to March 2014; thus, the fund sample of our study is free of survivorship bias.

Portfolio holdings of the mutual funds included in our sample have been obtained from the Spanish Securities and Exchange Commission (CNMV) and Morningstar. The matching of the two databases[3] allows us to control for all quarterly portfolio holdings and more than the 80% of the monthly portfolio holdings. We analyse 20,572 monthly portfolio holdings: 12,176 portfolio holdings of Euro domestic equity mutual funds and 8,296 portfolio holdings of Euro non-domestic equity mutual funds. Elton et al. (2010) provides evidence that monthly holdings capture roundtrip trades missed by semi-annual (34.2%) and quarterly data (18.5%) and permit a more precise estimation of the timing of trades. The comparison between two consecutive monthly portfolio holdings of a mutual

[2] The Spanish Securities and Exchange Commission (CNMV) establishes a classification of mutual funds according to the types of assets included in the portfolios. Euro equity mutual funds must invest more than 75% of their portfolios in equities and at least 60% of the total equity exposure must be issued by companies in the euro area. However, within this category there are different investment policies (funds focused on Spanish stocks and funds focused on Euro stocks), thus, we split the Euro equity category into two subsamples according to their investing objective. We label Euro domestic equity funds a subsample of funds that self-report their investing objective in the Spanish market and the rest of the funds in the Euro equity category are labelled as Euro non-domestic equity funds.

[3] The mutual fund holdings used in this study rely on the information on monthly portfolio holdings from the CNMV for each fund from December 1999 to December 2006. This information was provided for research purposes. However, the CNMV only provided us with quarterly portfolio holdings from March 2007 onwards. Therefore, we first matched the quarterly information provided by the CNMV with the information provided by Morningstar and, then, we included monthly information from Morningstar when it was available.

fund together with the stock information provided by Datastream[4] gives the number of shares of each stock which are bought or sold by the mutual fund during that period.

Table 1. 1 – Summary Statistics

This table shows the summary statistics of our mutual fund sample. Panel A presents the average statistics for Euro domestic equity mutual funds. Panel B presents the same information for Euro non-domestic equity mutual funds. For simplicity, we split our sample period into three subperiods: the pre-crisis period (2000–2007), the crisis period (2008–2011), and the post-crisis period (2012–2014). *No. of Funds* is the number of funds in our sample. *No. of Families* is the number of fund families in our sample. *Fund_size* is the monthly total net assets (TNA) of a fund in million euros. *Fund_age* is the age of a fund in years, we obtain the fund's age from its inception date. *Fund_No. of stocks* is the number of distinct stocks in the monthly portfolio holdings. *Fund_turnover* is the fund's annual turnover ratio. The study period ends in March 2014.

Panel A: Euro domestic equity mutual funds				Panel B: Euro non-domestic equity mutual funds			
	2000-07	2008-11	2012-14*		2000-07	2008-11	2012-14*
#Funds	144	106	74	*#Funds*	124	91	56
#Families	79	58	49	*#Families*	71	51	36
Fund_size				*Fund_size*			
Mean	69.67	41.72	67.93	Mean	65.08	23.95	43.49
Q1	100.32	45.03	70.16	Q1	75.48	24.15	52.12
Q5	7.46	6,38	7.92	Q5	5.05	3.47	5.37
Fund_age				*Fund_age*			
Mean	8	12	16	Mean	6	10	12
Q1	11	17	20	Q1	9	13	16
Q5	3	7	12	Q5	2	5	5
Fund_#stocks				*Fund_#stocks*			
Mean	43	40	38	Mean	60	50	50
Q1	52	45	43	Q1	71	60	62
Q5	33	31	29	Q5	48	39	40
Fund_turnover				*Fund_turnover*			
Mean	41%	40%	41%	Mean	55%	50%	43%
Q1	61%	60%	55%	Q1	80%	85%	71%
Q5	19%	17%	17%	Q5	28%	18%	11%

Table 1.1 shows the summary statistics of our fund sample. We observe that both the total number of funds and the total number of fund families have a downward trend. Mergers and acquisitions of funds and families in the Spanish fund industry mainly explain this result. Additionally, Table 1.1 shows that the average fund size decreased

[4] Datastream provides stock information about the prices considering the main capital operations.

during the crisis period from 2008–2011, but it recovered afterwards. We can also see that the average size is bigger in Euro domestic than in Euro non-domestic equity mutual funds. This size may be because retail Spanish investors feel more confident investing their money in their home market that thereby may highlight a potential home bias. Further, the average age is lower in Euro non-domestic equity mutual funds because this investment category appears later in the Spanish market than the Euro domestic equity category.

1.4 Methodology

We analyse the learning process in the mutual fund industry through the evolution of important trading decisions that have an important negative effect on the fund performance. We first determine the trading decisions for each fund in each month. From these, we isolate the important buying and selling decisions for funds during the whole sample period by applying three independent filters, each one with a deep-logic, as we will describe below. Second, we identify the most important errors, which are important decisions with a significantly negative economic impact on the subsequent performance of funds and, consequently, with a potentially significant influence on the learning process. We consider that the trading errors of the management could be a source of learning in the fund industry; however, we also think that the influence is not the same for all errors. Third, we determine the percentage of important errors over the total number of trading decisions in each year by each mutual fund. Fourth, we propose two models with dynamic panel data to test the evolution of the percentage of important trading errors over time as a measure of the learning process in our sample.

1.4.1 Important buys and sells

There are two approaches to capture mutual fund trading: the change in the portfolio weight of each stock in each mutual fund (Grinblatt and Titman, 1993) and the change in the number of shares (Alexander et al., 2007). We use the second approach to determine fund trades because it is more accurate and is not biased by passive changes in portfolio weights due to price changes during the trading period (Jiang et al., 2007).

For each stock *s* and each month *t*, we measure the change in the number of shares of each stock *s* held by mutual fund *i* from the end of month *t-1* to the end of month *t*.

$$\text{If} \quad (N^i_{s,t} - N^i_{s,t-1}) > 0 \quad \text{then} \quad \text{Buying decision} \tag{1.1}$$

$$\text{If} \quad (N^i_{s,t} - N^i_{s,t-1}) < 0 \quad \text{then} \quad \text{Selling decision} \tag{1.2}$$

Once we know the number of shares that funds have bought and sold, we calculate the amount of each trading decision by multiplying the change in the number of shares[5] by the average market price of stock *s* in month *t* (Alexander et al., 2007).

$$\text{If} \quad (N^i_{s,t} - N^i_{s,t-1}) > 0 \quad \text{then} \quad Buy^i_{s,t} = (N^i_{s,t} - N^i_{s,t-1}) \cdot \overline{P_{s,t}} \tag{1.3}$$

$$\text{If} \quad (N^i_{s,t} - N^i_{s,t-1}) < 0 \quad \text{then} \quad Sell^i_{s,t} = -(N^i_{s,t-1} - N^i_{s,t}) \cdot \overline{P_{s,t}} \tag{1.4}$$

where $Buy^i_{s,t}$ and $Sell^i_{s,t}$ represent the euro value of buying (positive trading amount) and selling (negative trading amount) decisions in each stock *s* of fund *i* in month *t*. $\overline{P_{s,t}}$ is the average market price of stock *s* for month *t*.

Focusing on the decisions that we consider errors, Singh et al. (2007) identify four aspects that errors affect: economic, social, psychological, and physiological. Following these authors, our underlying assumption is that mutual fund managers could pay more attention to the cause of trading errors and thus, learn from them when the negative economic influence of these errors on performance is very important because their jobs,

[5] We consider corporate actions, such as stock splits, to obtain the number of shares.

reputations, and salaries may depend on their performance records (Agarwal et al., 2009; Kempf et al., 2009). Further, the economic effect of a trading decision depends on both its relative importance and its subsequent return. For this reason, we first identify the important trading decisions with three independent filters based on their relative importance and then, we isolate the important decisions with significantly negative subsequent returns.

We calculate the relative importance of each trading decision as the weight of the amount of decision on the fund size measured by the total net assets.

$$\text{Buy-Weight}_{s,t}^{i} = \frac{Buy_{s,t}^{i}}{TNA_{t}^{i}} \quad or \quad \text{Sell-Weight}_{s,t}^{i} = \frac{Sell_{s,t}^{i}}{TNA_{t}^{i}} \tag{1.5}$$

Once we know the relative importance of each trading decision, we identify the important buying and selling decisions of each fund with three independent filters. The three filters capture these premises, which we consider to be necessary to identify the important trading decisions for a fund: 1) a relatively high importance with respect to the fund's TNA, 2) a relatively significantly high importance with respect to other trading decisions made by the fund, and 3) a relatively significantly high importance with respect to other trading decisions of the other funds in the same stock. In sum, we consider that a trading decision is important when it simultaneously fulfils the three independent filters.

With the first filter, we assume that a trading decision in stock *s* by mutual fund *i* in the month *t* is important when it represents a high percentage on the fund TNA in this month. In this way, we control for the potential influence that the trading decision has in terms of performance and risk, considering that this influence is more significant for decisions that represent a high percentage on the fund TNA.

Therefore, we orthogonalise the distribution of the trading decision weights for each fund to control for the potential time bias of the month analysed. We select the 10%[6] of the trading decision with the higher weight for each fund during its existence in the sample. Distinguishing between the buying and the selling decisions, the top (or the bottom) 5% tail refers to the most important buying decisions (or the most important selling decisions) according to the first filter:

$$\textit{If} \quad \textit{Buy-Weight}_{s,t}^{i} \geq 95^{th} \textit{ percentile Weight}^{i}$$

$$\textit{then} \quad \textit{Buy}_{s,t}^{i} \in \textit{Important buying decisions}^{i} \textit{ in the first filter} \tag{1.6}$$

$$\textit{If} \quad \textit{Sell-Weight}_{s,t}^{i} \leq 5^{th} \textit{ percentile Weight}^{i}$$

$$\textit{then} \quad \textit{Sell}_{s,t}^{i} \in \textit{Important selling decisions}^{i} \textit{ in the first filter} \tag{1.7}$$

where 95^{th} *percentile* $Weight^{i}$ and 5^{th} *percentile* $Weight^{i}$ are, respectively, the above and below values which are the highest and lowest 5% of the values in the distribution of the trading decision weights of fund *i* during its existence in the sample.

For the second filter, we assume that a trading decision is important when its relative weight is significantly higher than the weight of other trading decisions by the same mutual fund in other stocks in the same month. This filter ensures that the trading decisions that are considered important have a significantly higher influence in terms of performance and risk than the rest of the decisions made by fund *i*.

We first compare the relative importance of each trading decision in stock *s* by mutual fund *i* in month *t* with the average relative importance of the rest of the trading decisions in other stocks by fund *i* in month *t* that distinguishes between buying and selling.

[6] To avoid any potential bias and to offer robust results, we have considered different cutoffs (one lower, 5% and another higher, 20%) and we have followed the same steps in the three filters using these alternative cutoffs.

Secondly, following the orthogonalisation in the first filter, we select the 5% of the buying decisions and the 5% of the selling decisions with the higher weight difference for each fund during its existence after controlling for the potential bias of the month analysed. Therefore, according to the second filter, we identify the important trading decisions as follows:

$$\textit{If} \qquad \textit{Buy-Weight}^{i}_{s,t} - \overline{\textit{Buy-Weight}^{i}_{p\text{-}s,t}} \geq 95^{th} \textit{ percentile Diff-Weight}^{i} \tag{1.8}$$

$$\textit{then Buy}^{i}_{s,t} \in \textit{Important buying decisions}^{i} \textit{ in the second filter}$$

$$\textit{If} \qquad \textit{Sell-Weightl}^{i}_{s,t} + \overline{\textit{Sell-Weightl}^{i}_{p\text{-}s,t}} \leq 5^{th} \textit{ percentile Diff-Weight}^{i} \tag{1.9}$$

$$\textit{then Sell}^{i}_{s,t} \in \textit{Important selling decisions}^{i} \textit{ in the second filter}$$

where $\overline{\textit{Buy-Weight}^{i}_{p\text{-}s,t}}$ and $\overline{\textit{Sell-Weightl}^{i}_{p\text{-}s,t}}$ are, respectively, the average weight of buying and selling decisions in the stock set *p* held by fund *i* that excludes stock *s* in the month *t*. 95^{th} *percentile Diff-Weight*^{i} and 5^{th} *percentile Diff-Weight*^{i} are, respectively, the above and below values which are the highest and lowest 5% of the values in the distribution of the weight differences for fund *i* during its existence in the sample.

For the third filter, we consider that a trading decision taken by fund *i* in a given stock and month is important when its relative importance is higher than the relative importance of the trading decisions taken by the rest of funds in the same stock and month.[7] This filter identifies the trading decision in a given stock whose potential influence on the performance of fund *i* is significantly higher than on the performance of the rest of the funds.

First, we compare the relative importance of a trading decision by mutual fund *i* in stock *s* in month *t* with the average relative importance of the trading decisions of the

[7] In buys, we obtain the average after considering all the funds that are included in our sample in each period *t* but, in sells, we only consider the funds that hold the stock in the previous month, *t-1*, because any fund can buy a stock but only the funds that hold a stock can sell it.

rest of the funds in this stock *s* and in month *t*. Once these excess weights have been obtained for each mutual fund, we also select the 5% of the buying decisions and the 5% of the selling decisions with this higher excess weight as in the previous filters. Therefore, according the third filter, we identify the important trading decision as follows:

$$\text{If} \quad Buy\text{-}Weight^{i}_{s,t} - \overline{Buy\text{-}Weight^{n-i}_{s,t}} \geq 95^{th}\ percentile\ Diff\text{-}Weight,^{i,n-i}$$

$$\text{then} \quad Buy^{i}_{s,t} \in Important\ buying\ decisions^{i}\ \ in\ the\ third\ filter \qquad (1.10)$$

$$\text{If} \quad Sell\text{-}Weightl^{i}_{s,t} + \overline{Sell\text{-}Weight^{n-i}_{s,t}} \leq 5^{th}\ percentile\ Diff\text{-}Weight,^{i,n-i}$$

$$\text{then} \quad Sell^{i}_{s,t} \in Important\ selling\ decisions^{i}\ in\ the\ third\ filter \qquad (1.11)$$

where $\overline{Buy\text{-}Weight^{n-i}_{s,t}}$ and $\overline{Sell\text{-}Weight^{n-i}_{s,t}}$ are, respectively, the average weight of the buying and selling decisions by the rest of the funds in our sample that excludes fund *i* in stock *s* and month *t*. 95^{th} *percentile* $Diff\text{-}Weight^{i,n-i}$ and 5^{th} *percentile* $Diff\text{-}Weight^{i,n-i}$ are, respectively, the above and below values which are the highest and lowest 5% of the values in the distribution of the weight differences of fund *i* with respect to the rest of the funds *n-i* during its existence in the sample.

Finally, we consider an example of overcoming the three filters simultaneously. First, the amount of the buying decision represents 18.64% of the TNA of fund *i* in March 2000. This decision fulfils the first filter after the orthogonalisation since this is among the 5% of the buying decisions with the higher weigh for fund *i* during its existence in the sample. Second, the average weight of the other buying decisions in other stocks different from the stock *s* of fund *i* in March 2000 represents 0.60% of its TNA. Thus, the weight difference with stock *s* is significantly higher and it fulfils the second filter after the orthogonalisation. Third, the average weight of the buying decisions in stock s by the other mutual funds in March 2000 represents 0.11% of their TNA. Thus, the difference in fund *i* with respect to the other funds is also significantly higher and fulfils the third filter after the orthogonalisation.

Table 1. 2 – Stock trades

This table shows the yearly average figures for the stock trading in our mutual fund sample. Panel A presents the trading data about Euro domestic equity mutual funds in our sample. Panel B presents the same information about Euro non-domestic equity mutual funds in our sample. For simplicity, we split our sample period into three subperiods: the pre-crisis period (2000–2007), the crisis period (2008–2011), and the post-crisis period (2012–2014). The study period ends in March 2014.

Panel A: Euro domestic equity mutual funds			
	2000-2007	2008-2011	2012-2014*
Average no. buys	14,728	11,896	8,635
Average no. buys by fund	141	131	137
Average % important buys	7.86%	5.52%	5.72%
Average no. sells	14,106	13,536	6,459
Average no. sells by fund	135	147	100
Average % important sells	7.32%	6.69%	7.20%

Panel B: Euro non-domestic equity mutual funds			
	2000-2007	2008-2011	2012-2014*
Average no. buys	14,086	11,006	7,877
Average no. buys by fund	198	155	176
Average % important buys	7.26%	4.86%	6.25%
Average no. sells	15,479	14,454	6,146
Average no. sells by fund	218	201	132
Average % important sells	5.44%	4.47%	5.05%

Table 1.2 presents the average number of buys and sells and the average number of important buying and selling decisions of our sample. It shows a consistent decrease over time of the number of buys and sells in both Euro domestic and Euro non-domestic equity mutual funds. This evidence may be related to the decline in the turnover ratio of our sample (see Table 1.1). However, Table 1.2 shows that the percentage of important buys and sells that have fulfilled our three independent filters remain highly stable, although they are slightly lower during the crisis period.

1.4.2 Important errors in important trading decisions

In the previous sub-section, we selected the most important trading decisions for the sample period of each mutual fund. The objective of the next step is to detect which of these important decisions are important errors. We assume that an important error comes from an important decision that has a hugely negative economic effect on the mutual fund's performance. This identification is based on the hypothesis that you learn when something hurts (Singh et al., 2007).

First, we identify trading errors as important buys (sells) of stocks whose performance is negative (positive). Second, we obtain the economic effect of each important error by mutual fund *i* in month *t* for stock *s* by multiplying its future performance by its portfolio weight. To demonstrate that our results are consistent regardless of the time horizon that we use to compute the subsequent effect of the errors, we evaluate the performance of any stock *s* considering Jensen's alpha using rolling windows of 60, 120, and 240 daily data. The objective is to observe whether the results are similar to the errors in the very short term (3-month alpha) and in longer terms (6-month and 12-month alphas).[8]

$$\textit{Buy economic impact}^{i}_{s,t} = \textit{Buy-Weight}^{i}_{s,t} \ . \ \alpha_{s,t} \tag{1.12}$$

$$\textit{Sell economic impact}^{i}_{s,t} = \textit{Sell-Weightl}^{i}_{s,t} \ . \ \alpha_{s,t} \tag{1.13}$$

where $\alpha_{s,t}$ is the Jensen's alpha of the stock *s* in the month *t.*

Third, we identify both the quintiles of important buys and sells with the most negative influence on the future fund performance by considering all funds across the sample period. Fourth, we compute the yearly percentage of important errors of each

[8] To obtain Jensen's alpha (1968), we use the Ibex 35 total return index and the Euro Stoxx-50 total return index as the benchmarks in Euro domestic and in Euro non-domestic equity mutual funds, respectively. We also use the daily return of one-day repos of Spanish Treasury bills as the proxy for the risk-free return.

mutual fund by dividing the number of important errors obtained each year by the total number of mutual fund trades that year for each of the three time horizons used to compute the subsequent effect of the errors. We obtain the percentage of important errors to avoid potential biases in the number of wrong decisions due to a decreasing trend in the number of trades per fund over time (Table 1.2). Appendix 1.1 has the graphs that show the evolution of the percentage of important errors over time.

1.4.3 Learning process in the mutual fund industry

To measure the ability of the mutual funds to learn from their important trading errors, we study the evolution of the percentage of these important errors over time. Our null hypothesis is that the percentage of important errors is not significantly different over time. Hence, rejecting this null hypothesis provides evidence of a trend over time. Additionally, if this trend is negative, it means the learning process is currently in the maturity stage of the Spanish equity mutual funds.

We use a model with dynamic panel data to test the relationship between the percentage of important errors and the time variable of the mutual funds. We apply this model to errors whose subsequent effect is calculated at 3 months (important errors with 3-month alpha), 6 months (important errors with 6-month alpha) and 12 months (important errors with 12-month alpha). The literature recommends this method for a database with a large number of individuals, mutual funds in our study, and a small number of time periods (Roodman, 2006). For this reason, we have computed the percentage of important errors by fund and year with the monthly data. Our choice of panel data facilitates the combination of time series, cross-sections, and unbalanced data (Wooldridge, 2010). In addition, the dynamic panel data model facilitates the incorporation of an endogenous structure through a one-year lagged variable that captures the unobserved time invariant effects due to individual patterns. Following the econometric research (e.g., Roodman, 2009), we use lags of the dependent variable in our model as an explanatory variable to avoid an endogenous relationship that could lead to misspecifications.We apply the dynamic model of generalised method of moments (GMM)[9] of Arellano and Bower (1995) and Blundell and Bond (1998) as follows: [10]

$$\begin{aligned} \%Important\ errors_{i,t} = {} & \alpha_{i,t} + \gamma_{i,t}\%Important\ errors_{i,t-1} + \beta_1 Time_t + \\ & + \beta_2 Size_{i,t} + \beta_3 Age_{i,t} + \beta_4 No.\ of\ stocks_{i,t} + \\ & + \beta_5 Turnover_{i,t} + \beta_6 Market\ return_t + \varepsilon_{i,t} \end{aligned} \quad (1.14)$$

for t = 1, ..., 15 years

for i = 1, ..., 145 Euro domestic equity mutual funds

for i = 1, ..., 147 Euro non-domestic equity mutual funds

where $\%Important\ errors_{i,t}$ is the percentage of important errors for fund *i* and year *t*. $\alpha_{i,t}$ is the constant variable. $\gamma_{i,t}$ is the coefficient of the variable $\%\ Important\ errors_{i,t-1}$ (1-year lag of percentage of important errors for fund *i*). $Time_t$ ranges from 1 in the first year of our sample period to 15 in the last year. The sample period runs from 2000 to 2014. $Size_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*. $Age_{i,t}$ is the age of mutual fund *i* divided by the average age of all funds included in our sample in year *t*. $No.\ of\ stocks_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*. $Turnover_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*. $Market\ return_t$ is the return of the benchmark. We use Ibex-35 as the benchmark for Euro domestic equity mutual funds and EuroStoxx-50 for Euro non-domestic equity mutual funds. $\varepsilon_{i,t}$ is the residual term of the model.

[9] Following Mileva (2007) and Roodman (2009), we check that we can apply the dynamic model to our data with the tests of Sargan (1958) and Arellano and Bond (1991).

[10] We run Equation 1.14 considering mutual funds as the decision-making units rather than mutual fund managers. Following Tindale and Winget (2019), decision-making and its quality are not individual affairs. Furthermore, we identify the manager replacements in our mutual fund sample and then, we apply the Chow test to study the effect of a manager replacement on the percentage of important errors in our sample. The Chow test provides evidence that 87% of the managers' replacements in our sample do not represent a significant structural change in the percentage of important errors.

On the one hand, the lagged dependent variable (*Important errors*$_{i,t-1}$) can control for the individual unobserved skills of each fund that are persistent over time and assures the better specification of our model. On the other hand, the coefficient (β_1) associated with *Time*$_t$ captures the evolution of the percentage of important errors in important trading decisions over time. Therefore, a negative value of this coefficient could provide evidence of the learning process given that the funds in our comprehensive sample would overall have fewer errors during the sample period. Additionally, to verify the robustness of our results, we add five control variables about fund characteristics and the market environment which may influence the percentage of important errors: the size, age, number of stocks, turnover ratio, and the market return of the funds and their portfolios.

The size (*Size*$_{i,t}$) of each mutual fund is computed from its TNA. We carry out a cross-sectional normalisation for a better identification of larger funds. We divide the size of each mutual fund by the average size of all the funds included in our sample in each year. This normalisation is because the average size of each mutual fund and, thus, the average size of all the mutual funds can vary over time. Additionally, we argue that the probability of detecting important decisions and, as a consequence, important errors, is greater in smaller funds. Therefore, fund size may have an important influence on the efficiency of the families of mutual funds (Pollet and Wilson, 2008; Pástor et al., 2015). Further, even though there is a lack of research about the influence of fund size, we propose that it may influence learning of mutual funds at the organizational level.

We compute the age (*Age*$_{i,t}$) of each mutual fund from its inception date. Then, we carry out a cross-sectional normalisation to identify younger/older funds with respect to the average age of the industry in each year. We divide the age of each mutual fund by the average age of all the funds included in our sample in each year. Therefore, we avoid the correlation problem with the time variable in Equation 1.14. We argue that fund age may affect investment style and, thus, the trading decisions of managers. According to Ferreira et al. (2013), the effect of fund age on the efficiency of a trading decision can run in both directions. Younger mutual funds may be more agile and dedicated to obtaining better performance to survive but youth may have a disadvantage due to the lack of experience during the start-up period and the higher costs.

We define the diversification level (*No. of stocks*$_{i,t}$) from the number of stocks held in the portfolio. Our hypothesis is that the diversification level may have an influence on the efficiency of trading decisions and the probability of making important errors. We consider that the higher the level of diversification of the fund, the lower the relative importance of each trading decision and, thus, the lower the probability of important errors. Pollet and Wilson (2008) show a positive relation between portfolio diversification and fund efficiency. However, the literature finds that the effect of diversification on the efficiency of trading decisions may also run in the opposite direction. Droms and Walker (1995) argue that more diversified portfolios are related to lower risk and lower returns.

We include the variable turnover ratio (*Turnover*$_{i,t}$) because we consider that it can influence the probability of making important trading errors and the ability of mutual fund managers to learn. The underlying assumption is that the higher the turnover ratio, the greater the probability of managers making errors. We also propose that this ratio may influence the ability of fund managers to learn from their errors due to their higher levels of trading activity. Grinblatt and Titman (1994) argue that turnover is significantly and positively related to managers' skills to earn extra returns. However, Barber and Odean (2000) present evidence that excessive trading leads to poor investment performance, while a low portfolio turnover achieves returns close to the benchmark.

Finally, we include market return (*Market Return*$_{t}$) as a control variable in the model because the probability of an important error may not be the same in bull markets as in bear markets. Indeed, Kacperczyk et al. (2014) and Alda (2018) argue that the skills of managers depend on economic conditions and find more evidence of stock-picking ability in managers during bull markets.

In addition to this learning model of the mutual fund industry as a whole, we also propose the analysis of the learning process in each mutual fund family. However, we cannot apply our previous model individually to many of our companies due to the low ratio between the number of observations and the number of coefficients to estimate in the model. As an alternative, we add a set of dummy variables for each company.

The dummy variable ($Family_{i,t}$) is one when the mutual fund is managed by the analysed fund family, and zero otherwise, and it interacts with the time variable ($Time_t$). We use this interaction ($Family_{i,t} x Time_t$) to compare the learning level of each mutual fund family with respect to the global learning level of the mutual fund industry over time. Thus, we must run the following Equation 1.15 for each fund family.

We apply the dynamic model of generalised method of moments (GMM) of Arellano and Bower (1995) and Blundell and Bond (1998) as follows:

$$\begin{aligned} \%\ Important\ errors_{i,t} = {} & \alpha_{i,t} + \gamma_{i,t}\ \%Important\ errors_{i,t-1} + \\ & + \beta_1 Time_t + \beta_2 Size_{i,t} + \beta_3 Age_{i,t} + \\ & + \beta_4 No.\ of\ stocks_{i,t} + \beta_5 Turnover_{i,t} + \\ & + \beta_6 Market\ return_t + \beta_7 (Family_{i,t}\ x\ Time_t) + \varepsilon_{i,t} \qquad (1.15) \end{aligned}$$

for t = 1, ..., 15 years

for i = 1, ..., 145 Euro domestic equity mutual funds

for i = 1, ..., 147 Euro non-domestic equity mutual funds

where $\%\ Important\ errors_{i,t}$ is the percentage of important errors for fund *i* and year *t*. $\alpha_{i,t}$ is the constant variable. $\gamma_{i,t}$ is the coefficient of the variable $\%\ Important\ errors_{i,t-1}$ (1-year lag of percentage of important errors for fund *i*). $Time_t$ ranges from 1 in the first year of our sample period to 15 in the last year. The sample period runs from 2000 to 2014. $Size_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*. $Age_{i,t}$ is the age of mutual fund *i* divided by the average age of all funds included in our sample in year *t*. *No. of* $stocks_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*. $Turnover_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*. *Market* $return_t$ is the return of the benchmark. We use the Ibex-35 as the benchmark for Euro domestic equity mutual funds and EuroStoxx-50 as that for Euro non-domestic equity mutual funds. $Family_{i,t}$ has a value equal to one when the mutual fund is managed by the analysed family in year *t*, and zero otherwise. $\varepsilon_{i,t}$ is the residual term of the model.

1.5 Results

1.5.1 Learning in the mutual fund industry

We use the GMM dynamic model of Arellano and Bower (1995) and Blundell and Bond (1998) to study the learning process in the Spanish equity mutual fund industry. Tables 1.3 and 1.4 present the results of Equation 1.14 for Euro domestic and non-domestic equity mutual funds, respectively. Both tables show a negative and significant relationship between the time variable ($Time_t$) which captures the trend in our model and the percentage of important trading errors. Hence, we reject the null hypothesis that the percentage of important errors is not significantly different over time, that is, the percentage of important trading errors in the Spanish equity mutual fund industry decreases significantly over time.[11] These important errors are a consequence of the

[11] We apply alternative specifications in Equation 1.14 for robustness proposes. First, we perform Equation 1.14 on a quarterly basis and we use also the Fixed Effect (FE) model on monthly, quarterly and annual frequency, and we obtain a significant negative relationship between the percentage of important errors and time (see Appendix 1.2 for more details). Second, we add a quadratic term of the time variable, and the main results remain similar to our original model specification (see Appendix 1.3 for more details). Third, we include the market volatility as an additional control variable, also obtaining consistent results (see Appendix 1.4 for more details).

important buys and sells that fulfil the three independent filters explained in the methodology section.[12] Additionally, these important errors have a significant and negative economic influence on fund performance. Therefore, our findings support the hypothesis that you learn when something hurts. This evidence is consistent when we compute the subsequent effect of important errors at a short horizon (Jensen's alpha at 3 months) and when we consider longer horizons (Jensen's alpha at 6 and 12 months).[13]

We consider that the identification of this decreasing trend of the percentage of important errors as a learning process that shows the overall ability of the mutual fund industry to learn from its past trading errors. The results of our chapter suggest that behind the errors there is a source of learning that leads mutual funds to make fewer errors over time (Reason, 1999; Marsick and Watkins, 2015). Past errors are a key tool for learning because when we acquire insight and knowledge about our past errors, we can prevent future errors. In the same line, Gervais and Odean (2001) support that traders learn from their failures, observing the consequences of their actions. The findings of this chapter also support the hypothesis that the more negative the impact of errors, the greater the motivation to learn and to avoid making the same errors in the future. Zhao (2011) finds a positive relationship between the negative feelings caused from making errors and the motivation to learn from them.

[12] We also apply Equation 1.14 to errors from non-important decisions. The results are different from the conclusions drawn from Tables 1.3 and Table 1.4. That is, time does not influence the percentage of trading errors, thereby rejecting a significant learning evidence from non-important decisions.

[13] The results shown in Table 1.3 and Table 1.4 have been obtained considering the quintiles of important buys and sells with the most negative influence on fund performance for all the funds across our sample period. We have also obtained similar findings for quartiles and deciles, thereby providing even more robustness to this empirical evidence (see Appendix 1.5 for more details).

Table 1. 3 – Learning results in Euro domestic equity mutual funds

This table presents the results of Equation 1.14 for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month-alpha. The dependent variable *%Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *No. stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*; *Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*; and *Market return*$_t$ is the Ibex-35 total return in year *t*. We use the Ibex-35 as the benchmark for Euro domestic equity mutual funds. *** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0175***	0.0082***	0.0094***	0.0209***	0.0256***	0.0103***
% Important errors$_{t-1}$	0.1060***	0.0823***	0.0799***	0.2591***	0.2042***	0.1086***
Time	-0.0004**	-0.0002***	-0.0005***	-0.0004*	-0.0006**	-0.0003***
Fund_size	-0.0015*	-0.0012***	-0.0013**	0.0008	0.0013	-0.0006
Fund_age	-0.0030	0.0011	0.0027	0.0019	-0.0035	-0.0009
Fund_#stocks	-0.0003***	-0.0002***	-0.0003***	-0.0005***	-0.0005***	-0.0002***
Fund_Turnover	0.0197***	0.0199***	0.0274***	0.0214***	0.0137***	0.0071***
Market return	-0.0060***	-0.0074***	-0.0055***	-0.0089***	-0.0035	-0.0013***
Wald Chi-Squared Test	193.85***	114.41***	445.37***	348.10***	106.59***	113.48***
Sargan Test	94.50	95.24	92.48	92.39	88.56	88.32
Autocorrelation (1)	-2.42**	-2.31**	-2.36**	-4.32***	-4.87***	-3.45***
Autocorrelation (2)	0.26	0.96	0.93	1.08	0.46	-1.27
No. observations	1,081	1,049	966	1,234	1,216	1,247

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table 1. 4 – Learning results in Euro non-domestic equity mutual funds

This table presents the results of Equation 1.14 for Euro non-domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month-alpha. The dependent variable *%Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *No. stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*; *Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*; and *Market return*$_t$ is the EuroStoxx-50 total return in year *t.* We use the EuroStoxx-50 as the benchmark for Euro equity mutual funds. *** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0267***	0.0305***	0.0137**	0.0306***	0.0385***	0.0381***
% Important errors$_{t-1}$	0.0500**	0.1018***	0.1076***	0.1120***	0.1011*	0.1439***
Time	-0.0002	-0.0008***	-0.0007***	-0.0013***	-0.0013***	-0.0012***
Fund_size	-0.0020	-0.0029***	-0.0014*	-0.0001	-0.0022**	-0.0012
Fund_age	-0.0021	0.0004	0.0067	0.0052	0.0072	0.0067
Fund_#stocks	-0.0003***	-0.0004***	-0.0003***	-0.0005***	-0.0006***	-0.0006***
Fund_Turnover	0.0091***	0.0059***	0.0092***	0.0173***	0.0177***	0.0154***
Market return	-0.0067***	-0.0138***	0.0013	-0.0069***	-0.0086***	-0.0093***
Wald Chi-Squared Test	66.65***	139.77***	50.47***	102.74***	88.93***	86.84***
Sargan Test	77.09	39.98	23.08	79.78	69.64	16.83
Autocorrelation (1)	-2.04**	-2.78**	-4.05***	-3.94***	-3.42***	-4.19***
Autocorrelation (2)	-1.42	-0.39	-0.50	-1.89	-1.87	-1.42
No. observations	927	897	796	1,050	1,102	1,143

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

The lagged dependent variable (% Important errors$_{i,t-1}$) is a better control for endogeneity bias in the model and its positive and significant influence indicates that each fund presents individual patterns in its trading abilities, which tend to persist over time. Due to these individual skills, some funds are more prone to making important errors. Therefore, a mutual fund that makes an important error in the past has a higher likelihood of making an important error in the future than a fund that does not. Furthermore, we find that the smaller the time gap between current important errors and past important errors, the more significant the relationship among them is.

Therefore, the funds that make the greatest number of important errors in the past are also those that make the greatest number of important errors in the future that is not contradictory with global learning in which all funds generally have fewer important errors over time, and is based on the result associated to the coefficient for the time variable ($Time_t$).

With respect to our control variables, size and age do not show a clear influence on the decreasing trend of errors but we find significant relationships between important trading errors and both the number of stocks held by the mutual fund and its turnover ratio. We find that more diversified funds with lower turnover ratios make fewer important trading errors.

With respect to the diversification, the results could be explained by the fact that each trading decision tends to represent a relatively smaller value with respect to the TNA in more diversified fund portfolios than in more concentrated fund portfolios. Therefore, the probability of making important trading decisions and, as a consequence, of making important trading errors could be higher in less diversified funds in accordance with the Pollet and Wilson (2008) who find a positive relation between portfolio diversification and fund efficiency.

With regard to the portfolio turnover variable, the result is in line with the rationale that when the turnover ratio is lower, the probability of making an error is also lower due to there being fewer trading decisions than in mutual funds with higher turnover ratios. This result is also consistent with the conclusion of Barber and Odean (2000) who find that a low portfolio turnover allows higher returns.

Additionally, we find a negative relationship between the percentage of important errors and the market return. Therefore, the probability of an important error is higher with lower market returns, that is, important trading errors are more likely during bearish than during bullish markets. This is consistent with the conclusions of Kacperczyk et al. (2014) and Alda (2018) who consider that managers' skills vary with market conditions and find more evidence of managers' stock-picking ability in a bullish market.

1.5.2 Learning in the mutual fund industry: a family approach

In the previous sub-section, we provide evidence of learning from important errors in the maturity stage of the Spanish mutual fund industry. The next step in our empirical analysis is to study how this learning process is driven by the mutual fund families. We test whether the learning evidence previously detected is consistently driven by most of the fund families registered in the Spanish industry. To do so, we compare the previously found learning level of the whole industry with the learning level of each individual family.

We argue that different groups of mutual fund families may coexist that depends on the level of their learning process: (1) fund families whose level of learning is higher than the industry level, (2) fund families whose level of learning is similar to the industry level, and (3) fund families whose level of learning is lower than the industry level.

First, we apply Equation 1.15 for each fund family. Second, we classify all the families into the three previously defined groups according to the results of the slope interaction between the dummy variable and the time variables in Equation 1.15. With this slope, we can compare the learning level of each fund family with respect to the global learning level of the whole mutual fund industry over time. Table 1.5 presents the percentages of each family group based on both the sign and the significance of the interaction slope.

Table 1. 5 – Learning results: a fund family approach

Learning results: a fund family approach: This table presents the percentage of mutual fund families based on both the sign and the significance of the slope of the interaction between the dummy variable $Family_{i,t}$ and $Time_t$ (β_7) in Equation 1.15 for each fund family included in our sample. Panel A has the results for families which manage Euro domestic equity funds, and Panel B has the results for families which manage Euro non-domestic equity mutual funds. Similar to Tables 1.3 and 1.4, the learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month alpha.

	Buys			Sells		
	Important errors 3-month alpha	Important errors 6-month alpha	Important errors 12-month alpha	Importan t errors 3-month alpha	Important errors 6-month alpha	Important errors 3-month alpha
*Family*x*Time* Negative and Stat. Significant β_7	35.21%	32.00%	33.33%	27.40%	30.67%	32.39%
*Family*x*Time* Non Significant β_7	35.21%	37.33%	38.67%	35.62%	41.33%	42.25%
*Family*x*Time* Positive and Stat. Significant β_7	29.58%	30.67%	28.00%	36.99%	28.00%	25.35%

	Buys			Sells		
	Important errors 3-month alpha	Important errors 6-month alpha	Important errors 12-month alpha	Importan t errors 3-month alpha	Important errors 6-month alpha	Important errors 3-month alpha
*Family*x*Time* Negative and Stat. Significant β_7	30.65%	37.78%	23.88%	17.91%	35.94%	30.65%
*Family*x*Time* Non Significant β_7	25.81%	24.44%	17.91%	29.85%	26.56%	27.42%
*Family*x*Time* Positive and Stat. Significant β_7	43.55%	37.78%	58.21%	52.24%	37.50%	41.94%

The learning level in fund families is higher than or not significantly different from the global learning level of the mutual fund industry in cases in which the slope of the interaction variable ($Family_{i,t}$x$Time_t$) in Equation 1.15 is significantly negative or not significant. Table 1.5 shows that the learning level of approximately 70% (or above 60%) of fund families is higher than or similar to the learning level of the whole mutual fund industry of Euro domestic (or Euro non-domestic) equity mutual funds.

On the contrary, the learning level in fund families is lower than in the whole mutual fund industry in cases of significantly positive slopes of the interaction variable ($Family_{i,t}$x$Time_t$) in Equation 1.15. Table 1.5 shows that approximately 30% (over 40%) of families of Euro domestic (Euro non-domestic) equity mutual funds learn less than the whole mutual fund industry or even do not learn. Nonetheless, our approach cannot split up the percentage of families into these two groups.

Our findings support that learning from important trading errors in the Spanish industry of equity mutual funds is driven by a large number of mutual fund families. These findings are generally consistent for buying and selling trading decisions and for trading errors obtained from different time horizons.

1.5.3 Learning in the mutual fund industry: an approach using the characteristics of fund families

In the previous sub-section, we find that mutual funds in most families learn from their trading errors in the Spanish equity mutual fund industry. Based on this result, our objective now is to study whether the families with a higher learning level have common characteristics. Following Cambon and Losada (2014), we study the learning process of the fund families through two main dimensions: the family size and the dependence of the fund family on banking and insurance groups.

1.5.3.1. Learning results by size of mutual fund families

Spanish mutual fund industry is characterised by an important concentration given that the 10 largest (top 10) fund families manage more than 75% of the total fund assets (Inverco, 2018). We suggest that it is important to bear in mind this distinctive characteristic of the Spanish market when we study the learning process because, due to the highly concentrated market structure the level of competition that the top 10 families face is different to the level within the group of smaller families. Consequently, the learning level may also be different between the top 10 and the smaller families. Indeed, though there is a lack of research in this aspect regarding the mutual fund industry, Jashapara (2003) examines the effect of competition on organizational learning at business level, finding that competitive forces encourage learning processes focused on efficiency. The underlying idea is based on the conclusions of Adams and Lamont (2003) and Hatch and Dyer (2004) who considered organizational learning as a strategic asset to sustain competitive advantage.

Therefore, we aim to determine whether there are significant differences between the level of learning of the top 10 fund families registered in Spain and the level of learning of smaller fund families. The family size is determined by the total net assets under management. We use Equation 1.15 but in this new approach, the dummy variable that interacts with the time variable is called *TOP-10* and takes a value of one when the mutual fund is managed by one of the top 10 families and zero otherwise. We can compare the learning level of the group of the top 10 families with that of the other families in the market with the slope of the interaction variable ($TOP\text{-}10_{i,t} x Time_t$).

Table 1. 6 – Learning results by fund family size (Euro domestic equity mutual funds)

This table presents the results of the Equation 1.15 with the dummy variable named TOP-10 for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables that are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *No. stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*; *Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*; and *Market return*$_t$ is the Ibex-35 total return in year *t*. We use the Ibex-35 as the benchmark for Euro domestic equity mutual funds. *TOP-10*$_{i,t}$ *xTime*$_t$ is the interaction between the dummy variable TOP-10 and the time variable.*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0271***	0.0085***	0.0137***	0.0094***	0.0143***	0.0209***
% Important errors$_{t-1}$	0.1008***	0.0730***	0.0700***	0.0912***	0.1850***	0.0838***
Time	-0.0005**	-0.0003***	-0.0007***	-0.0002**	-0.0003**	-0.0003**
Fund_size	-0.0010	-0.0011**	-0.0010**	-0.0009**	0.0009**	0.0016**
Fund_age	-0.0159***	0.0008	-0.0003	-0.0011	0.0029	-0.0066
Fund_#stocks	-0.0002***	-0.0002***	-0.0003***	-0.0002***	-0.0004***	-0.0003***
Fund_Turnover	0.0206***	0.0202***	0.0285***	0.0177***	0.0158***	0.0077***
Market return	-0.0051***	-0.0072***	-0.0069***	-0.0041***	-0.0040***	-0.0015
TOP-10 xTime	0.0008**	0.0004***	0.0004***	0.0001	-0.0001	0.0003
Wald Chi-Squared Test	396.44***	118.83***	446.14***	493.53***	368.74***	254.43***
Sargan Test	93.14	93.77	89.18	96.64	89.75	89.15
Autocorrelation (1)	-2.42**	-2.32**	-2.36**	-4.28***	-4.87***	-3.46***
Autocorrelation (2)	0.24	0.34	0.96	1.77	0.46	-1.29
No. observations	1,081	1,049	966	1,234	1,216	1,247

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table 1. 7 – Learning results by fund family size (Euro non-domestic equity mutual funds)

This table presents the results of the Equation 1.15 with the dummy variable named TOP-10 for Euro non-domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables that are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *No. stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*; *Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t* and *Market return*$_t$ is the EuroStoxx-50 total return in year *t.* We use the EuroStoxx-50 as the benchmark for Euro non-domestic equity mutual funds. *TOP-10*$_{i,t}$*xTime*$_t$ is the interaction between the dummy variable TOP-10 and the time variable.*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0285***	0.0319***	0.0394***	0.0311***	0.0336***	0.0394***
% Important errors$_{t-1}$	0.0418***	0.0502***	0.1907***	0.1125***	0.1475***	0.1907***
Time	-0.0001	-0.0005**	-0.0010**	-0.0012***	-0.0011***	-0.0010**
Fund_size	-0.0016	-0.0024	0.0002	-0.0001	-0.0006	0.0002
Fund_age	-0.0041	-0.0087**	0.0037	0.0049	0.0093	0.0037
Fund_#stocks	-0.0003***	-0.0003***	-0.0007***	-0.0005***	-0.0007***	-0.0007***
Fund_Turnover	0.0096***	0.0087**	0.0173***	0.0173***	0.0189***	0.0173***
Market return	-0.0065***	-0.0122***	-0.0079***	-0.0069***	-0.0075***	-0.0079***
TOP-10 xTime	-0.0007	0.0001	0.0001	-0.0001	0.0001	0.0001
Wald Chi-Squared Test	554.90***	518.39***	503.90***	103.34***	109.49***	123.80***
Sargan Test	80.48	48.72	84.30	77.40	81.36	84.30
Autocorrelation (1)	-2.10**	-3.05***	-4.61***	-3.93***	-3.51***	-4.61***
Autocorrelation (2)	-0.88	0.24	-1.06	-1.89	-1.73	-1.06
No. observations	927	897	796	1,050	1,102	1,143

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

The null hypothesis is that there are no differences between the top 10 and the other fund families. A significantly positive (negative) slope of the interaction variable would show that the learning level of the top 10 families is lower (higher) than that of the smaller families. Tables 1.6 and 1.7 present the results of Equation 1.15 with the dummy variable *TOP-10* for Euro domestic and Euro non-domestic equity mutual funds, respectively. With the only exception that for the buy decisions of the Euro domestic equity mutual funds, we find that family size does not play a significant role in explaining the learning process in the highly concentrated Spanish mutual fund industry. That is, the different level of competition between the largest and the smaller families does not generally affect the learning process in this industry.

1.5.3.2. Learning process by independence of fund families from financial service groups.

In the previous sub-section, we emphasised that a high concentration is one of the main characteristics in the Spanish mutual fund industry. Another specific characteristic of the Spanish market is the relatively high importance of fund families that are controlled by banks and insurance groups. Cambon and Losada (2014) study the structure of mutual fund industry in Spain. They show that most of the assets of mutual funds are managed by families belonging to credit institutions, highlighting the model of universal banking as distinctive characteristic of this market. In fact, approximately 90% of families belong to a banking or an insurance group in Spain; this percentage being significantly higher than in other important European mutual fund markets such as Germany, Portugal, Italy, France, and the UK (EFAMA, 2018).

Table 1. 8 – Learning results by independence of fund family from financial service groups (Euro domestic equity mutual funds)

This table presents the results of the Equation 1.15 with the dummy variable named Independent for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables that are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *No. stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t*; *Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*; and *Market return*$_t$ is the Ibex-35 total return in year *t*. We use the Ibex-35 as the benchmark for Euro domestic equity mutual funds. *Independent*$_{i,t}$*xTime*$_t$ is the interaction between the dummy variable Independent and the time variable. *** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0096***	0.0078***	0.0092***	0.0207***	0.0270***	0.0097**
% Important errors$_{t-1}$	0.0984***	0.0835***	0.0753***	0.2653***	0.2114***	0.1593***
Time	-0.0003***	-0.0002**	-0.0005***	-0.0005**	-0.0007***	-0.0006***
Fund_size	-0.0008*	-0.0012**	-0.0012**	0.0009	0.0013	0.0008
Fund_age	-0.0016	0.0007	0.0021	0.0015	-0.0049	-0.0004
Fund_#stocks	-0.0002***	-0.0002***	-0.0007***	-0.0005***	-0.0005***	-0.0002***
Fund_Turnover	0.0183***	0.0199***	0.0279***	0.0222***	0.0153***	0.0075**
Market return	-0.0036***	-0.0074***	-0.0054***	-0.0090***	-0.0038**	-0.0014*
IndependentxTime	0.0009*	0.0004**	0.0008	0.0011*	0.0012**	0.0015**
Wald Chi-Squared Test	732.02***	113.53***	464.11***	347.03***	220.56***	611.20***
Sargan Test	96.87	94.46	92.86	96.41	91.05	88.62
Autocorrelation (1)	-2.42**	-2.31**	-2.37**	-4.27***	-4.87***	-3.45***
Autocorrelation (2)	0.25	0.95	0.93	1.81	0.48	-1.28
No. observations	1,081	1,049	966	1,234	1,216	1,247

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table 1. 9 – Learning results by independence of fund family from financial service groups (Euro non-domestic equity mutual funds)

This table presents the results of the Equation 1.15 with the dummy variable named Independent for Euro equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha, and 12-month-alpha. The dependent variable *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year, the sample period covers from 2000 to 2014. *Size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t*; and *Market return*$_t$ is the EuroStoxx-50 total return in year *t.* We use the EuroStoxx-50 as the benchmark for Euro non-domestic equity mutual funds. *Independent*$_{i,t}$*xTime*$_t$ is the interaction between the dummy variable Independent and the time variable. *** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0348***	0.0298***	0.0139**	0.0302***	0.0332***	0.0387***
% Important errors$_{t-1}$	0.0209*	0.0563**	0.0978**	0.1125***	0.1504***	0.1920***
Time	-0.0004	-0.0006**	-0.0006**	-0.0013***	-0.0011***	-0.0008**
Fund_size	-0.0028***	-0.0026	-0.0013	-0.0001	-0.0006	0.0001
Fund_age	-0.0007	-0.0056	0.0061	0.0058	0.0089	0.0037
Fund_#stocks	-0.0005***	-0.0003***	-0.0002***	-0.0005***	-0.0007***	-0.0007***
Fund_Turnover	0.0079***	0.0071*	0.0090***	0.0174***	0.0190***	0.0174***
Market return	-0.0074***	-0.0127***	0.0013	-0.0069***	-0.0075***	-0.0081***
IndependentxTime	-0.0006	-0.0003	-0.0008	-0.0003	0.0001	-0.0006
Wald Chi-Squared Test	745.40***	216.29***	525.50***	102.21***	108.18***	122.71***
Sargan Test	80.13	53.67	60.33	78.76	80.90	84.56
Autocorrelation (1)	-2.06**	-3.10***	-4.02***	-3.94***	-3.50**	-4.62***
Autocorrelation (2)	-1.06	0.31	-0.54	-1.89	-1.69	-1.05
No. observations	927	897	796	1,050	1,102	1,143

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Therefore, we study the learning with respect to the families' dependence on or independence from financial services groups. Independent families are not a part of financial services groups, while dependent families belong to a banking or an insurance group.

We test whether there are significant differences in the learning level between independent and dependent families. The null hypothesis of this contrast is that there are no differences. Similar to our analysis of fund company size, we use Equation 1.15 with a dummy variable called *Independent* instead of *TOP-10*. The dummy *Independent* takes a value of one when the mutual fund belongs to an independent family, and zero otherwise. Therefore, the interpretation of the slope of the interaction variable ($Independent_{i,t}$x$Time_t$) is the same as in the previous subsection.

Tables 1.8 and 1.9 present the results of Equation 1.15 with the dummy variable *Independent* for Euro domestic and Euro non-domestic equity mutual funds, respectively. In Table 1.8, we find that the learning level in the dependent families is higher than for the independent families in only some of the cases analysed. Table 1.9 rejects the existence of significant differences in the learning level of dependent and independent families for Euro equity mutual funds. Hence, in general terms, families' dependence on financial groups is not important in explaining the learning process in the Spanish equity mutual fund industry.

1.6 Conclusions

Our study is the first to examine the ability of the Spanish equity mutual fund industry to learn from its important trading errors. It is motivated by the lack of research on learning processes in portfolio management and by their important implications for the main agents involved in the mutual fund industry. We consider that past errors are a key tool in the learning process, given that managers suffer the consequences of these negative past decisions. Our identification of important errors is based on the hypothesis that decision-makers have incentives to learn from them.

In our study, an important error is defined as an important trading decision that has a significantly negative effect on the subsequent performance of the mutual fund. These important decisions have a relatively high importance with respect to the fund's total net assets and this relative importance must be significantly higher than other trading decisions by the same fund and by other funds in our sample.

In the first part of our analysis, we find that the percentage of important trading errors decreases significantly over time that demonstrates significant learning by managers. Despite the inclusion of the dependent variable lagged as instruments to control for endogeneity bias and several control variables on fund characteristics and market conditions (the fund's size, age, turnover ratio, diversified portfolio holdings, and return and volatility in the market) that may have an influence on the learning process, the decreasing pattern in errors maintains its significance. Furthermore, these findings are consistent for buys and sells and for different time horizons that are used to compute the subsequent economic effect of important errors on fund performance. In addition, in a global learning context, we conclude that some funds are more prone to make important errors than other funds due to individual skills and then, the funds that make the greatest number of important errors in the past are also those that make the greatest number of important errors in the future.

In the second part of our empirical analysis, we find that the large number of the fund families in Spain drives its learning process. Furthermore, we study the learning process regarding two important dimensions of these fund families: their size and their dependence on banking and insurance groups. In general, we find that neither of these characteristics play significant roles in the learning process of the Spanish equity mutual fund industry.

Our approach is based on measuring the learning through the evolution of the percentage of important trading errors over time. However, it would be interesting for further research to examine whether important errors have any positive effect on future trading abilities and fund performance.

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Appendix 1.1: Figures on the evolution of important errors

Figure A1. 1 – The evolution of the percentage of important trading errors (Euro domestic equity mutual funds)

These graphs show the evolution of the percentage of important trading errors in buys and sells for Euro domestic equity mutual funds (Domestic) from January 2000 to March 2014, considering the different time horizons to compute the subsequent effect of these errors: 3-month alpha (α_{3m}), 6-month alpha (α_{6m}) and 12-month-alpha (α_{12m}).

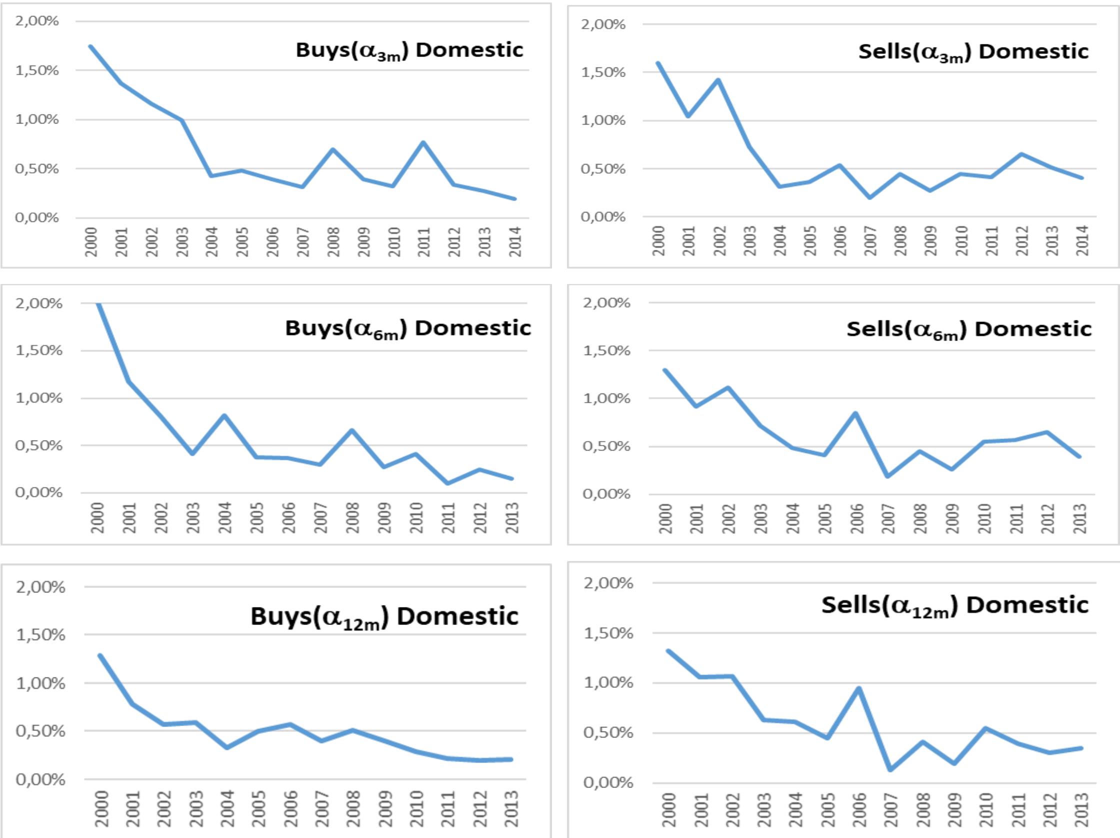
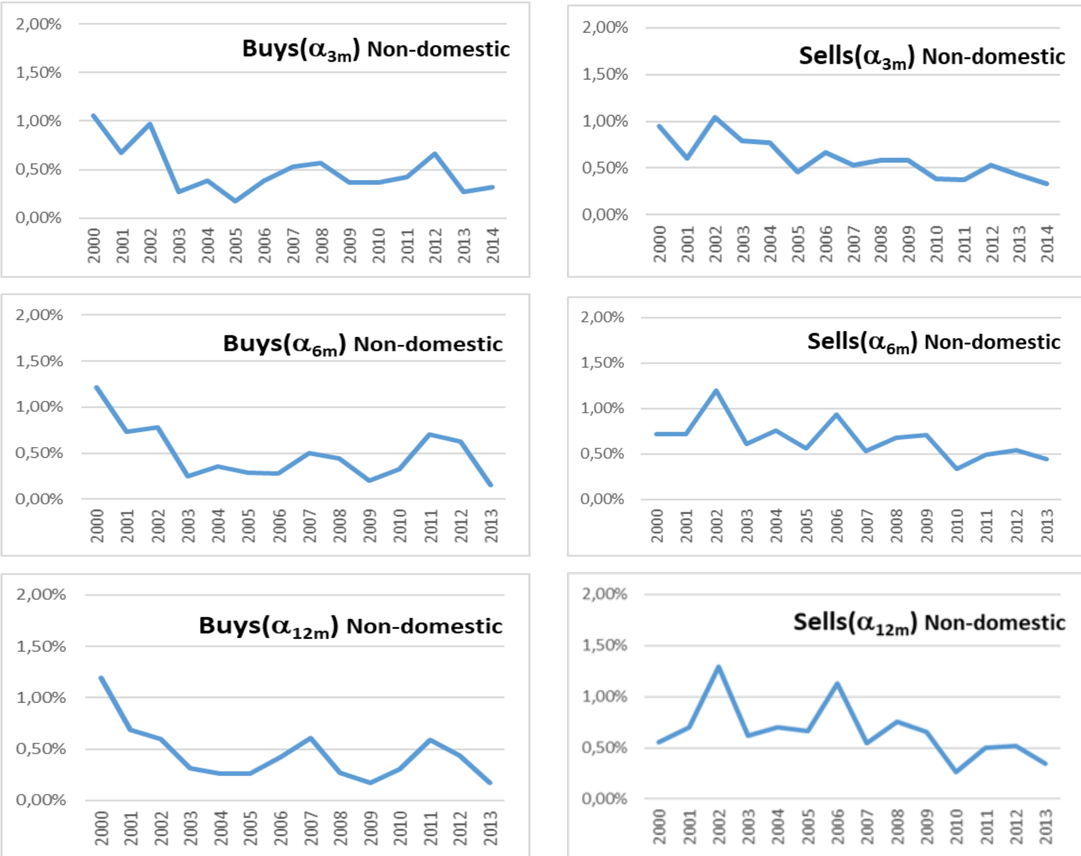


Figure A1. 2 – The evolution of the percentage of important trading errors (Euro non-domestic equity mutual funds)

These graphs show the evolution of the percentage of important trading errors in buys and sells for Euro non-domestic equity mutual funds (Non-domestic) from January 2000 to March 2014, considering different time horizons to compute the subsequent effect of these errors: 3-month alpha (α_{3m}), 6-month alpha (α_{6m}) and 12-month-alpha (α_{12m}).



Appendix 1.2: Robustness analyses of the learning results

Table A1. 1 – Learning results in Euro domestic equity mutual funds: on a quarterly basis

This table presents the results of the Equation 1.14 for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *%Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in quarter *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-quarter lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first quarter of our sample period to 57 in the last quarter; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in quarter *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in quarter *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in quarter *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in quarter *t;* and Market *return*$_t$ is the Ibex-35 total return in quarter *t*, we use the Ibex-35 as the benchmark for Euro domestic equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0358***	0.0131***	0.0259*	0.0175***	0.0282***	0.0249***
% Important errors$_{t-1}$	0.1040***	0.1117***	0.0656***	0.1068	0.0667**	0.0512
Time	-0.0001**	-0.0002***	-0.0001***	-0.0003*	-0.0002**	-0.0001
Fund_size	0.0019	-0.0011	-0.0030	-0.0015	-0.0020	-0.0020
Fund_age	-0.0159	-0.0004	-0.0073	-0.0034	-0.0011	-0.0003
Fund_#stocks	-0.0005***	-0.0003*	-0.0003***	-0.0003***	-0.0004***	-0.0005***
Fund_Turnover	0.0787***	0.0175***	0.0732***	0.0192***	0.0805***	0.0751***
Market return	-0.0116***	-0.0072***	-0.0050*	-0.0058***	-0.0066**	-0.0047***
Wald Chi-Squared Test	212.64***	124.31***	324.69***	76.61***	206.29***	69.32***
Sargan Test	116.74	115.87	61.29	31.37	114.89	110.42

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 2 – Learning results in Euro non-domestic equity mutual funds: on a quarterly basis

This table presents the results of the Equation 1.14 for Euro non-domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *%Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in quarter *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-quarter lag of the dependent variable regardless of the time horizon computed; ***Time***$_t$ ranges from 1 in the first quarter of our sample period to 57 in the last quarter; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in quarter *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in quarter *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in quarter *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in quarter *t;* and *Market return*$_t$ is the EuroStoxx-50 total return in quarter *t, w*e use the EuroStoxx-50 as the benchmark for Euro equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0349***	0.0417***	0.0250***	0.0056	0.0353*	0.0469***
% Important errorst-1	0.1131*	0.0580***	-0.0728	0.0992**	0.0682*	0.0743
Time	-0.0004**	-0.0148***	-0.0003**	0.0220**	-0.0002*	-0.0001
Fund_size	-0.0024	-0.0017**	-0.0009	0.0026	-0.0035	-0.0016
Fund_age	-0.0031	-0.0001	0.0038	0.0001	-0.0006	-0.0166
Fund_#stocks	-0.0004***	-0.0004***	-0.0004***	-0.0005***	-0.0006*	-0.0006**
Fund_Turnover	0.0084**	0.0428***	0.0269***	0.0799***	0.0788***	0.0820***
Market return	-0.0077**	0.0015	0.0002	0.0009	0.0005	-0.0058
Wald Chi-Squared Test	128.09***	180.14***	138.39***	82.38***	28.48***	46.34***
Sargan Test	80.78	95.92	91.74	112.17	109.79	110.22

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 3 – Learning results in Euro domestic equity mutual funds: on a yearly basis (FE)

This table presents the results of the Equation 1.14 with FE model for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and Market *return*$_t$ is the Ibex-35 total return in year *t*, we use the Ibex-35 as the benchmark for Euro domestic equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0142***	0.0021***	0.1713***	-0.0077***	-0.0044***	-0.0043***
Time	-0.0007***	-0.0007***	-0.0007***	-0.0187***	-0.0185***	-0.0198***
Fund_size	0.0002	0.0001	-0.0008*	-0.0011	-0.0017	-0.0017
Fund_age	-0.0022**	-0.0033***	-0.0023**	-0.0008	-0.0007***	-0.0006
Fund_#stocks	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0001***	0.0001***
Fund_Turnover	0.0299***	0.0202***	0.0181***	0.0003***	-0.0003***	-0.0003***
Market return	-0.0087***	-0.0099***	-0.0055***	0.0263***	0.0241***	0.0250***
F	266.61***	253.82***	206.35***	239.82***	170.69***	179.98***
R2	12.85%	13.07%	12.10%	12.75	12.32%	12.08%

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 4 – Learning results in Euro non-domestic equity mutual funds: on a yearly basis (FE)

This table presents the results of the Equation 1.14 with FE model for Euro non-domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year, the sample; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and *Market return*$_t$ is the EuroStoxx-50 total return in quarter *t*, we use the EuroStoxx-50 as the benchmark for Euro equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	-0.0091***	0.0155***	0.0109***	0.2133***	0.0240***	0.0255***
Time	-0.0171**	-0.0002***	-0.0008***	-0.0006***	-0.0005***	-0.0006***
Fund_size	-0.0011	0.0004	-0.0003	0.0001	-0.0007	-0.0005
Fund_age	-0.0002	-0.0017	-0.0022***	0.0018	0.0016	0.0023
Fund_#stocks	0.0008	-0.0002***	-0.0001***	-0.0004***	-0.0003***	-0.0004***
Fund_Turnover	-0.0003***	0.0117***	0.0098***	0.0185***	0.0181***	0.0179***
Market return	-0.0117***	-0.0131***	-0.0002	-0.0071***	-0.0086***	-0.0084***
F	84.96***	67.00***	69.91***	103.18***	110.27***	100.50***
R2	15.64%	18.93%	12.95%	12.23%	12.18%	12.10%

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 5 – Learning results in Euro domestic equity mutual funds: on a quarterly basis (FE)

This table presents the results of the Equation 1.14 with FE model for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in quarter *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-quarter lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first quarter of our sample period to 57 in the last quarter; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in quarter *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in quarter *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in quarter *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in quarter *t;* and Market *return*$_t$ is the Ibex-35 total return in quarter *t,* we use the Ibex-35 as the benchmark for Euro domestic equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0166***	0.0155***	0.0144***	-0.0009	-0.0009	-0.0053
Time	-0.0002***	-0.0002***	-0.0002***	-0.0210***	-0.0215***	-0.0238***
Fund_size	0.0002	0.0002	-0.0006**	-0.0015	0.0022	-0.0026*
Fund_age	-0.0028***	-0.0027***	-0.0015*	-0.0002	-0.0001***	-0.0001
Fund_#stocks	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.0001***	0.0001***
Fund_Turnover	0.0862***	0.0861***	-0.0804***	0.0003***	-0.0003***	-0.0004***
Market return	-0.0143***	-0.0155***	-0.0044*	0.1102***	0.1024***	0.1062***
F	75.53***	43.79***	36.50***	68.80***	75.68***	76.52***
R^2	10.81%	9.86%	10.59%	9.04%	7.46%	7.69%

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 6 – Learning results in Euro non-domestic equity mutual funds: on a quarterly basis (FE)

This table presents the results of the Equation 1.14 with FE model for Euro non-domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in quarter *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-quarter lag of the dependent variable regardless of the time horizon computed; ***Time***$_t$ ranges from 1 in the first quarter of our sample period to 57 in the last quarter; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in quarter *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in quarter *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in quarter *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in quarter *t;* and *Market return*$_t$ is the EuroStoxx-50 total return in quarter *t*, we use the EuroStoxx-50 as the benchmark for Euro equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0193***	0.0172***	0.0152***	0.0304***	0.0335***	0.0370***
Time	-0.0001**	-0.0005**	-0.0006***	-0.0001**	-0.0001**	-0.0002***
Fund_size	0.0001	0.0006	-0.0001	0.0001	-0.0001	-0.0002
Fund_age	-0.0019**	-0.0025***	-0.0035***	-0.0012	-0.0017	-0.0009
Fund_#stocks	-0.0002***	-0.0002***	-0.0002***	-0.0004***	-0.0004***	-0.0005***
Fund_Turnover	0.0486***	0.0456***	0.0339***	0.0615***	0.0637***	0.0675***
Market return	-0.0023***	-0.0065**	-0.0039	-0.0141***	-0.0124***	-0.0186***
F	175.91***	145.48***	108.83***	171.16***	191.65***	214.79***
R^2	7.14%	6.42%	4.78%	5.78	6.15%	6.97%

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Appendix 1.3: Learning results considering the quadratic time term

Table A1. 7 – Learning results in Euro domestic equity mutual funds: the quadratic term of the time variable

This table presents the results of the Equation 1.14 with the quadratic term of the time variable for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and Market *return*$_t$ is the Ibex-35 total return in year *t,* we use the Ibex-35 as the benchmark for Euro domestic equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0153***	0.0163***	0.0264***	0.0193***	0.0233***	0.0194***
% Important errors$_{t-1}$	0.0922***	0.1112***	0.0701**	0.2504***	0.2026***	0.0774***
Time	-0.0034***	-0.0030***	-0.0028***	-0.0035***	-0.0029**	-0.0018**
Time^2	0.0001***	0.0001***	0.0001***	0.0002***	0.0001***	0.0001**
Fund_size	-0.0016**	-0.0007	-0.0008	0.0006	0.0013	-0.0015**
Fund_age	0.0073	0.0021	-0.0055	0.0090	0.0051	-0.0004
Fund_#stocks	-0.0002***	-0.0098***	-0.0156***	-0.0202***	-0.0004***	-0.0002***
Fund_Turnover	0.0205***	0.0163***	0.0280***	0.0217***	0.0155***	0.0085***
Market return	-0.0050***	-0.0063***	-0.0062***	-0.0080***	-0.0033	-0.0017
Wald Chi-Squared Test	217.19***	168.57***	245.01***	335.72***	115.06***	113.48***

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 8 – Learning results in Euro non-domestic equity mutual funds: the quadratic term of the time variable

This table presents the results of the Equation 1.14 with the quadratic term of the time variable for Euro non-domestic equity mutual funds from January 2000 to March 2014. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Time*$_t$*^2* is the quadratic term of the time variable; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and *Market return*$_t$ is the EuroStoxx-50 total return in quarter *t*, we use the EuroStoxx-50 as the benchmark for Euro equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0329***	0.0304***	0.0160***	0.0358***	0.0439***	0.0444***
% Important errors$_{t-1}$	0.0447**	-0.0948***	0.0983***	0.1054***	0.0963*	0.1376***
Time	-0.0020***	-0.0012***	-0.0012	-0.0031****	-0.0036***	-0.0037***
Time^2	0.0001***	0.0001	0.0001	0.0001*	0.0001**	0.0082
Fund_size	-0.0016	-0.0032***	-0.0014*	0.0001	-0.0020*	0.0001**
Fund_age	-0.0017	0.0017	0.0048	0.0057	0.0089	-0.0010
Fund_#stocks	-0.0003***	-0.0003***	-0.0002***	-0.0005***	-0.0006***	-0.0006***
Fund_Turnover	0.0091***	0.0047***	0.0094***	0.0174***	0.0176***	0.0154***
Market return	-0.0068***	-0.0134***	0.0009	-0.0070***	-0.0086***	-0.0093***
Wald Chi-Squared Test	70.30***	140.20***	59.25***	104.41***	91.94***	90.57***

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Appendix 1.4: Learning results considering the market volatility

Table A1. 9 – Learning results in Euro domestic equity mutual funds: the market volatility

This table presents the results of the Equation 1.14 with the market volatility variable for Euro domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Time*$_t$*^2* is the quadratic term of the time variable; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t;* *Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and *Market Volatility*$_t$ is the average of the Stoxx 50 Volatility in year *t* as the measure of the market volatility.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0129**	0.0053**	0.0093**	0.0205***	0.0272***	0.0119***
% Important errors$_{t-1}$	0.1017***	0.0846***	0.0753***	0.2420***	0.1948***	0.1040***
Time	-0.0004**	-0.0002**	-0.0005***	-0.0003*	-0.0006**	-0.0003***
Fund_size	-0.0016*	-0.0011**	-0.0010*	0.0006	0.0012	-0.0007
Fund_age	-0.0033	-0.0007	0.0007	-0.0020	-0.0051	-0.0017
Fund_#stocks	-0.0003***	-0.0002***	-0.0003***	-0.0005***	-0.0004***	-0.0001***
Fund_Turnover	0.0193***	0.0200***	0.0267***	0.0211***	0.0142***	0.0068***
Market Volatility	0.0001**	0.0001***	0.0001	0.0001***	0.0001	-0.0002
Wald Chi-Squared Test	183.04***	91.64***	59.77***	323.5***	94.87***	114.85***

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 10 – Learning results in Euro non-domestic equity mutual funds: the market volatility

This table presents the results of the Equation 1.14 with the market volatility variable for Euro non-domestic equity mutual funds from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and *Market Volatility*$_t$ is the average of the Stoxx 50 Volatility in year *t* as the measure of the market volatility.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0348***	0.0272***	0.0180***	0.0197***	0.0332***	0.0368***
% Important errors$_{t-1}$	0.0153	-0.1252***	0.1007***	0.0864**	0.0714	0.1161**
Time	-0.0001	-0.0005***	-0.0009***	-0.0011***	-0.0011**	-0.0010*
Fund_size	-0.0029***	-0.0028***	-0.0014*	-0.0001	-0.0021**	-0.0009
Fund_age	-0.0091	-0.0063***	0.0091	0.0021	0.0010	-0.0010
Fund_#stocks	-0.0005***	-0.0003***	-0.0003***	-0.0005***	-0.0005***	-0.0006***
Fund_Turnover	0.0093***	0.0033***	0.0090***	0.0172***	0.0171***	0.0143***
Market Volatility	0.0002**	0.0003***	-0.0001**	0.0004***	0.0003***	0.0002*
Wald Chi-Squared Test	66.87***	218.26***	53.77***	115.99***	88.55***	77.08***

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Appendix 1.5: Robustness analyses of the learning results considering different cut-off points

Table A1. 11 – Learning results in Euro domestic equity mutual funds: quartiles

This table presents the results of the Equation 1.14 with the quartiles of important trading decisions with the most negative influence on fund performance for all the domestic equity mutual funds across our sample period from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and Market *return*$_t$ is the Ibex-35 total return in year *t*, we use the Ibex-35 as the benchmark for Euro domestic equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0087***	0.0179**	0.0075	0.0093*	0.0105	0.0222***
% Important errors$_{t-1}$	0.0981***	0.0864**	0.0785***	0.1953***	0.2015***	0.1384**
Time	-0.0003**	-0.0004**	-0.0006*	-0.0003*	-0.0005**	-0.0008*
Fund_size	0.0009	-0.0013	-0.0018	0.0006	-0.0002	0.0007
Fund_age	0.0001	-0.0027	-0.0030	0.0095	0.0109*	-0.0049
Fund_#stocks	-0.0002***	-0.0004***	-0.0008***	-0.0004***	-0.0004***	-0.0004***
Fund_Turnover	0.0236***	0.0298***	0.0070***	0.0220***	0.0188***	0.0183***
Market return	-0.0042**	-0.0078***	-0.0014**	-0.0071***	-0.0060***	-0.0032*
Wald Chi-Squared Test	98.78***	148.42***	32.03***	97.56***	74.87***	35.67***
Sargan Test	29.50	92.49	91.70	33.99	29.62	31.00

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 12 – Learning results in Euro non-domestic equity mutual funds: quartiles

This table presents the results of the Equation 1.14 with the quartiles of important trading decisions with the most negative influence on fund performance for all the non-domestic equity mutual funds across our sample period from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t;* *Fund_Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t;* and *Market return*$_t$ is the EuroStoxx-50 total return in year *t*, we use the EuroStoxx-50 as the benchmark for Euro equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0435***	0.0263***	0.0147***	0.0243**	0.0389***	0.0442***
% Important errors$_{t-1}$	-0.0025**	0.1219***	0.1569***	0.1293**	0.1447**	0.1370**
Time	-0.0003*	-0.0009***	-0.0005**	-0.0012**	-0.0010**	-0.0012***
Fund_size	-0.0031***	-0.0016	-0.0018**	0.0006	-0.0001	-0.0010
Fund_age	-0.0074	0.0002	0.0005	0.0071	-0.0060	0.0046
Fund_#stocks	-0.0005***	-0.0003*	-0.0002***	-0.0004***	-0.0006***	-0.0007***
Fund_Turnover	0.0113***	0.0147**	0.0127***	0.0170***	0.0176***	0.0205***
Market return	-0.0073***	-0.0064***	0.0011	-0.0059**	-0.0074**	-0.0067*
Wald Chi-Squared Test	33.81***	55.35***	275.47***	36.78***	46.03***	64.43***
Sargan Test	89.71	21.21	27.82	25.41	31.80	83.92

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 13 – Learning results in Euro domestic equity mutual funds: deciles

This table presents the results of the Equation 1.14 with the deciles of important trading decisions with the most negative influence on fund performance for all the domestic equity mutual funds across our sample period from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t; Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ *is* the turnover ratio of mutual fund *i* in year *t;* and Market *return*$_t$ is the Ibex-35 total return in year *t,* we use the Ibex-35 as the benchmark for Euro domestic equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0160	0.0196***	0.0075	0.0101**	0.0106**	0.0044***
% Important errors$_{t-1}$	0.0624**	0.0110*	0.0785	0.0638**	0.0367*	0.0683***
Time	-0.0083**	-0.0003**	-0.0006**	-0.0005*	-0.0002***	-0.0001***
Fund_size	-0.0006	-0.0022**	-0.0018	-0.0013	-0.0015*	-0.0009**
Fund_age	0.0004	0.0048	-0.0030	-0.0007*	0.0006	0.0007
Fund_#stocks	-0.0002**	-0.0002***	-0.0008*	-0.0002**	-0.0002***	-0.0001***
Fund_Turnover	0.0067**	0.0086***	0.0079***	0.0066**	0.0085***	0.0065***
Market return	-0.0041**	-0.0046***	-0.0014*	-0.0044***	-0.0056***	-0.0049***
Wald Chi-Squared Test	122.42***	125.45***	132***	126.74***	170.51***	157.21***
Sargan Test	95.94	92.88	92.87	95.06	31.53	95.06

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

Table A1. 14 – Learning results in Euro non-domestic equity mutual funds: deciles

This table presents the results of the Equation 1.14 with the deciles of important trading decisions with the most negative influence on fund performance for all the non-domestic equity mutual funds across our sample period from January 2000 to March 2014. The learning results are divided into buys and sells after considering different time horizons to compute the subsequent effect of these errors: 3-month alpha, 6-month alpha and 12-month-alpha. The dependent variable *% Important errors*$_{i,t}$ is the percentage of important errors for fund *i* in year *t*. The explanatory variables which are included in this table are: *% Important errors*$_{i,t-1}$ is the 1-year lag of the dependent variable regardless of the time horizon computed; *Time*$_t$ ranges from 1 in the first year of our sample period to 15 in the last year; *Fund_size*$_{i,t}$ is the TNA of mutual fund *i* divided by the average TNA of all funds included in our sample in year *t*; *Fund_age*$_{i,t}$ is the normalised age of mutual fund *i* given that we divided the age of each fund by the average age of all funds included in our sample in year *t* to avoid correlation problems with the time variable; *Fund_#stocks*$_{i,t}$ is the number of different stocks held by mutual fund *i* in year *t; Fund_Turnover*$_{i,t}$ is the turnover ratio of mutual fund *i* in year *t;* and *Market return*$_t$ is the EuroStoxx-50 total return in year *t*, we use the EuroStoxx-50 as the benchmark for Euro equity mutual funds.

	BUYS			SELLS		
	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha	Important errors with 3-month alpha	Important errors with 6-month alpha	Important errors with 12-month alpha
Constant	0.0230***	0.0084***	0.0076**	0.0208***	0.0198*	0.0299***
% Important errors$_{t-1}$	0.0907	0.1313**	0.0474**	0.1011**	0.0338**	0.1430**
Time	-0.0008**	-0.0002***	-0.0001***	-0.0005**	-0.0008**	-0.0004**
Fund_size	-0.0007	-0.0006	-0.0008	-0.0009	0.0036	0.0054
Fund_age	0.0045	-0.0001*	0.0004	-0.0003	-0.0005	-0.0009
Fund_#stocks	-0.0004***	-0.0048***	-0.0001**	-0.0003***	-0.0002**	-0.0004***
Fund_Turnover	0.0152***	0.0006***	0.0056***	0.0082***	0.0216***	0.0089***
Market return	-0.0080***	-0.0018	-0.0004	-0.0044***	-0.0122***	-0.0064***
Wald Chi-Squared Test	146.88***	213.13***	169.70***	33.40***	44.78***	142.86***
Sargan Test	19.49	27.61	119.92	21.28	97.05	29.23

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.

CHAPTER 2:

DIVERSIFICATION AND MANAGER AUTONOMY IN FUND FAMILIES: IMPLICATIONS FOR INVESTORS

-Autonomy is a requirement for effectiveness-

Jack Lang

Synopsis

This chapter aims to investigate the consequences for investors of investing in a single fund family. In essence, we focus on the correlation among portfolio holdings of funds with effects in terms of under-diversification for mutual fund investors, especially, if they invest in the same fund family. We also explore the fund manager autonomy in portfolio holding allocation within families and determine the characteristics of those fund families with higher autonomy. Our results show that a higher correlation among funds not only implies that families offer a lower diversification to investors; it also has a negative effect on their performance. However, investors' performance benefits from a higher manager autonomy. Consequently, investors who select a single fund family could obtain higher returns in smaller fund families with considerable experience that do not belong to a banking or insurance group, as in the former, diversification and manager autonomy are higher.

2.1 Introduction

The development of the mutual fund industry has resulted in a large number of individual investors who participate in financial markets, delegating their portfolio management to fund managers who have become the main type of institutional investors (Chen and Qin, 2017). This is demonstrated by the €15.6 billion of Net Assets managed by 60,000 funds in the European Mutual Fund Industry (European Fund and Asset Management Association, EFAMA, 2018).

As documented over the years, portfolio diversification is one of the main benefits obtained from mutual funds by unsophisticated investors (Markowitz, 1952; Sharpe, 1964; Statman, 2004; and Goetzmann and Kumar, 2008, among others). However, Moreno and Rodríguez (2013) argue that mutual funds are not always well diversified. Therefore, investors should hold more than one mutual fund in order to reduce the idiosyncratic risk in a portfolio of funds.

In selecting mutual funds, researchers find that individual investors first seem to pick a fund family, and then they select the funds in which they invest. This mental process implies the concentration of their investments in a single mutual fund family (Massa, 2003). In order to reinforce the idea of investment in a single fund family, Gerken et al. (2018) find that investors who have previously invested in a particular family are significantly more likely to choose a fund from that same family when they decide to invest in mutual funds again. This can be explained by the fact that investors are able to move their money in and out of funds within a family at a lower cost (Clare et al., 2014). Therefore, as shown in literature, when building their diversified portfolio of funds, investors seem to pick funds within fund family they are familiar with.

Deepening into the behaviour of fund families, Elton et al. (2007) find that mutual fund returns within a family tend to be highly correlated, and they argue that the increased correlation is primarily due to common stocks in portfolio holdings. Chen et al. (2004) also show that the fund performance is related to the fund family. According to Elton et al. (2007), fund managers within the same family have access to the same information, both external and internal research analyses, what results in similar portfolio holdings. In addition, the potential existence of guidelines from the family's top-management (i.e. investment directors) also generates similar portfolios and implies a reduction of the autonomy of managers (Kacperczyk and Seru, 2012).

In line with prior research, the main objective of this chapter is to further investigate investors' diversification and the implications in terms of performance of diversifying within a fund family or across families. As opposed to previous literature, we do not only study whether the funds which belong to the same family are more correlated than funds in different families, we examine the characteristics of the most correlated fund pairs. The reason behind this analysis is that there may be funds with different characteristics such as size, age, number of stocks in the portfolio and fees within a fund family, which could affect the similarity level among them. In addition, our aim is to study whether the level of diversification between funds is significantly higher in some families than in others and the characteristics of these more diversified families. Therefore, we identify families in which investors would be less affected by under-diversification, if they decided to concentrate their funds in the same family. In addition, we evaluate the influence of diversification and fund manager autonomy in a family on the returns of an investor who selects this family.

Focusing on the decision-making process of mutual funds, fund manager decisions are influenced by both, the personal characteristics of managers and the external factors. The former include their past experience (Menkhoff et al., 2006; Kempf et al., 2017), their cognitive bias (Cuthbertson et al., 2016), their own intuition (Brown and

Davies, 2017) and their level of familiarity with the stocks (Pool et al., 2012; 2015), among others. Some example of external factors are analyst recommendations (Brown et al., 2014), competition or co-operation with other managers (Kempf and Ruenzi, 2008; Simutin, 2013; Evans et al., 2020); the family management strategy, which may involve a centralised or decentralised decision making process (Kacperczyk and Seru, 2012).

Apart from the above mentioned factors, managers in the same family may also have some common features that lead managers to hold more similar portfolio holdings than managers of different families. In this line, Sevcenko and Ethiraj (2018) also suggest that the existence of a monitoring relationship in the mutual fund companies allows new managers to know the company-specific skills.

Concerning the level of portfolio holding differentiation between funds within a family, previous literature reveals different positions. Some authors provide evidence of fund decisions' coordination within families allows to take advantage of the family resources and maximise its value (Khorana and Servaes, 2004; Elton et al., 2007; Evans et al., 2020). Gerken et al. (2018) also document the high importance of family reputation when investors select a family that is determined by the performance of all the funds within a family. In addition, Casavecchia and Ge (2019) note that fund managers who are part of families with a higher level of specialisation possess better stock-picking skills. However, Massa (2003) and Khorana and Servaes (2012) note that it is important that investors perceive each fund as a differentiated product for families to increase their family market share. In this line, Mamaysky and Spiegel (2002) consider that individual investors take advantage of research relating to the family when the portfolio of new funds differ as much as possible from existing funds in the fund family.

Although considerable effort has been devoted to examining the portfolio differentiation within families and its influence on the family market share, the economic and diversification implications for fund investors that concentrate their investment in one fund family remain more unknown.

This chapter analyses Euro equity mutual funds from December 1999 to June 2018 in the Spanish mutual fund market, contributing to the literature on several aspects. Firstly, we analyse the correlation between portfolio holdings within the same family and between different families in order to conclude the diversification implications for investors who concentrate all of their fund investments in a single family. We address this correlation with the portfolio overlap measure. Our hypothesis is based on the idea that the higher the level of portfolio overlap between two funds, the higher the correlation between both funds and the lower the level of diversification for an investor who decides to invest in those two funds. We confirm a higher fund overlap within a family as documented in Elton et al. (2007). Therefore, individual investors can achieve better diversification if they do not focus on a single family and distribute their fund investments across different families. We also identify the characteristics of fund pairs with a high correlation.

Secondly, the chapter analyses the characteristics of families with a lower potential diversification for investors due to a higher correlation between the portfolio holdings of their funds. The type of fund family may also play an important role due to the high degree of concentration in the Spanish mutual fund market and the existence of a higher number of bank-owned fund management companies than in other European markets (EFAMA, 2018b). We find that larger families, which belong to a banking group and which do not have a considerable experience in the mutual fund market, show the highest portfolio overlap. Nevertheless, we do not only investigate the characteristics of the fund families with the highest portfolio overlap, we also deepen in the analysis of the autonomy in portfolio holding allocations of stock sectors within families. We propose a measure to examine the autonomy in stock-picking on a twofold approach, depending on whether the general investment outline corresponds to the whole fund sample or to each fund family. Our results show that the autonomy in portfolio allocations of stock sectors is higher in smaller fund families with wider experience that do not belong to a banking group.

Thirdly, we study whether the similitude of portfolio holdings within family and thereby whether the family diversification, as well as manager autonomy within families is a determinant of the performance of investors who select a single family for all their fund investments. We find that a higher diversification and a higher autonomy of managers within families are positive factors for investors' performance.

Therefore, the findings seem to reveal that investors who concentrate all funds in the same family could obtain higher returns in smaller fund families with wide experience that do not belong to a banking group, because in these families the diversification and manager autonomy are higher. These results have a relevant economic and social impact in the Spanish fund industry due to the high concentration and the high dependence on the banking sector (Ferreira and Ramos, 2009; Ferreira et al., 2013). Note that individual investors delegate more than 40% of investment money to the five largest fund families that belong to banking groups. Hence, the savings of a large proportion of Spanish investors depend on the efficiency of these families.

The findings of this study also have several implications for fund managers and fund families. Managers who work in management companies with a lower level of manager's autonomy in decision-making are less likely to stand out from others in this same company and therefore this limits their probability of promotion. Our study is also of interest for fund families because of the relation between past performance and future fund flows (Sirri and Tufano, 1998). In addition, this study is interesting for financial supervisors to guide their supervision towards the insurance of investor protection and the efficiency of the market. According to Delpini et al. (2019; 2020), a high similarity among mutual funds is a sign of an industry with a high systemic risk and fragility, and consequently, a high possibility of contagion and propagation of the market shocks.

The remainder of this chapter is organised as follows. Section 2 describes the data. Section 3 presents the results of the portfolio overlap of fund pairs. Section 4 presents the results of the portfolio overlap within a fund family. Section 5 presents the results on the fund manager autonomy in the portfolio allocation. Section 6 presents the influence of portfolio overlap and fund manager autonomy on the individual investors' returns. Section 7 concludes.

2.2 Data and methodology

2.2.1 Data

We study the correlation of portfolio holdings between fund pairs in the same family and different families and its influence on individual investors' performance and diversification in the Spanish equity mutual fund industry from December 1999 to June 2018. The review of previous literature reveals that there are several authors who have studied holdings concentration. Elton et al. (2007) examine the extent of overlap in stock holdings for US mutual funds from 1998 to 2002 and Pool et al. (2015) study portfolio overlap of actively managed US equity funds whose managers live in the same city from 1996 to 2010. More recently, Evans et al. (2020) study common ownership/portfolio overlap in US mutual funds over the 1990-2015 period.

Our chapter evaluates the extent of overlap between fund portfolio holdings in the Spanish Euro equity official category. The Spanish Securities Exchange Commissions (CNMV) establishes a classification of mutual funds according to the types of assets included in the portfolios. Euro equity funds must invest more than 75% of their portfolio holdings in equities, and at least 60% of the total equity exposure must be issued by companies of the Euro area. Our sample is free of survivorship bias as it includes both, funds that have already disappeared and surviving funds. ETFs, index funds and funds with less than two years of data were excluded. In addition, we also control the mergers and acquisitions of fund and fund families as well as when one fund becomes managed by another different family. Our final sample includes 276 Euro equity mutual funds managed by 108 management companies (that is fund families), of which 63 companies manage more than one fund.

The monthly portfolio holdings of mutual funds included in our sample were obtained from the CNMV and Morningstar. The former provided monthly portfolio from 1999 to 2006 for research purposes. After 2006, CNMV provides quarterly holdings. Therefore, we complete these official reports with monthly information from Morningstar when it is available. We match both databases using the ISIN code of mutual funds and stocks and analyse a total of 24,561 portfolio holdings.

CNMV also provides information about the characteristics of mutual funds and of fund families such as the inception date of funds, the fees, the monthly past annual gross and net return, and the fund family to which they belong. We also obtain the monthly size of each fund family as the sum of the total net assets of all fund categories within the family in the industry. Additionally, based on its governance structure, we distinguish between fund families that depend on a banking or insurance company (named as banking group for brevity reasons hereafter) or not (independent fund families). Finally, stock information is obtained from Datastream.

Table 2. 1 – Summary Statistics of the sample

Panel A and Panel B report summary statistics of the mutual fund sample and fund families, respectively at four date points: Dec1999, Dec2005, Dec2011 and Jun2018. Panel C reports the average summary statistics of funds by the largest families (Families_Q1) and the smallest families (Families_Q5) at these four date points. *#Funds* is the number of funds in our sample. *Fund_size* is the monthly total net assets of funds in million euros. *Fund_age* is the age of funds in years from its inception date. *Fund_#stocks* is the number of stocks in portfolio holdings. *Fund_fees* is the management and deposit fee. *Fund_return* is the annual past gross return. *#Families* is the number of fund families in our sample, we distinguish between families that belong to a banking or insurance group *(banking-families)* and families that are independent *(independent-families)*. *Family_size* is the monthly total net assets of all funds managed by fund families in the Spanish industry in million euros. *Family_EuroEquity* is the monthly total net assets managed by families in the euro equity category in million euros. *Family_age* is the age of fund families in years, obtained from the inception date of the oldest fund in the family. *HHI* is the normalised Herfindahl–Hirschman Index that ranges from 0 to 1. *CR-4* index is the market share percentage of the four largest families.

		Dec1999	Dec2005	Dec2011	Jun2018
Panel A: Summary statistics of the mutual fund sample					
#Funds		139	165	126	89
Fund_size	Mean	84.68	76.78	35.01	148.63
	Q1	116.56	102.58	36.00	180.92
	Q5	7.68	8.88	4.78	18.68
Fund_age	Mean	4.14	8.04	13.15	17.77
	Q1	8.38	11.66	17.50	24.00
	Q5	1.32	4.53	8.79	12.64
Fund_#stocks	Mean	49.71	47.30	42.89	48.30
	Q1	59.00	57.00	53.00	58.00
	Q5	34.00	35.00	32.00	34.00
Fund_fees	Mean	0.17%	0.15%	0.16%	0.15%
	Q1	0.21%	0.19%	0.19%	0.18%
	Q5	0.12%	0.12%	0.14%	0.12%
Fund_return	Mean	10.78%	24.52%	-14.84%	3.95%
	Q1	15.81%	27.06%	-12.06%	8.37%
	Q5	3.47%	21.59%	-17.31%	-0.97%
Panel B: Summary statistics of the fund family sample					
#Families		72	69	56	51
#Banking families		59 (81.94%)	56 (81.16%)	45 (80.36%)	36 (70.59%)
#Independent families		13 (18.06%)	13 (18.84%)	11 (19.64%)	15 (29.41%)
Family_size	Mean	1,947.82	2,858.46	2,283.66	5,167.97
	Q1	1,709.23	2,226.71	2,641.46	4,951.42
	Q5	81.36	9.88	5.78	19.68
	HHI	0.1453	0.1015	0.0810	0.0895
	CR-4	56.49%	54.40%	54.26%	52.93%
Family_EuroEquity	Mean	163.48	183.59	78.77	259.38
	Q1	126.30	195.06	77.28	259.87
	Q5	7.72	10.65	8.69	18.21
	HHI	0.1200	0.0762	0.1409	0.1065
	CR-4	55.91%	46.83%	58.18%	54.82%
Family_age	Mean	9.40	15.88	21.13	26.88
	Q1	12.07	18.87	25.53	31.58
	Q5	8.34	14.28	20.19	25.29
Panel C: Summary statistics of mutual funds by family					
Average Fund_size	Families_Q1	156.79	157.29	66.21	376.50
	Families_Q5	13.48	25.36	14.64	30.43
Average Fund_age	Families_Q1	4.66	6.62	14.96	21.73
	Families_Q5	4.18	7.92	12.53	14.93
Average Fund_#stocks	Families_Q1	69.59	51.65	36.31	48.88
	Families_Q5	38.75	41.64	44.76	51.44
Average Fund_fees	Families_Q1	0.15%	0.14%	0.17%	0.16%
	Families_Q5	0.16%	0.15%	0.16%	0.14%
Average Fund_return	Families_Q1	14.45%	26.84%	-18.11%	3.79%
	Families_Q5	4.70%	24.32%	-12.58%	3.28%

Panel A of Table 2.1 reports the summary statistics of our fund sample at different date points. It is noteworthy that the number of funds decrease over time. According to Climent (2013), this effect is related to the severe merging process caused by the strong reorganisation of the banking system in the Spanish market in recent years. Focusing on the characteristics of funds and families, we observe that the average total net assets of funds (*Fund_size*) is lower in December 2011 with respect to December 2005, which comes as no surprise given the global financial crisis. However, the trend of average fund size has recovered during the last years, reaching in June 2018 higher average size since December 2011. This recovery may be encouraged by low interest rates offered by bank deposits that have been replaced by mutual funds for many investors in recent years and the increase in investors' confidence in professional investment advice.

The value of monthly fees shown in Table 2.1 does not undergo a significant change and the average number of stocks decreases slightly. Based on the past 12-month gross return, we can see that it is lower in December 2011 due to the economic crisis compared to the other three date points.

Panel B of Table 2.1 reports the summary statistics of the fund families in our sample. In line with the evolution of the number of funds, we also observe a negative pattern in the number of fund families. In addition, although the percentages of banking families that belong to a banking or insurance group is noteworthy higher, the weight of independent families increases slightly over the sample period, from 18.06% in December 1999 to 29.41% in June 2018. With respect to the concentration level, Panel B shows that the market share percentage of the four largest families is around 50% throughout the whole sample period, both considering the total assets in the industry and the assets within the Euro equity category of our sample. Hence, our sample is representative of the Spanish mutual fund industry. In addition, the normalised Herfindahl–Hirschman index

(HHI) values of our study are similar to what is shown by Ferreira and Ramos (2009), who examine mutual fund industry competition and concentration in 27 countries. These authors report that the HHI in the European markets ranges from 0.04 to 0.219. The Spanish industry has a higher HHI with respect to other European markets such as U.K (0.040), France (0.066); Italy (0.069) and Germany (0.071).

Panel C of Table 2.1 shows that the average size and the average age of funds is remarkably higher within the largest families than within the smallest families. However, the differences are small in terms of the fees and past returns. Regarding to the number of stocks held in portfolio holdings, funds managed by the largest families seem to be more diversified in the early years of the sample period, however, both in December 2011 and June 2018, the diversification level is higher in the portfolio holding within the smallest families.

2.2.2 Methodology

The first objective of the chapter is to analyse the correlation between two funds within the same family and the correlation across families and hence, investor diversification. We approach this correlation as the portfolio overlap between fund pairs. According to Elton et al. (2007) and Pool et al. (2015), we measure the pairwise overlap as the sum of minimum fraction in each stock k held by both funds in month t.[14]

$$\textit{Portfolio overlap}_{i,j,t} = \sum_{k \epsilon \Psi_{i,j,t}} min(w_{i,k,t};\ w_{j,k,t})\ x\ 100 \qquad (2.1)$$

where $\textit{Portfolio overlap}_{i,j,t}$ is the portfolio overlap between funds i and j in month t. $w_{i,k,t}$ is the portfolio weight of stock k in the fund i in month t. $w_{j,k,t}$ is the portfolio weight of stock k in the fund j in month t. $\Psi_{i,j,t}$ is the set of all stocks held by fund i and fund j in

[14] For robustness purposes, we also obtain the portfolio overlap according to the measure used in Delpini et al. (2019) and Fricke and Fricke (2021), see Appendix 2.1 for more details.

month t. The higher the portfolio overlap between two funds, the higher the correlation between two funds and the lower the diversification level for an investor who decides to invest in those two funds.

We also obtain the correlation between two funds at the industry and sector levels. Every stock is classified by sector and by industry according to FTSE Russel Industry Classification Benchmark (ICB) obtained from Datastream. To measure the portfolio overlap at the sector or at the industry levels, in Equation 2.1 k becomes the sector or the industry.

2.3 Resemblance of fund portfolio holdings

Panel A of Table 2.2 reports that the average portfolio overlap at stock level between any two funds in the sample is 30.50% during the sample period. Similarly, Elton et al. (2007) find that up to 34% of total net assets are held in common stocks for funds with the same investment objective. However, we observe that the annual average portfolio overlap decreases from 32.17% to 23.20% during the sample period. Regarding the sector and industry levels, Table 2.2 also reveals that the average overlaps are 58.89% and 66.14%, respectively, which as expected, are considerably higher than at the stock level. The results reveal a decrease in the average portfolio overlap that is lower at the sector and industry levels than at the stock level.[15]

[15] The annual results of portfolio overlap at the sector and at the industry levels are in Appendix 2.2.

Table 2. 2 – Overall results of the portfolio overlap at the fund pair level

Panel A, Panel B and Panel C report the results of portfolio overlap at the stock level, at the sector level and at the industry level, respectively. This table shows, for each year, the overall average portfolio overlap and the number of fund pairs within the same fund family and the number of fund pairs in different families, as well as their average overlap. In this table, we present a yearly report of the number of funds during the sample period, unlike in Table 2.1 where we present the total number only at three specific points during the sample period. The last column shows the results of the mean difference test between both specific averages with the *p*-value in parentheses. We apply the mean difference test for unpaired samples with different variance (in all cases the null hypothesis is rejected in the test of equal variance).[16] In all columns, the annual average is obtained with the monthly portfolio overlap data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Year	Portfolio overlap	#fund pairs (*same fund family*)	#fund pairs (*different fund family*)	Portfolio overlap (*same fund family*)	Portfolio overlap (*different fund family*)	Mean-difference test
Panel A: Stock						
2000	32.17%	282	11,520	44.35%	31.88%	12.47%*** (0.000)
2001	30.95%	341	13,827	37.98%	30.76%	7.22%*** (0.000)
2002	30.20%	354	14,261	36.73%	30.05%	6.68%*** (0.000)
2003	32.23%	340	15,175	39.02%	32.08%	6.93%*** (0.000)
2004	33.57%	337	13,592	41.54%	33.37%	8.17%*** (0.000)
2005	33.07%	391	14,415	40.21%	32.87%	7.34%*** (0.000)
2006	31.27%	421	15,621	37.18%	31.11%	6.07%*** (0.000)
2007	29.27%	474	16,648	35.43%	29.03%	6.40%*** (0.000)
2008	30.70%	468	16,032	35.22%	30.49%	4.73%*** (0.000)
2009	29.27%	422	14,054	35.64%	29.02%	6.61%*** (0.000)
2010	27.61%	255	10,917	34.46%	27.39%	7.06%*** (0.000)
2011	27.74%	236	9,864	34.92%	27.53%	7.39%*** (0.000)
2012	26.86%	193	7,712	34.51%	26.64%	7.88%*** (0.000)
2013	26.14%	166	6,289	33.09%	25.95%	7.14%*** (0.000)
2014	26.57%	97	4,619	31.79%	26.45%	5.33%*** (0.000)
2015	27.05%	104	5,203	31.79%	26.93%	4.85%*** (0.000)
2016	25.10%	93	4,737	27.66%	25.04%	2.61%*** (0.000)
2017	23.12%	75	4,260	28.71%	22.96%	5.75%*** (0.000)
2018	23.20%	65	4,061	28.73%	23.08%	5.65%*** (0.000)
Dec1999-Jun2018	30.50%	994	32,982	37.36%	30.31%	7.05%*** (0.000)
Panel B: Sector						
Dec1999-Jun2018	58.89%	994	32,982	64.18%	58.75%	5.43%*** (0.000)
Panel C: Industry						
Dec1999-Jun2018	66.14%	994	32,982	70.92%	66.61%	4.91%*** (0.000)

[16] For robustness purposes, we also apply the Kruskal-Wallis nonparametric test to examine the existence of differences between the portfolio overlap of fund pairs from the same family and from different families. The statistical significance of the results is the same. Note that this test has also been applied in Tables 2.4 and 2.6.

Following Elton et al. (2007), we differentiate between the fund pairs where both funds belong to the same management company (that is in the same fund family) and the fund pairs in different families. These authors initially argue two positions. On the one hand, they consider that the portfolio overlap of fund pairs in the same family could be lower than across families, suggesting that a fund family has incentives to offer non-correlated portfolio holdings to prevent investors from going outside of the family to seek a higher diversification between funds, following Khorana and Servaes (2004). On the other hand, Elton et al. (2007) also contemplate that there are reasons to expect that the portfolio overlap may be higher within fund families than outside of them due to the access to the same information or the extent of a family management strategy. Similarly, Chen et al. (2004) and Cici et al. (2018) show that most mutual funds operate as part of fund families; the latter make strategic decisions that have an influence on the operation and performance of their funds.

We analyse 994 fund pairs with 167,848 portfolio overlap observations where both funds are in the same fund family and 32,982 fund pairs with 1,549,658 portfolio overlap observations where both funds are in different fund families. We compare the portfolio overlap between both groups and our first null hypothesis tested is:

2.1H_0: There are no significant differences between the portfolio overlap of fund pairs within the same fund family and fund pairs in different families.

Table 2.2 shows that, from December 1999 to June 2018, the average portfolio overlap of fund pairs within the same fund family and the average of fund pairs in different families at stock level are 37.36% and 30.31%, respectively. This finding reveals a difference between both groups equal to 7.05%, which is statistically significant at the 1% level. This finding is consistent with financial literature (Elton et al., 2007; Pool et al., 2015). We also find a statistically significant difference between the overlap of fund pairs within the same family and the overlap of fund pairs in different families when we measure the overlap at sector and industry levels. The results obtained when focusing on the industry and the sector increase the robustness of our conclusions, given that by using the stock for stock comparison, we omit a potential overlap in sector or industry that can occur when stocks are different.

We apply a panel data model to determine the characteristics of fund pairs with higher portfolio overlap at the stock level. Specifically, we estimate the following random effects (RE) model according to the result of Hausman test.

$$\begin{aligned} \mathit{Portfolio\ overlap}_{i,j,t} = f\,(&\mathit{Fund\_size}_{i,j,t}; \mathit{Fund\_age}_{i,j,t}; \mathit{Fund\_\#stocks}_{i,j,t};\\ &\mathit{Fund\_fees}_{i,j,t}; \mathit{Fund\_return}_{i,j,t}; \mathit{Fund\_family}_{i,j,t};\\ &\mathit{Time}_t; \varepsilon_{i,j,t}) \end{aligned} \tag{2.2}$$

where the dependent variable is the $\mathit{Portfolio\ overlap}_{i,j,t}$ between funds *i* and *j* in month *t* at the stock level and the independent variables are dummy variables. In order to define these dummy variables, we calculate the percentile rank of each characteristic for all the funds in our sample every month *t* (*Fund_size*; *Fund_age*; *Fund_#stocks*; *Fund_fees*; *Fund_return*), and we determine the quintile into which funds *i* and *j* are. For each characteristic, we include four dummy variables: *Same* takes a value equal to 1 when, in month *t*, funds *i* and *j* are in the same quintile and 0 otherwise. *BothQ1* takes a value equal to 1 when, in month *t*, funds *i* and *j* are in the top quintile. *BothQ5* takes a value equal to 1 when, in month *t*, funds *i* and *j* are in the bottom quintile. *Opposite* is equal to 1 when in month *t*, either fund *i* or fund *j* is in the top quintile and in the other is in the bottom quintile. As a robustness test for the results in Table 2.2, the model also controls for whether or not a pair of funds belong to the same fund family. $\mathit{Fund\_family}_{i,j,t}$ is equal to 1 when funds *i* and *j* in month *t* are in the same fund family and 0, otherwise. In addition, we include the $Time_t$ variable in order to test the pattern of the portfolio overlap over time. $Time_t$ ranges from 1 in the first month to 223 in the last month.

Fund_size: is measured as the total net assets. According to Kacperczyk and Seru (2007), larger funds enjoy a greater reputation and pay higher wages, employing managers who are more skilled. Therefore, our hypothesis is based on the idea that managers of larger funds may have common information because they have more resources to access this information, and consequently, the portfolio overlap would be higher in fund pairs where both funds are among the largest.

Fund_age: is determined from mutual fund inception. Some authors argue that young funds are at a disadvantage as they might suffer from lack of market experience (Agnesens, 2013; Ben and Hellara, 2011). Chevalier and Ellison (1997) show that young funds behave differently from old funds with respect to the flow-performance relationship. Thus, the incentives of fund manager to alter the riskiness of portfolio is also different in both fund groups. In this line, we suggest that the fund age may influence the investment style and the management decisions by mutual fund managers.

Fund_fees: we include the management and the deposit fees of each fund. According to the previous literature, the effect of fund fees on managerial ability and fund behaviour is not clear. Prather et al. (2004) find a positive impact of fees on performance if these expenses are to support research. Gil-Bazo and Ruiz-Verdú (2009) find that fund performance worsens with increasing fund management fees, while Chen et al. (2004) argue that there is no relationship between management fees and fund performance. We suggest that fund fees may be related to a greater research effort and, therefore, managers of funds with higher fees have a higher level of information that leads them to make similar decisions in their portfolio holdings.

Fund_#stocks: we obtain the number of stocks from portfolio holdings. Our intuition is based on the idea that the similarity of number of stocks held may be related to the portfolio overlap in a fund pair. Kacperczyk et al. (2005) find that managers of more diversified funds (that is with higher number of different stocks) hold a portfolio that closely resembles the total market portfolio. However, concentrated funds, which are the funds with a lower number of stocks, follow distinct investment styles. In accordance with these authors, we think that the portfolio overlap may be higher for the fund pairs in which both funds have a high number of stocks.

Fund_return: is the past annual gross return. Previous literature has documented that fund managers may have different reactions to extreme results of funds. On the one hand, managers of funds with a high past performance, may close positions influenced by the disposition effect (Cici, 2012). On the other hand, managers of funds that show the lowest past return may start to make different decisions or may follow a strategy of risk shifting based on a desire to improve their outcome in order to avoid withdrawals of funds by investors (Chen et al., 2010) because their reputations and salaries may depend on their performance record (Massa et al., 2009). However, others may continue to make similar decisions influenced by their cognitive biases or top-management strategies. In addition, the top-management could replace these managers, given that there is an inverse relationship between the likelihood of managerial replacement and past fund performance (Khorana, 1996).

Time: we include this variable because the Spanish mutual fund industry has suffered important structural changes due to the intense restructuring process of the financial sector in recent years. Therefore, we could expect that these structural changes have been able to influence the portfolio overlap pattern.

Table 2. 3 – Portfolio overlap and characteristics of mutual funds

This table shows the results obtained by estimating Equation 2.2 using RE with robust standard errors, which is supported by the Hausman test, from December 1999 to June 2018. Where the dependent variable is the $Portfolio\ Overlap_{i,j,t}$ at the stock level and the independent variables are dummy variables. We calculate the percentile rank of each fund-month in each characteristic (*Fund_size*, *Fund_age*, *Fund_#stocks*, *Fund_fees* and *Fund_return*) and we determine the quintile into which mutual funds are. For these characteristics, the model includes four dummy variables: *Same* takes a value equal to 1 when fund *i* and *j* in month *t* are in the same quintile; *BothQ1* takes a value equal to 1 when funds *i* and *j* in month *t* are in the top quintile; *BothQ5* takes a value equal to 1 when fund *i* and *j* in month *t* are in the bottom quintile; Opposite is equal to 1 when in month *t*, either fund *i* or fund *j* is in the top quintile and in the other is in the bottom quintile; $Fund\_family_{i,j,t}$ is equal to 1 when, in month *t*, funds *i* and *j* are in the same family; and $Time_t$ ranges from 1 in the first month to 223 in the last month. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		Coefficient	
	Constant	0.309***	(0.000)
Fund_size	Same	-0.001	(0.432)
	BothQ1	0.021***	(0.000)
	BothQ5	-0.010***	(0.000)
	Opposite	-0.002**	(0.027)
Fund_age	Same	0.005***	(0.000)
	BothQ1	-0.015***	(0.005)
	BothQ5	-0.031***	(0.000)
	Opposite	0.000	(0.666)
Fund_#stocks	Same	0.012***	(0.000)
	BothQ1	0.009***	(0.000)
	BothQ5	-0.021***	(0.000)
	Opposite	-0.016***	(0.000)
Fund_fees	Same	0.010***	(0.000)
	BothQ1	0.015***	(0.000)
	BothQ5	-0.008***	(0.000)
	Opposite	0.000	(0.784)
Fund_return	Same	0.010***	(0.000)
	BothQ1	-0.009***	(0.000)
	BothQ5	-0.001	(0.279)
	Opposite	-0.010***	(0.000)
Fund_family		0.068***	(0.000)
Time		-0.003***	(0.000)
#Observations		1,374,463	
Wald		2,241.69***	(0.000)
R-squared		6.22%	
VIF		1.23	

Table 2.3 shows the results of Equation 2.2.[17] The coefficient of the dummy variable *Fund_family* is positive and statistically significant; this result gives robustness

[17] In order to deal with possible endogeneity concerns, we also define Equations 2.2, 2.4 and 2.10 with independent variables lagged by one month. The results obtained are robust and are in Appendix 2.3.

to the finding of Table 2.2, showing that the portfolio overlap is higher for fund pairs within the same family than for fund pairs in different families. This result is in line with the findings of Elton et al. (2007) and Pool et al. (2015) who argue that this is due to shared analysts and other shared stock-selection resources. Regarding the *Time* variable, the results provide evidence on a significantly negative pattern over time. This finding corroborates the decrease of the average portfolio overlap shown in Table 2.2.

Focusing on the fund characteristics, we find that when two funds have very different sizes, or both are among the smallest funds; their portfolio overlap is significantly lower. In this line, Pool et al. (2015) also find that the overlap between funds that have different sizes is lower, statistically significant at the 1% level. However, we also find that in a pair where both funds are the largest, the portfolio overlap is significantly higher. These results are in line with our hypothesis that managers of large funds may have common skills and access to a common higher level of information.

According to the age variable, we find a significantly lower portfolio overlap amongst fund pairs in which both funds have very different ages. These results are in line with our hypothesis that fund managers alter the riskiness of portfolio holdings at different levels depending on the fund age. We also find that portfolio overlap is significantly higher in fund pairs with similar ages, but when these funds are not amongst neither the youngest nor the oldest funds. The oldest funds, which have sufficient experience in the market, could develop their own portfolio holding strategy allocation. While the youngest funds, which face the challenge of getting market share, have incentives to offer differentiated portfolios as much as possible from those existing funds according to Mamaysky and Spiegel (2002) and Khorana and Servaes (2012).

Table 2.3 also shows that the portfolio overlap is significantly higher (lower) in fund pairs that have the highest (lowest) number of stocks held in portfolio holdings and the highest (lowest) fees. With regard to the number of stocks variable, the result is line with the conclusion of Kacperczyk et al. (2005) who argue that managers of more diversified funds hold portfolios that look like the total market portfolio and more concentrated funds follow distinct investment styles.

With respect to the fees variable, the results could be explained by the relationship between fund fees and a greater research effort. Thus, managers of funds with higher fees have a higher level of matching information that leads them to make similar decisions.

In relation to the past annual gross return, we find that the portfolio overlap is higher in fund pairs that have similar past annual gross returns, but we do not observe this result in cases where fund pairs have the highest or lowest past annual gross return. These results confirm our hypothesis that fund managers' reactions to an extreme performance may be different and consequently, the portfolio overlap between their funds is lower.

2.4 Portfolio overlap across families and its determinants

Our results show a higher correlation between fund pairs within the same family. In this section, we focus on portfolio holding similarities within a fund family. Previous literature reveals evidence that the top-management strategies are not the same in all families, thus, we may think that neither is the correlation between their funds. Evans et al. (2020) contribute to the literature on heterogeneity in management strategies between families, reconciling evidence of the coexistence of cooperative families and competitive families in the US mutual fund industry. In this line, we examine whether there are families that have a significantly higher portfolio overlap between their funds in order to study the existence of heterogeneity between families regarding the family portfolio overlap. Therefore, in this section, we test the following null hypothesis:

2.2H₀: There are no significant differences between the portfolio overlap of different fund families.

We calculate the monthly family portfolio overlap as the average portfolio overlap of fund pairs within this fund family.

$$Family\ portfolio\ overlap_{f,t} = \overline{Portfolio\ Overlap_{i,j,t}}\ x\ 100 \tag{2.3}$$

where $Family\ portfolio\ overlap_{f,t}$ is the portfolio overlap within fund family *f* in month *t*. $Portfolio\ Overlap_{i,j,t}$ is the portfolio overlap between funds *i* and *j* in month *t* when both funds belong to the same fund family *f*.

Table 2.4 shows that the average family portfolio overlap in the Spanish industry is equal to 33.31% at the stock level and it is 62.46% and 70.70% at the sector and industry levels, respectively.[18] The findings also reveal that the family overlap at stock level decreases over time. We also obtain the family overlap weighted by the total net assets in Euro equity category and the family overlap weighted by the number of funds managed in this category. The findings at stock level show the weighted averages are higher than the equal-weighted average overlap which reveals evidence that the largest families with the highest number of funds have a higher family portfolio overlap. To test our null hypothesis, we split families into terciles according to their family overlap. We find that the average family portfolio overlap at stock level of fund families which are in the top tercile (*T1*) and the average of those which are in the bottom tercile (*T3*) are 55.55% and 15.67%, respectively, with a difference equal to 39.89% that is statistically significant at the 1% level. Therefore, we reject the null hypothesis that all fund families have the same portfolio overlap between their funds. We obtain similar results when we measure the portfolio overlap at sector and industry levels.

[18] The annual results of portfolio overlap at the sector and at the industry levels are in Appendix 2.2.

Table 2. 4 – Family portfolio overlap

Panel A, Panel B and Panel C report the results of portfolio overlap at the stock level, at the sector level and at the industry level, respectively. This table shows the average family portfolio overlap and the average family portfolio overlaps weighted by total net assets in Euro equity category and weighted by number of Euro equity funds. The average overlap of families that are in the top tercile *(T1)* and the average overlap of families that are in the bottom tercile (*T3*). The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. We apply the mean-difference test for paired samples. In all columns, the annual average is obtained with the monthly portfolio overlap data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock						
Year	Family	Family	Family	Family	Family	Mean-difference test
2000	39.06%	43.67%	41.30%	70.07%	13.50%	56.57%*** (0.000)
2001	36.59%	39.94%	37.39%	62.98%	15.04%	47.95%*** (0.000)
2002	34.98%	39.57%	35.64%	62.14%	12.55%	49.59%*** (0.000)
2003	36.05%	38.35%	36.93%	62.78%	14.78%	48.00%*** (0.000)
2004	38.13%	40.63%	39.10%	63.20%	18.13%	45.07%*** (0.000)
2005	34.19%	36.37%	36.78%	55.77%	16.82%	38.95%*** (0.000)
2006	32.29%	34.19%	34.55%	53.63%	15.19%	38.44%*** (0.000)
2007	30.71%	31.49%	32.39%	50.77%	15.53%	35.24%*** (0.000)
2008	30.19%	32.09%	33.66%	51.52%	16.08%	35.44%*** (0.000)
2009	30.94%	32.86%	33.62%	45.26%	18.65%	26.61%*** (0.000)
2010	27.73%	32.60%	32.61%	47.89%	19.14%	28.75%*** (0.000)
2011	28.18%	32.58%	34.41%	50.34%	19.95%	30.39%*** (0.000)
2012	32.88%	31.06%	33.08%	47.21%	16.81%	30.40%*** (0.000)
2013	37.19%	31.45%	32.11%	47.55%	15.80%	31.75%*** (0.000)
2014	35.47%	31.34%	30.92%	48.45%	15.10%	33.36%*** (0.000)
2015	35.23%	32.84%	31.21%	52.22%	15.14%	37.08%*** (0.000)
2016	38.12%	30.65%	27.57%	48.59%	14.20%	34.39%*** (0.000)
2017	35.49%	31.86%	28.30%	50.26%	13.71%	36.55%*** (0.000)
2018	33.83%	30.62%	28.63%	50.26%	13.97%	36.29%*** (0.000)
Dec1999-Jun2018	33.31%	34.57%	33.87%	55.55%	15.67%	39.89%*** (0.000)
Panel B: Sector						
Dec1999-Jun2018	62.46%	61.61%	62.73%	76.79%	49.63%	27.17%*** (0.000)
Panel C: Industry						
Dec1999-Jun2018	70.70%	69.84%	70.73%	83.52%	58.20%	25.32%*** (0.000)

Once we find that there are families with a significantly higher portfolio overlap, we apply a panel data model to examine the family characteristics that enhance portfolio overlap.[19]

$$Family\ portfolio\ overlap_{f,t} = f\,(Bank_{f,t};\ Family\_size_{f,t};\ Family\_age_{f,t};$$
$$Family\_\%EuroEquity_{f,t};\ \varepsilon_{f,t}) \qquad (2.4)$$

where $Family\ portfolio\ overlap_{f,t}$ is the portfolio overlap within fund family *f* in month *t* at stock level. $Bank_{f,t}$ takes a value equal to 1 when a fund family depends on a banking or insurance company according to its governance structure. $Family\_size_{f,t}$ is the log-normal of total size of fund family *f* in month *t*. $Family\_age_{f,t}$ is the age of fund family *f* obtained from the inception date of the oldest fund in the family. $Family\_\%EuroEquity_{f,t}$ is the percentage of the assets under management in the Euro equity category with respect to the total assets under management in the industry within fund family *f* in month *t*.

Bank: Tykvová (2006) indicates that private independent fund companies typically concentrate in particular industries and establish networks in this industry within company. Therefore, we believe that there may be a higher family portfolio overlap within the independent fund families for a high degree of specialisation.

Family_size: is measured as the total assets under management within a family. According to Chen et al. (2004), the size of a fund erodes fund performance. However, Zhao (2004) argues that mutual fund families obtain benefits by charging fees to investors in all funds and, therefore, they have incentives to take action with the objective of

[19] Our panel data shows autocorrelation and heteroscedasticity. Hence, we require a methodology that corrects the standard errors to solve these issues. Prais-Winsten, Generalised Least Squares (GLS), FE and RE with robust standard errors models take into account autocorrelation and heteroscedasticity. To verify the robustness of our results, we estimate Equations 2.4 and 2.10 using these four models. Regarding the FE and RE models, the Hausman test indicates that the FE model is the preferred specification. However, the time-invariant independent variables will be ignored by this specification (in Equations 2.4 and 2.10 the *Bank* variable has not change over the sample period in each family and hence, this affects as a time-invariant variable) and in this case, the RE model may be a viable alternative (Hill et al., 2020).

increasing the investor inflows and therefore of maximising the total assets under management. In addition, based on these findings, we consider that fund families have incentives to offer new funds although these funds are similar to existing funds in order to increase the total assets under management, but preventing the existence of too large funds in the family. The result of the influence of family size on family portfolio overlap is interesting for individual investors because of the high market concentration in the Spanish market.

We also include the interaction between *Bank* and *Family_size* in order to distinguish larger fund families which belong to a banking group from the remaining families. We consider that within these families, the managers can have access to a high number of internal and external information reports because in this way the entire fund family benefits from the resources. In addition, based on the results of Table 2.4, which show that the TNA-weighted average is higher than the equal-weighted average overlap, we could expect the coefficient of this interaction to be positive and significant because the largest families belong to banking groups. Furthermore, our hypothesis is based on the idea that when we focus on the ownership of their own stocks by banking groups, the overlap is greater in fund families belonging to this banking group than in other families belonging to other banking groups. In this line, Massa and Rehman (2008) provide evidence that the ownership of an asset management company can have a significant impact on the portfolio holdings of funds.[20]

[20] Previous literature has documented several factors and reasons that influence the bank-affiliated funds' decisions to increase their holdings of the parent banks' stocks. Golez and Marin (2015) document that fund managers serve the interest of the owners of asset management firms (the banks) with the aim to support their stock prices, specially, at the time of large price drops. In this sense, Gil-Bazo et al. (2020) show that the bank-affiliated funds support the prices of bonds issued by their parent banks during the Global Financial Crisis, GFC, in 2008 and the European sovereign debt crisis in 2011. Gómez-Bezares and Przychodzen (2018) also argue that the significant positive tendency to buy the parent banks' equity for their bank-affiliated funds is motivated by both external pressure and individual taste.

Family_age: we consider that families start with fewer resources and less ability to control the information of a large number of stocks and thus, our hypothesis is that the family portfolio overlap may be higher in families with a short experience in the fund market.

Family_%EuroEquity: we also include the weight of the Euro equity funds category within each family. Following the resources-based theory of the companies (see e.g. Silverman, 1999 cited by Casavecchia and Ge, 2019), the fund families with a greater focus on a certain category could possess more institutional advantages from experience and learning. In this line, Van Nieuwerburgh and Veldkamp (2010) argue that the private information acquisition through specialized learning results in a higher degree of asset concentration. Kacperczyk et al. (2005) also show that a higher degree of industry concentration is a measure of informational advantages. Therefore, the weight of the Euro equity funds category within a fund family may influence the family portfolio overlap. Specifically, our hypothesis is that the overlap may be higher in families with a higher weight in this category.

The results of the different models applied in Table 2.5 are robust. The findings reveal evidence that the family portfolio overlap is higher in families which do not belong to a banking or insurance company, in line with the conclusions of Sahlman (1990) and Barry (1994) about the higher degree of specialisation of private independent fund management companies. However, when we include the interaction between the dummy variable *Bank* and the variable *Family_size*, we find a higher family overlap in the larger banking families; these are the families which belong to larger banking groups. These results confirm our null hypothesis that these larger families may have interest in offering new funds, even when these new funds have similar portfolio holdings as existing funds. With this practice, the fund families would prefer to avoid very large funds in cases where size erodes performance. In addition, large banking groups usually have the stock of their banks listed in stock exchange. When we focus on the overlap in portfolios of stocks of banking groups, we find a statistically significant overlap in the family which belongs to this specific group than in the rest of the families which belong to other banking groups.[21]

Table 2. 5 – The fund family characteristics that enhance portfolio overlap

This table shows the results obtained by estimating Equation 2.4 using Prais-Winsten, GLS, FE and RE with robust standard errors from December 1999 to June 2018. Where the dependent variable is *Family portfolio overlap*$_{f,t}$ that is the portfolio overlap within fund family *f* in month *t* at the stock level and the independent variables are: *Bank*$_{f,t}$ that takes a value equal to 1 when a fund family depends on a banking or insurance company regarding its governance structure; *Family_size*$_{f,t}$ is the log-normal of the total size of fund family *f* in month *t; Bank*$_{f,t}$ *x Family_size*$_{f,t}$ is the interaction between the dummy variable *Bank*$_{f,t}$ and the variable *Family_size*$_{f,t}$ *; Family_age*$_{f,t}$ is the age of fund family *f* in month *t* obtained from the inception date of the oldest fund in the family*; and Family_%EuroEquity*$_{f,t}$ is the percentage of the assets under management in the Euro equity category with respect to the total size of fund family *f* in month *t.* The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Prais-Winsten	GLS	Prais-Winsten	GLS	FE (*robust standard errors*)	RE (*robust standard errors*)
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	0.113***	-0.025	0.729***	0.479***	0.190***	0.112***
	(0.000)	(0.627)	(0.000)	(0.000)	(0.001)	(0.003)
Bank	-0.123***	-0.076***	-0.828***	-0.684***		-0.126**
	(0.000)	(0.000)	(0.000)	(0.000)		(0.016)
Family_size	0.026***	0.033***	-0.024**	-0.007	-0.064**	-0.061**
	(0.000)	(0.000)	(0.034)	(0.468)	(0.034)	(0.035)
Bank x Family_size			0.056***	0.478***	0.097**	0.099**
			(0.000)	(0.000)	(0.026)	(0.013)
Family_age	-0.004***	-0.005***	-0.004***	-0.005***	-0.005**	-0.006**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.045)	(0.037)
Family_%EuroEquity	0.040**	0.074***	0.062***	0.074***	0.272**	0.280*
	(0.039)	(0.006)	(0.001)	(0.003)	(0.012)	(0.082)
R-squared	23.74%		24.34%		8.17%	8.14%
Wald	118.18***	93.33***	169.88***	119.26***	124.52***	124.70***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman Test						26.12***
						(0.000)
#Observations	5,667	5,667	5,667	5,667	5,667	5,667

[21] In the first, second and third largest fund families according to total net asset under management in the Spanish industry which belong to a banking group, we find that the family overlap in their banking group stock is equal to 4.23%, 4.56% and 2%, respectively. In all cases, the overlap is statistically significantly higher than in the rest of families belonging to other groups.

There resulted are very remarkable in the Spanish mutual fund industry due to the high concentration and the high dependence on the banking sector with respect to other European markets as documented in previous studies (Ferreira and Ramos, 2009; Ferreira et al., 2013). According to data reported by Inverco (2018), the top 10 and top 5 fund management companies manage more than 75% and 40% of the total fund assets as opposed to other fund industries such as the UK market, where the top 10 and top 5 fund families represents the 45% and the 26% of the total fund assets (The Investment Association, 2018), In addition, the 87% of Spanish funds are managed by banking groups, a percentage of funds notably higher with respect to other European countries: France (23%); UK (25%); Portugal (38%) and Germany (69%) (EFAMA, 2018).

Table 2.5 also shows that the family overlap is higher in younger families, which may have fewer resources, and less ability to control information. Finally, the results show that the family portfolio overlap is higher in the families with a higher weight in the Euro equity category. In line with previous studies on the fund family specialization (Kacperczyk et al., 2005; Van Nieuwerburgh and Veldkamp, 2010; Casavecchia and Ge, 2019), the top management of these families may allocate more resources in this category from which all of the family managers could benefit.

2.5 Drivers of the level of autonomy of managers

Several studies have focused on behaviours within fund families (Chen et al., 2004; Elton et al., 2007; Cici et al., 2018). They argue that most mutual funds operate as part of fund families which make strategic decisions that have an influence on the operations and performance of their own funds. However, these authors are implicitly considering the existence of coordination between decisions within fund families, focusing on the top management of a fund family, but neglecting the decisions at the individual level of fund managers (Kempf and Ruenzi, 2008). Fund managers make differential decisions that may provide a significantly different result (positive or negative) to investors allowing the managers to promote themselves and stand out from others whether the return is significantly positive. In this sense, Agarwal et al. (2009) indicate that managerial incentives depend on fund performance. Mason et al. (2016) also argue that fund managers' position, reputation and salary depend on their performance records.

Our hypothesis is based on the idea that the managers' decisions can be explained by both the influence of family top-management and the autonomy of fund managers. Kacperczyk and Seru (2012) consider the coexistence of two different family organisational structures: centralised and decentralised. They show that decentralised funds offer greater autonomy to their managers, as well as incentives and flexibility to produce more valuable information and thus, more benefits for investors than the centralised decision-making process. In this section, we first compute the fund manager autonomy within families and then, we study whether the fund manager autonomy is the same in all fund families, being the null hypothesis:

2.3H_0: There are no significant differences in autonomy between different fund families.

In line with Elton et al. (2007) who argue that a common family approach could result in similar exposures to various industries, we consider the portfolio overlap at the sector level as the approach of the general investment outline. Then, within this investment strategy, managers can choose specific stocks that are held in portfolio holdings. We evaluate this choice capacity on a twofold approach depending on whether the general investment outline corresponds to the whole fund sample or whether it corresponds to each fund family. Firstly, we compare for each fund pair i and j in month t the excess overlap (*Excess Overlap*) at the industry level (*Portfolio Overlap (industry)*) over the stock level (*Portfolio Overlap (stock)*) as follows:

$$\textit{Excess Overlap}_{i,j,t} = \textit{Portfolio Overlap (industry)}_{i,j,t} - \textit{Portfolio Overlap (stock)}_{i,j,t} \quad (2.5)$$

Note that the higher the excess overlap at the industry level over the stock level the higher level of autonomy of these two fund managers in the selection of stocks within a certain industry because their portfolios at the stock level are more different than at the industry level. Even if they have a similar general investment outline, the resulting portfolios differ in terms of stocks when they select different specific stocks.

Secondly, we obtain the fund manager autonomy for each fund *i* in each month *t* with the average of its excess overlap values following two different approaches. In the first approach (*Fund manager autonomy inter-family*), the general investment outline corresponds to the whole fund sample and hence, the fund manager autonomy for each fund *i* is obtained with all the excess overlap values regardless of whether the fund *i* is compared with funds within its same family *f* or with funds of other families.. In the second approach (*Fund manager autonomy intra-family*), the general investment outline corresponds to the fund family and thus, the fund manager autonomy for each fund *i* is obtained with the excess overlap values of the comparisons with other funds that belong to the same family *f*.

$$\textit{Fund manager autonomy inter-family}_{i,t} = \overline{\textit{Excess Overlap}_{i,t}} \;\; \forall\, i \neq j \textit{ and } \forall\, i \in f \quad (2.6)$$

$$\textit{Fund manager autonomy intra-family}_{i,t} = \overline{\textit{Excess Overlap}_{i,t}} \;\; \forall\, i \neq j \textit{ and } \forall\, i,j \in f \quad (2.7)$$

Thirdly, we obtain the level of autonomy for each fund family *f* with the average of the fund manager autonomy values of all funds within the family, both at inter level (*Inter-family autonomy*) and intra level (*Intra-family autonomy*) as follows:

$$\textit{Inter-family autonomy}_{f,t} = \overline{\textit{Fund manager autonomy inter-family}_{i,t}} \quad \forall\, i \in f \quad (2.8)$$

$$\textit{Intra-family autonomy}_{f,t} = \overline{\textit{Fund manager autonomy intra-family}_{i,t}} \quad \forall\, i \in f \quad (2.9)$$

Table 2. 6 – Manager autonomy within fund families

This table shows the average autonomy of managers within fund families, the average weighted by total net assets in Euro equity category and by number of Euro equity funds, the average within families that are in the top tercile *(T1)* and in the bottom tercile (*T3*). Panel A reports the results of inter-family autonomy and Panel B reports the results of intra-family autonomy as defined in Equations 2.8 and 2.9. The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. In all columns, the annual data is obtained using the monthly data. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Inter-family autonomy

	family autonomy	family autonomy (*TNA-weighted*)	family autonomy (#funds-*weighted*)	family autonomy (*T1*)	family autonomy (*T3*)	Mean-difference test (*T1-T3*)
2000	48.66%	55.15%	49.76%	54.97%	42.16%	12.81%*** (0.000)
2001	48.66%	46.91%	44.86%	53.79%	43.63%	10.16%*** (0.000)
2002	47.20%	41.29%	42.49%	52.45%	41.53%	10.92%*** (0.000)
2003	47.94%	46.29%	45.90%	53.57%	41.77%	11.80%*** (0.000)
2004	48.90%	50.67%	47.60%	54.84%	42.43%	12.41%*** (0.000)
2005	48.71%	54.34%	49.23%	54.72%	41.91%	12.81%*** (0.000)
2006	48.83%	41.12%	42.71%	54.44%	43.50%	10.95%*** (0.000)
2007	47.96%	47.33%	43.67%	55.39%	42.91%	12.48%*** (0.000)
2008	47.79%	47.91%	48.04%	53.63%	41.85%	11.78%*** (0.000)
2009	46.84%	30.95%	49.53%	53.43%	40.98%	12.45%*** (0.000)
2010	50.38%	38.39%	49.85%	56.08%	44.52%	11.55%*** (0.000)
2011	50.36%	39.70%	47.10%	56.27%	44.59%	11.68%*** (0.000)
2012	49.79%	53.02%	48.47%	56.18%	44.00%	12.18%*** (0.000)
2013	51.48%	54.87%	48.38%	57.87%	45.90%	11.97%*** (0.000)
2014	52.42%	50.07%	48.90%	58.98%	46.41%	12.56%*** (0.000)
2015	51.88%	52.27%	50.01%	58.67%	45.54%	13.13%*** (0.000)
2016	52.71%	48.60%	50.46%	59.09%	46.35%	12.74%*** (0.000)
2017	53.06%	52.12%	51.68%	59.43%	46.46%	12.97%*** (0.000)
2018	52.63%	52.65%	51.73%	59.08%	45.75%	13.33%*** (0.000)
Dec1999-Jun2018	49.72%	47.47%	47.82%	55.03%	43.32%	11.71%*** (0.000)

Panel B: Intra-family autonomy

	family autonomy	family autonomy (*TNA-weighted*)	family autonomy (#funds-*weighted*)	family autonomy (*T1*)	family autonomy (*T3*)	Mean-difference test (*T1-T3*)
2000	32.52%	31.51%	31.95%	51.54%	13.28%	38.26%*** (0.000)
2001	33.70%	31.93%	33.53%	49.98%	16.87%	33.10%*** (0.000)
2002	33.73%	30.70%	32.41%	52.38%	14.98%	37.40%*** (0.000)
2003	31.80%	30.88%	30.94%	47.80%	15.88%	31.92%*** (0.000)
2004	32.73%	31.91%	31.64%	47.96%	17.51%	30.45%*** (0.000)
2005	36.63%	33.97%	34.11%	50.74%	22.49%	28.24%*** (0.000)
2006	37.89%	35.18%	35.18%	54.93%	22.03%	32.90%*** (0.000)
2007	36.37%	36.87%	33.87%	56.71%	21.93%	34.79%*** (0.000)
2008	37.04%	37.10%	36.37%	55.55%	20.86%	34.69%*** (0.000)
2009	38.14%	32.10%	36.34%	52.79%	24.32%	28.47%*** (0.000)
2010	38.75%	33.70%	37.82%	53.21%	25.18%	28.03%*** (0.000)
2011	37.10%	32.69%	35.95%	52.61%	23.53%	29.08%*** (0.000)
2012	39.37%	33.07%	37.61%	54.41%	26.95%	27.45%*** (0.000)
2013	39.67%	34.15%	38.34%	55.74%	26.26%	29.48%*** (0.000)
2014	42.05%	38.96%	41.02%	56.27%	27.49%	28.78%*** (0.000)
2015	42.17%	40.91%	41.38%	56.51%	26.79%	29.72%*** (0.000)
2016	45.20%	42.82%	44.72%	58.19%	29.75%	28.44%*** (0.000)
2017	46.19%	42.49%	45.70%	60.34%	29.42%	30.92%*** (0.000)
2018	45.54%	43.24%	44.63%	60.08%	29.43%	30.65%*** (0.000)
Dec1999-Jun2018	38.02%	35.26%	36.80%	53.26%	21.64%	31.61%*** (0.000)

To examine whether the autonomy of managers is similar for all fund families, we split families into terciles according to these measures. Table 2.6 shows that we reject the null hypothesis in the mean-difference test between the average autonomy of managers within families that are in the top tercile (*T1*) and the average of those are in the bottom tercile (*T3*). Therefore, our findings indicate that the autonomy is significantly higher in some families than others, regardless of the level of autonomy meause used.

We also observe that, in general, both the average weighted by total net assets and the average weighted by number of funds are lower than the equal-weighted average. This result reveals the autonomy of managers is higher in smaller families that could be explained by the fact that smaller families have less resources to obtain both internal and external reports on specific stocks from which fund managers' decisions can be adressed.

Once we found that there are families with a significantly higher autonomy of managers than others, we apply a panel data model to detect the family characteristics that enhance the autonomy among funds within a family. Specifically, we use the following model.

$$\begin{aligned} \textit{Intra-family autonomy}_{f,t} = f\,(&\textit{Bank}_{f,t};\ \textit{Family\_size}_{f,t};\ \textit{Family\_age}_{f,t};\\ &\textit{Family\_\%EuroEquity}_{f,t};\ \varepsilon_{f,t}) \end{aligned} \tag{2.10}$$

where $\textit{Intra-family autonomy}_{f,t}$ is the autonomy level of managers within fund family *f* in the portfolio holding allocation. $\textit{Bank}_{f,t}$ takes a value equal to 1 when fund family *f* is dependent on a banking or insurance group in accordance with the governance structure. $\textit{Family\_size}_{f,t}$ is the log-normal of total size of fund family *f* in month *t*. $\textit{Family\_age}_{f,t}$ is the age of fund family *f* obtained from the inception date of the oldest fund in the family. $\textit{Family\_\%EuroEquity}_{f,t}$ is the percentage of the assets under management in the Euro equity category with respect to the total size of fund family *f* in month *t*.

We suggest that in the large fund families that belong to a banking group, the top-management may have a greater influence on the selection of stocks within a specific sector, because the top-management may have a higher level of stock information obtained in other areas of analysis within the group. Jordan et al. (2012) find that the bank-affiliated institutional investors follow strongly recommendations issued by their own analysts. In addition, large families have more resources and more analysts that could have a significant influence on the trading decisions of fund managers. Therefore, our hypothesis is that there is less fund manager autonomy in the portfolio holding allocation within larger families which belong to banking groups.

Table 2. 7 – The fund family characteristics that enhance the manager autonomy

This table shows the results obtained by estimating Equation 2.10 using Prais-Winsten, GLS, FE and RE with robust standard errors from December 1999 to June 2018. Where the dependent variable is $Intra\text{-}family\ autonomy_{f,t}$ which is the autonomy level of managers within fund family *f* in month *t* at the stock level and the independent variables are: $Bank_{f,t}$ is equal to 1 if a fund family depends on the banking or insurance company according to its governance structure; $Family\_size_{f,t}$ is the log-normal of total size of fund family *f* in month *t;* $Bank_{f,t}$ *x* $Family\_size_{f,t}$ is the interaction between the dummy variable $Bank_{f,t}$ and the variable $Family\_size_{f,t}$; $Family\_age_{f,t}$ is the age of fund family *f* obtained from the inception date of the oldest fund in the family; and $Family\_\%EuroEquity_{f,t}$ is the percentage of the value in the Euro equity category with respect to the total size of fund family *f* in month *t.* The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Prais-Winsten	GLS	Prais-Winsten	GLS	FE (*robust standard errors*)	RE (*robust standard errors*)
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	0.525***	0.488***	0.261	0.218**	0.529***	0.273**
	(0.000)	(0.000)	(0.345)	(0.019)	(0.005)	(0.033)
Bank	0.129***	0.088***	0.431***	0.418***		0.108***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.006)
Family_size	-0.025***	-0.023***	-0.004	-0.002	0.058**	0.053**
	(0.000)	(0.000)	(0.550)	(0.827)	(0.015)	(0.017)
Bank x Family_size			-0.024***	-0.025***	-0.084**	-0.086***
			(0.002)	(0.001)	(0.016)	(0.005)
Family_age	0.007***	0.007***	0.007***	0.007***	0.002**	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)	(0.013)
Family_%EuroEquity	0.023	0.068***	0.014	0.055**	0.100	-0.094
	(0.119)	(0.002)	(0.348)	(0.015)	(0.343)	(0.335)
R-squared	50.56%		50.55%		14.27%	14.22%
Wald	351.44***	197.97***	351.27***	187.85***	123.90***	119.90***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman Test					27.68***	
					(0.000)	
#Observations	5,667	5,667	5,667	5,667	5,667	5,667

The results of the different models applied in Table 2.7 are robust. The findings report evidence of a lower fund manager autonomy in the portfolio holding allocation within larger families which belong to a banking group. Additionally, we also analyse the effect of family age on the manager autonomy. The results shown in Table 2.7 shows a higher autonomy in the stock-picking within a specific sector for older fund families. This finding is in line with the study of Kozubíková et al. (2016) who test whether the time spent in the market of a company influences the autonomy of employees. They report that the older companies tent to provide a higher freedom and flexibility to develop and implement new ideas and initiatives due to the high company's positioning and stability within the market.

2.6 Performance of investors in a single fund family

Previous literature reveals evidence that individual investors usually concentrate all of their fund investment in a single fund family. Our objective is to test whether this initial selection of fund family plays an important role in investors' performance. We hypothesise that the level of overlap of the funds and manager autonomy in the portfolio holding allocation within a fund family could influence that performance. Elton et al. (2007) argue that investors are negatively affected when they pick a fund family with a high correlation between its funds. Kacperczyk and Seru (2012) also show that, compared with funds from families with a centralised decision-making process, funds from decentralised families offer greater autonomy to their managers, as well as incentives and flexibility to produce more valuable information and thus, resulting in more benefits for investors. Therefore, we suggest that individual investors could obtain benefits from a higher level of management autonomy in a setting in which fund managers freely pick stocks within each sector.

In this section, to examine whether the family portfolio overlap and the fund manager autonomy within a family influence the performance of the fund and thus, the results for investors who decide to invest in it, we apply the following FE model according to the result of Hausman test:

$$\begin{aligned} \textit{Excess Family return}_{f,t} = \alpha + B_1 \textit{ Excess Family portfolio overlap}_{f,t} + \\ + B_2 \textit{ Excess Intra-family autonomy}_{f,t} + \varepsilon_{f,t} \end{aligned} \qquad (2.11)$$

where $\textit{Excess Family return}_{f,t}$ is the difference between the average daily net return of all funds in fund family *f* and the average daily net return of the rest of funds that are in other families different from family *f* on day *t*. $\textit{Excess Family portfolio overlap}_{f,t}$ is the difference between the average portfolio overlap of family *f* and the average portfolio overlap of all families. $\textit{Excess Intra-family autonomy}_{f,t}$ is the difference between the average autonomy in family *f* and the average autonomy from all families.

In Equation 2.11, the independent variables of each fund are included as the deviation from the average of all funds in our sample.[22] We apply this model with daily return data, and we consider the constant monthly portfolio overlap data on every day of the month.

Table 2.8 shows the results of Equation 2.11. The findings reveal that the excess portfolio overlap in a family with respect to all funds in our sample has a statistically significantly negative influence on investors' returns whereas, the excess fund manager autonomy has a significantly positive influence.

[22] We obtain that the correlation coefficient between the variable $\textit{Excess Family portfolio overlap}_{f,t}$ and $\textit{Excess Intra-family autonomy}_{f,t}$ is negative and low, specifically, this is equal to -0.012.

Table 2. 8 – Family portfolio overlap, autonomy and investors return

This table shows the results obtained by estimating Equation 2.11 using FE with robust standard errors, which is supported by the Hausman test, from December 1999 to June 2018. Where the variable is *Excess Family return*$_{f,t}$ is the difference between the average daily net return of all funds in fund family *f* and the average daily net return of the rest of funds that are in other families different from family *f* on day *t* and the independent variables are: *Excess Family portfolio overlap*$_{f,t}$ is the excess of portfolio overlap of fund family *f* with respect to the average portfolio overlap of all funds on day *t*; and *Excess Intra-family autonomy*$_{f,t}$ is the difference between the average autonomy of managers in family *f* and the average autonomy of managers of all families. Net return data is provided daily and we consider that the monthly portfolio overlap data is constant during all the month. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Coefficient
Constant	-0.001***
	(0.001)
Excess Family portfolio overlap	-0.008**
	(0.027)
Excess Intra-family autonomy	0.013**
	(0.044)
Hausman Test	6.24**
R-squared	6.37%
Wald	62.30***
	(0.000)

Therefore, individual investors who concentrate their funds in a single family with a high family portfolio overlap have under-diversified their fund investment decisions, as we found in previous sections, and they obtained a lower return. However, investors seem to benefit from a lower similarity between fund portfolio holdings and a higher degree of fund manager autonomy in the portfolio holding allocation within a family. Fund managers have more incentives and flexibility to add value to the fund management within families where is a higher level of autonomy in the portfolio holding allocation according to Kacperczyk and Seru (2012). Therefore, in view of the fact that individual investors concentrate their investment in a single family (Massa 2003; Clare et al., 2014; Gerken et al., 2018) we conclude that the initial selection of a fund family is a crucial decision for investors' performance.

2.7 Conclusions

Earlier literature finds that individual investors concentrate their fund investment decisions in a single fund family and thus, the potential diversification and performance of investors are restricted to this selected fund family. This chapter investigates whether the similitude between the portfolio holdings of funds, as well as the fund manager autonomy within a family is a determinant of performance for individual investors who select this fund family.

We find a higher similitude between portfolio holdings of funds in the same family than across families. Consequently, the potential diversification is lower for individual investors who concentrate all of their fund investments in a single family. Furthermore, the potential diversification is especially lower when investors invest in funds that belong to the same family and when these funds are large and of roughly the same size, hold roughly the same high number of stocks their portfolio, charge similarly high fees, are of similar ages and have similar past annual gross, but when these funds are not amongst neither the youngest nor the oldest funds and do not have the highest or lowest past annual gross return.

We find a greater correlation between funds within the same management company and, as a consequence, a lower diversification for investors who concentrate their funds in the same family. The results also show a significant difference between some fund families and others. Specifically, the similitude between portfolio holdings is higher in larger families which belong to a banking group and do not have wide experience in the fund market. These families could have incentives to offer two twin funds rather than one large one in order to prevent the fund size from eroding its performance, while taking full advantage of family-wide research. This type of research, in less experienced families, would be focused on fewer stocks.

According to the economic implications for individual investors, we conclude that a higher similitude between portfolio holdings not only causes fund families to offer a lower diversification to individual investors, it also has a significantly negative economic effect on them. However, individual investors seem to benefit from a higher autonomy in portfolio holding allocation within stock sectors, which is a significant characteristic of smaller fund families with wide experience that do not belong to a banking group. Our findings reveal that investors could have incentives to invest in different families for a better diversification or in these families in which the potential diversification and fund manager autonomy are higher. These results are also interesting for the top management of mutual fund family because of the positive relation between past performance and future fund flows. Given that we find that diversification and manager autonomy manager have a positive impact on the investors' performance, the top management of fund families could consider encouraging diversification of portfolios between funds within the same family as well as manager's autonomy in decision-making.

Therefore, although academics show that investors often concentrate all of their fund investments in the same family, we suggest that investors could improve their diversification level by selecting funds across families, given that the portfolio overlap between fund pairs in different families is lower. In this line, it would be interesting for future research to examine whether there are family pairs that have a significant similarity and to study the characteristics of these families.

Finally, the conclusions of this study have economic consequences in particular in the Spanish mutual fund market due to the high similarity level among portfolios within the five largest banking fund families, which manage more than 40% of investors' investment funds. Hence, these findings are interesting for industry regulators because a large proportion of individual investors could have their investment fund decisions under-diversified. Nevertheless, the negative pattern of the portfolio overlap that is found could be an indication of an improvement in the efficiency within families and of a reduction in the systemic risk and fragility of the market, which functions as a mechanism for the propagation of shocks.

2. References

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Appendix 2.1: Robustness analyses of the portfolio overlap

Following the studies of Delpini et al. (2019) and Fricke and Fricke (2021), we adopt the cosine similarity between funds *i* and *j* to measure the portfolio overlap between the two portfolios as follows:

$$Portfolio\ Similarity_{i,j,t} = \frac{\sum_{k=1}^{K} w_{i,k,t}\, w_{j,k,t}}{\sqrt{\sum_{k=1}^{K} (w_{i,k,t})^2}\sqrt{\sum_{k=1}^{K} (w_{j,k,t})^2}} \qquad \text{(A2.1)}$$

where $Portfolio\ Similarity_{i,j,t}$ is the value of the portfolio similarity between funds *i* and *j* in month *t*; $w_{i,k,t}$ is the portfolio weight of stock *k* in the fund *i* in month *t*. $w_{j,k,t}$ is the portfolio weight of stock *k* in the fund *j* in month *t*. The magnitude of this metric depends on two factors: the number of common stocks and the weights attached to common stocks.

Table A2.1 provides the average portfolio similarity obtained in Equation A2.1. These results provide evidence about a higher similarity levels among portfolios than those reported by the portfolio overlap measure (Equation 2.1). Nevertheless, the Pearson correlation coefficient between both measures equals to 89.19%, 94.41% and 90.93% for the portfolio overlap at the stock, sector and industry levels, respectively (see Appendix 2.2 for more details). These correlation coefficients are statistically significant at 1%. Table A2.1 also reports a statistically significant higher similarity level in fund pairs within the same fund family than in fund pairs from different families. Figure A2.1 shows the evolution of the portfolio overlap and the portfolio similarity levels over time. As can be observed, both measures report a similar evolution over time

For robustness purposes, we also apply the similarity measure to the fund family analyses. The Pearson correlation coefficient between the family portfolio overlap values and the family portfolio similarity values is equal to 84.42% (statistically significant at the 1% level). The findings also lead us to reject the null hypothesis that all fund families have the same portfolio overlap between their funds. Finally, we obtain similar results on the characteristics of fund pairs with the highest portfolio overlap (Table A2.2) and the characteristics of fund families that enhance portfolio overlap among their funds (Table A2.3 y Table A2.4).

Table A2. 1– Overall results of the portfolio similarity at the fund pair level

Panel A, Panel B and Panel C report the results of portfolio similarity at the stock level, at the sector level and at the industry level, respectively. This table shows, for each year, the overall average portfolio similarity and the number of fund pairs within the same fund family and the number of fund pairs in different families, as well as their average overlap. In this table, we present a yearly report of the number of funds during the sample period, unlike in Table 1 where we present the total number only at three specific points during the sample period. The last column shows the results of the mean difference test between both specific averages with the *p*-value in parentheses. We apply the mean difference test for unpaired samples with different variance (in all cases the null hypothesis is rejected in the test of equal variance). In all columns, the annual average is obtained with the monthly portfolio similarity data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock							
Year	Portfolio similarity	#fund pairs (*same fund family*)	#fund pairs (*different fund family*)	Portfolio similarity (*same fund family*)	Portfolio similarity (*different fund family*)	Mean-difference test	
2000	43.51%	282	11,520	54.89%	43.24%	11.65%***	(0.000)
2001	40.78%	341	13,827	44.79%	40.68%	4.11%***	(0.000)
2002	39.72%	354	14,261	44.21%	39.62%	4.59%***	(0.000)
2003	42.80%	340	15,175	48.98%	42.67%	6.32%***	(0.000)
2004	45.71%	337	13,592	52.40%	45.54%	6.85%***	(0.000)
2005	45.74%	391	14,415	52.48%	45.55%	6.93%***	(0.000)
2006	42.80%	421	15,621	47.06%	42.68%	4.37%***	(0.000)
2007	38.36%	474	16,648	43.00%	38.18%	4.82%***	(0.000)
2008	37.73%	468	16,032	39.23%	37.66%	1.57%***	(0.000)
2009	37.16%	422	14,054	41.78%	36.99%	4.79%***	(0.000)
2010	36.06%	255	10,917	42.13%	35.87%	6.26%***	(0.000)
2011	37.31%	236	9,864	45.98%	37.06%	8.92%***	(0.000)
2012	34.73%	193	7,712	46.81%	34.37%	12.44%***	(0.000)
2013	35.26%	166	6,289	42.92%	35.05%	7.87%***	(0.000)
2014	35.59%	97	4,619	44.09%	35.39%	8.69%***	(0.000)
2015	39.31%	104	5,203	45.05%	39.16%	5.89%***	(0.000)
2016	36.21%	93	4,737	40.60%	36.12%	4.48%***	(0.000)
2017	33.61%	75	4,260	41.38%	33.46%	7.92%***	(0.000)
2018	34.80%	65	4,061	43.38%	34.63%	8.74%***	(0.000)
Dec1999-Jun2018	40.94%	994	32,982	46.69%	40.79%	5.90%***	(0.000)
Panel B: Sector							
Dec1999-Jun2018	69.40%	994	32,982	74.71%	69.26%	5.46%***	(0.000)
Panel C: Industry							
Dec1999-Jun2018	75.60%	994	32,982	79.91%	75.48%	4.43%***	(0.000)

Figure A2. 1 - Evolution of the portfolio overlap and portfolio similarity among fund pairs

This figure represents the evolution of the annual average for the portfolio overlap and the portfolio similarity among Spanish Euro equity funds obtained from monthly values from January 2000 to June 2018.

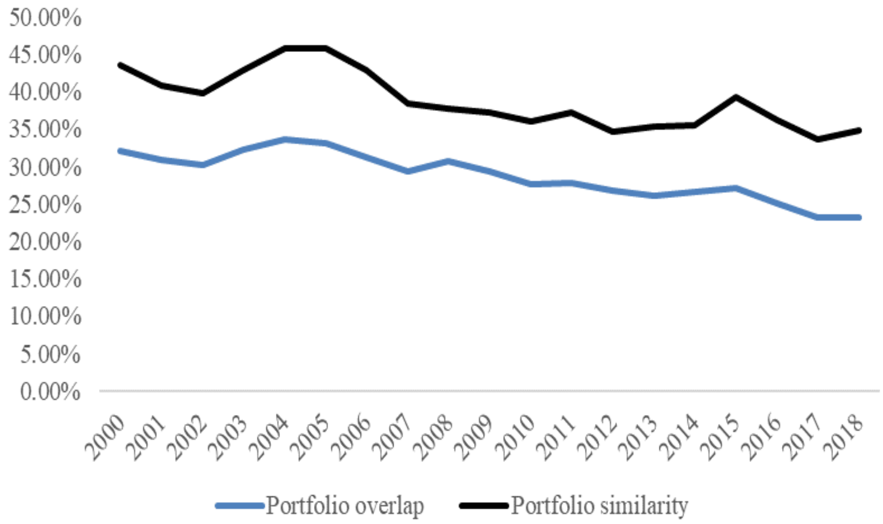

Table A2. 2 - Portfolio Similarity and characteristics of mutual funds

This table shows the results obtained by estimating Equation 2.2 using the portfolio similarity measure and RE with robust standard errors from December 1999 to June 2018, where the dependent variable is the *Portfolio Similarity*$_{i,j,t}$ at the stock level and the independent variables are dummy variables. We calculate the percentile rank of each fund-month in each characteristic (*Fund_size*, *Fund_age*, *Fund_#stocks*, *Fund_fees* and *Fund_return*) and we determine the quintile into which mutual funds are. For these characteristics, the model includes four dummy variables: *Same* takes a value equal to 1 when fund *i* and *j* in month *t* are in the same quintile; *BothQ1* takes a value equal to 1 when funds *i* and *j* in month *t* are in the top quintile; *BothQ5* takes a value equal to 1 when fund *i* and *j* in month *t* are in the bottom quintile; Opposite is equal to 1 when in month *t*, either fund *i* or fund *j* is in the top quintile and in the other is in the bottom quintile; *Fund_family*$_{i,j,t}$ is equal to 1 when, in month *t*, funds *i* and *j* are in the same fund family; and $Time_t$ ranges from 1 in the first month to 223 in the last month. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		Coefficient
	Constant	0.420*** (0.000)
Fund_size	Same	-0.001 (0.336)
	BothQ1	0.029*** (0.000)
	BothQ5	-0.021*** (0.000)
	Opposite	-0.010*** (0.000)
Fund_age	Same	0.005** (0.012)
	BothQ1	-0.014*** (0.000)
	BothQ5	-0.041*** (0.000)
	Opposite	-0.006 (0.458)
Fund_#stocks	Same	0.005*** (0.000)
	BothQ1	0.020*** (0.000)
	BothQ5	-0.014*** (0.000)
	Opposite	-0.008*** (0.000)
Fund_fees	Same	0.002** (0.013)
	BothQ1	0.022*** (0.000)
	BothQ5	-0.007*** (0.008)
	Opposite	0.001 (0.497)
Fund_return	Same	0.010*** (0.000)
	BothQ1	-0.010*** (0.000)
	BothQ5	-0.001 (0.357)
	Opposite	-0.014*** (0.000)
Fund_family		0.047*** (0.000)
Time		-0.004*** (0.000)
#Observations		1,374,347
Wald		1,496.63*** (0.000)
R-squared		6.01%
VIF		1.23

Table A2. 3 - Family portfolio similarity

Panel A, Panel B and Panel C report the results of portfolio similarity at the stock level, at the sector level and at the industry level, respectively. This table shows the average family portfolio similarity and the average family portfolio similarity weighted by total net assets in Euro equity category and weighted by number of Euro equity funds. The average similarity of families that are in the top tercile *(T1)* and the average similarity of families that are in the bottom tercile (*T3*). The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. We apply the mean-difference test for paired samples. In all columns, the annual average is obtained with the monthly portfolio similarity data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Year	Family portfolio similarity	Family portfolio similarity (*TNA-weighted*)	Family portfolio similarity (*#funds-weighted*)	Family portfolio similarity (*T1*)	Family portfolio similarity (*T3*)	Mean-difference test (*T1-T3*)	
Panel A: Stock							
2000	50.44%	54.87%	52.55%	83.73%	21.72%	62.01%***	(0.000)
2001	46.21%	47.19%	46.45%	75.40%	20.19%	55.20%***	(0.000)
2002	43.63%	45.24%	44.01%	73.97%	16.63%	57.33%***	(0.000)
2003	47.06%	46.20%	47.55%	77.48%	20.36%	57.11%***	(0.000)
2004	51.71%	50.09%	51.50%	80.89%	24.79%	56.09%***	(0.000)
2005	47.26%	48.69%	49.74%	72.05%	24.10%	47.95%***	(0.000)
2006	46.21%	47.90%	46.89%	70.99%	24.45%	46.53%***	(0.000)
2007	39.37%	37.42%	39.13%	61.53%	22.36%	39.16%***	(0.000)
2008	37.97%	36.61%	38.04%	64.57%	20.20%	44.36%***	(0.000)
2009	39.56%	44.61%	40.62%	61.24%	23.62%	37.62%***	(0.000)
2010	40.95%	43.19%	40.74%	61.87%	24.30%	37.57%***	(0.000)
2011	46.47%	42.51%	46.20%	67.81%	28.26%	39.54%***	(0.000)
2012	46.16%	38.63%	46.69%	66.33%	25.05%	41.27%***	(0.000)
2013	42.59%	37.35%	43.16%	60.61%	24.79%	35.81%***	(0.000)
2014	43.64%	42.92%	43.84%	67.13%	22.32%	44.81%***	(0.000)
2015	45.02%	46.21%	45.01%	68.66%	25.61%	43.04%***	(0.000)
2016	39.77%	42.81%	40.00%	64.45%	21.68%	42.77%***	(0.000)
2017	39.32%	43.35%	39.83%	62.80%	21.82%	40.97%***	(0.000)
2018	41.43%	42.72%	42.04%	64.83%	23.66%	41.16%***	(0.000)
Dec1999-Jun2018	44.03%	44.22%	44.52%	70.50%	22.63%	47.87%***	(0.000)
Panel B: Sector							
Dec1999-Jun2018	73.47%	71.32%	73.25%	89.23%	57.01%	32.22%***	(0.000)
Panel C: Industry							
Dec1999-Jun2018	80.33%	78.25%	80.09%	93.51%	65.84%	27.68%***	(0.000)

Table A2. 4 - The fund family characteristics that enhance portfolio similarity

This table shows the results obtained by estimating Equation 2.4 using the portfolio similarity and Prais-Winsten, GLS, FE and RE with robust standard errors from December 1999 to June 2018. Where the dependent variable is *Family Portfolio Similarity* $_{f,t}$ that is the portfolio overlap within fund family *f* in month *t* at the stock level and the independent variables are: *Bank*$_{f,t}$ that takes a value equal to 1 when a fund family depends on a banking or insurance company regarding its governance structure; *Family_size*$_{f,t}$ is the log-normal of the total size of fund family *f* in month *t; Bank*$_{f,t}$ *x Family_size*$_{f,t}$ is the interaction between the dummy variable *Bank*$_{f,t}$ and the variable *Family_size*$_{f,t}$ *; Family_age*$_{f,t}$ is the age of fund family *f* in month *t* obtained from the inception date of the oldest fund in the family*;* and *Family_%EuroEquity*$_{f,t}$ is the percentage of the assets under management in the Euro equity category with respect to the total size of fund family *f* in month *t.* The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Prais-Winsten	GLS	Prais-Winsten	GLS	FE (*robust standard errors*)	RE (*robust standard errors*)
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	0.494***	0.501***	0.502***	0.496***	0.540***	0.552***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank	-0.040***	-0.013**	-0.050***	-0.024***		-0.179***
	(0.002)	(0.034)	(0.001)	(0.005)		(0.000)
Family_size	0.001*	0.001*	-0.017	-0.012*	-0.023**	-0.018**
	(0.087)	(0.074)	(0.123)	(0.070)	(0.012)	(0.030)
Bank x Family_size			0.018**	0.013**	0.022**	0.016**
			(0.010)	(0.048)	(0.017)	(0.044)
Family_age	-0.002**	-0.004***	-0.002**	-0.004***	-0.005***	-0.007***
	(0.034)	(0.000)	(0.040)	(0.000)	(0.000)	(0.000)
Family_%EuroEquity	0.059***	0.033**	0.065***	0.032**	0.033	-0.007*
	(0.005)	(0.019)	(0.003)	(0.012)	(0.377)	(0.082)
R-squared	16.24%		16.26%		6.04%	6.04%
Wald	29.36***	32.95***	30.85***	89.95***	211.1***	84.2***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman Test					70.2*** (0.000)	
#Observations	5,667	5,667	5,667	5,667	5,667	5,667

Appendix 2.2: The portfolio overlap and the portfolio similarity at the sector and industry levels

Table A2. 5 – The sectors and industries of stocks within portfolio holdings

This table reports the industries and sectors to which the stocks within mutual funds' portfolio holdings according to FTSE Russel Industry Classification Benchmark (ICB) obtained from Datastream.

Industry	**Sector**
Technology	Technology
Telecommunications	Telecommunications
Health Care	Health Care
Financials	Banks
	Financial Services
	Insurance
Real Estate	Real Estate
Consumer Discretionary	Automobiles and Parts
	Consumer Products and Services
	Media
	Retailers
	Travel and Leisure
Consumer Staples	Food, Beverage and Tobacco
	Personal Care, Drug and Grocery Stores
Industrials	Construction and Materials
	Industrial Goods and Services
Basic Materials	Basic Resources
	Chemicals
Energy	Energy
Utilities	Utilities

Table A2. 6 – Overall results of the portfolio overlap among fund pairs at the sector level

This table shows, for each year, the overall average portfolio overlap at the sector level and the number of fund pairs within the same fund family and the number of fund pairs in different families, as well as their average overlap. In this table, we present a yearly report of the number of funds during the sample period. The last column shows the results of the mean difference test between both specific averages with the *p*-value in parentheses. We apply the mean difference test for unpaired samples with different variance (in all cases the null hypothesis is rejected in the test of equal variance). In all columns, the annual average is obtained with the monthly portfolio overlap data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Year	Portfolio overlap	#fund pairs (*same fund family*)	#fund pairs (*different fund family*)	Portfolio overlap (*same fund family*)	Portfolio overlap (*different fund family*)	Mean-difference test
2000	59.75%	282	11,520	69.94%	59.51%	10.42%*** (0.000)
2001	59.76%	341	13,827	67.07%	59.58%	7.48%*** (0.000)
2002	57.24%	354	14,261	61.86%	57.14%	4.71%*** (0.000)
2003	58.31%	340	15,175	62.78%	58.22%	4.55%*** (0.000)
2004	59.75%	337	13,592	65.50%	59.61%	5.88%*** (0.000)
2005	60.38%	391	14,415	65.39%	60.24%	5.14%*** (0.000)
2006	60.16%	421	15,621	64.02%	60.05%	3.97%*** (0.000)
2007	59.86%	474	16,648	61.91%	59.79%	2.12%*** (0.000)
2008	59.71%	468	16,032	64.82%	59.47%	5.34%*** (0.000)
2009	57.40%	422	14,054	62.48%	57.20%	5.28%*** (0.000)
2010	57.97%	255	10,917	62.85%	57.81%	5.04%*** (0.000)
2011	57.36%	236	9,864	61.65%	57.24%	4.41%*** (0.000)
2012	55.83%	193	7,712	61.44%	55.67%	5.77%*** (0.000)
2013	57.43%	166	6,289	61.18%	57.33%	3.84%*** (0.000)
2014	58.21%	97	4,619	62.13%	58.12%	4.00%*** (0.000)
2015	57.38%	104	5,203	62.77%	57.25%	5.52%*** (0.000)
2016	56.98%	93	4,737	60.56%	56.90%	3.66%*** (0.000)
2017	56.68%	75	4,260	61.78%	56.58%	5.20%*** (0.000)
2018	56.68%	65	4,061	61.70%	56.58%	5.12%*** (0.000)
Dec1999-Jun2018	58.89%	994	32,982	64.18%	58.75%	5.43%*** (0.000)

Table A2. 7 – Overall results of the portfolio overlap among fund pairs at the industry level

This table shows, for each year, the overall average portfolio overlap at the industry level and the number of fund pairs within the same fund family and the number of fund pairs in different families, as well as their average overlap. In this table, we present a yearly report of the number of funds during the sample period. The last column shows the results of the mean difference test between both specific averages with the *p*-value in parentheses. We apply the mean difference test for unpaired samples with different variance (in all cases the null hypothesis is rejected in the test of equal variance). In all columns, the annual average is obtained with the monthly portfolio overlap data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Year	Portfolio overlap	#fund pairs (*same fund family*)	#fund pairs (*different fund family*)	Portfolio overlap (*same fund family*)	Portfolio overlap (*different fund family*)	Mean-difference test
2000	66.94%	282	11,520	76.81%	66.70%	10.10%*** (0.000)
2001	66.43%	341	13,827	72.73%	66.27%	6.46%*** (0.000)
2002	64.08%	354	14,261	68.58%	63.98%	4.59%*** (0.000)
2003	64.90%	340	15,175	69.07%	64.81%	4.26%*** (0.000)
2004	66.77%	337	13,592	72.15%	66.64%	5.50%*** (0.000)
2005	67.43%	391	14,415	71.79%	67.31%	4.48%*** (0.000)
2006	66.48%	421	15,621	69.50%	66.40%	3.09%*** (0.000)
2007	66.62%	474	16,648	67.96%	66.57%	1.38%*** (0.000)
2008	65.70%	468	16,032	70.55%	65.47%	5.07%*** (0.000)
2009	63.99%	422	14,054	69.05%	63.80%	5.24%*** (0.000)
2010	65.60%	255	10,917	70.17%	65.45%	4.72%*** (0.000)
2011	65.94%	236	9,864	69.50%	65.84%	3.66%*** (0.000)
2012	65.46%	193	7,712	70.70%	65.31%	5.39%*** (0.000)
2013	66.58%	166	6,289	70.15%	66.48%	3.67%*** (0.000)
2014	67.06%	97	4,619	71.12%	66.97%	4.15%*** (0.000)
2015	66.83%	104	5,203	71.85%	66.70%	5.14%*** (0.000)
2016	67.34%	93	4,737	71.28%	67.26%	4.02%*** (0.000)
2017	67.22%	75	4,260	73.11%	67.10%	6.01%*** (0.000)
2018	66.77%	65	4,061	71.59%	66.68%	4.90%*** (0.000)
Dec1999-Jun2018	66.14%	994	32,982	70.92%	66.01%	4.91%*** (0.000)

Table A2. 8 – Family portfolio overlap at the sector level

This table shows the average family portfolio overlap at the sector level and the average family portfolio similarity weighted by total net assets in Euro equity category and weighted by number of Euro equity funds. The average similarity of families that are in the top tercile *(T1*) and the average similarity of families that are in the bottom tercile (*T3*). The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. We apply the mean-difference test for paired samples. In all columns, the annual average is obtained with the monthly portfolio similarity data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock							
Year	Family Overlap	Family overlap (*TNA-weighted*)	Family overlap (*#funds-weighted*)	Family Overlap (*T1*)	Family Overlap (*T3*)	Mean-difference test (*T1*-*T3*)	
2000	64.13%	67.87%	66.39%	82.45%	47.63%	34.83%***	(0.000)
2001	62.86%	66.37%	64.21%	79.93%	47.55%	32.38%***	(0.000)
2002	61.61%	64.21%	60.62%	79.36%	44.51%	34.85%***	(0.000)
2003	60.74%	62.55%	60.74%	78.48%	45.22%	33.27%***	(0.000)
2004	63.37%	65.68%	63.78%	79.13%	49.78%	29.36%***	(0.000)
2005	62.27%	63.11%	63.24%	76.34%	49.67%	26.67%***	(0.000)
2006	62.46%	62.25%	63.55%	75.60%	50.38%	25.22%***	(0.000)
2007	61.11%	61.66%	60.26%	75.75%	52.32%	23.43%***	(0.000)
2008	62.67%	62.00%	63.89%	77.95%	49.42%	28.53%***	(0.000)
2009	62.91%	54.91%	62.49%	75.71%	48.22%	27.49%***	(0.000)
2010	61.57%	55.98%	62.22%	76.45%	50.33%	26.12%***	(0.000)
2011	62.83%	55.11%	61.10%	74.33%	50.47%	23.86%***	(0.000)
2012	64.27%	54.92%	60.57%	72.04%	51.00%	21.04%***	(0.000)
2013	63.53%	56.71%	61.33%	71.16%	52.56%	18.60%***	(0.000)
2014	61.85%	61.19%	62.30%	73.60%	52.71%	20.88%***	(0.000)
2015	60.88%	64.07%	63.43%	74.12%	53.63%	20.48%***	(0.000)
2016	62.58%	63.86%	62.44%	73.65%	51.67%	21.98%***	(0.000)
2017	62.49%	64.64%	64.64%	75.54%	53.24%	22.30%***	(0.000)
2018	62.41%	64.41%	65.96%	77.53%	55.21%	22.32%***	(0.000)
Dec1999-Jun2018	62.46%	61.61%	62.73%	76.80%	49.30%	27.20%***	(0.000)

Table A2. 9 – Family portfolio overlap at the industry level

This table shows the average family portfolio overlap at the industry level and the average family portfolio similarity weighted by total net assets in Euro equity category and weighted by number of Euro equity funds. The average similarity of families that are in the top tercile *(T1)* and the average similarity of families that are in the bottom tercile (*T3*). The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. We apply the mean-difference test for paired samples. In all columns, the annual average is obtained with the monthly portfolio similarity data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock							
Year	Family Overlap	Family overlap (*TNA-weighted*)	Family overlap (*#funds-weighted*)	Family Overlap (*T1*)	Family Overlap (*T3*)	Mean-difference test (*T1-T3*)	
2000	71.11%	75.13%	73.18%	86.17%	56.15%	30.01%***	(0.000)
2001	69.82%	71.79%	70.62%	85.33%	54.77%	30.56%***	(0.000)
2002	68.60%	70.15%	67.38%	85.06%	51.58%	33.47%***	(0.000)
2003	67.79%	69.10%	67.34%	83.72%	52.40%	31.31%***	(0.000)
2004	70.84%	72.53%	70.83%	84.46%	58.29%	26.16%***	(0.000)
2005	70.78%	70.25%	70.82%	82.47%	59.28%	23.19%***	(0.000)
2006	70.34%	69.27%	70.21%	82.07%	58.26%	23.80%***	(0.000)
2007	70.30%	68.34%	66.20%	82.55%	59.02%	23.52%***	(0.000)
2008	72.30%	69.10%	69.91%	83.83%	56.29%	27.53%***	(0.000)
2009	72.98%	64.91%	69.94%	82.51%	56.68%	25.82%***	(0.000)
2010	72.80%	66.24%	69.83%	83.94%	58.87%	25.06%***	(0.000)
2011	74.23%	65.26%	69.33%	82.85%	58.79%	24.06%***	(0.000)
2012	73.00%	64.12%	69.61%	81.11%	61.07%	20.03%***	(0.000)
2013	70.52%	65.60%	70.45%	80.50%	61.26%	19.24%***	(0.000)
2014	68.68%	70.30%	71.58%	83.71%	60.72%	22.99%***	(0.000)
2015	67.81%	73.75%	72.99%	82.78%	63.49%	19.28%***	(0.000)
2016	70.09%	73.81%	73.65%	82.04%	63.95%	18.08%***	(0.000)
2017	70.54%	74.77%	76.49%	83.99%	65.06%	18.93%***	(0.000)
2018	70.80%	74.31%	75.74%	84.44%	65.43%	19.00%***	(0.000)
Dec1999-Jun2018	70.70%	69.84%	70.73%	83.52%	58.20%	25.32%***	(0.000)

Table A2. 10 – Overall results of the portfolio similarity among fund pairs at the sector level

This table shows, for each year, the overall average portfolio similarity at the sector level and the number of fund pairs within the same fund family and the number of fund pairs in different families, as well as their average overlap. In this table, we present a yearly report of the number of funds during the sample period. The last column shows the results of the mean difference test between both specific averages with the *p*-value in parentheses. We apply the mean difference test for unpaired samples with different variance (in all cases the null hypothesis is rejected in the test of equal variance). In all columns, the annual average is obtained with the monthly portfolio overlap data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Year	Portfolio overlap	#fund pairs (*same fund family*)	#fund pairs (*different fund family*)	Portfolio overlap (*same fund family*)	Portfolio overlap (*different fund family*)	Mean-difference test
2000	70.90%	282	11,520	80.91%	70.67%	10.24%*** (0.000)
2001	70.46%	341	13,827	76.65%	70.30%	6.35%*** (0.000)
2002	67.45%	354	14,261	70.27%	67.38%	2.89%*** (0.000)
2003	68.86%	340	15,175	72.68%	68.78%	3.90%*** (0.000)
2004	70.44%	337	13,592	76.72%	70.28%	6.44%*** (0.000)
2005	71.87%	391	14,415	76.99%	71.72%	5.27%*** (0.000)
2006	71.78%	421	15,621	75.28%	71.68%	3.60%*** (0.000)
2007	70.49%	474	16,648	72.18%	70.43%	1.75 %*** (0.000)
2008	69.83%	468	16,032	74.92%	69.59%	5.33%*** (0.000)
2009	66.74%	422	14,054	72.07%	66.54%	5.53%*** (0.000)
2010	67.60%	255	10,917	73.75%	67.40%	6.35%*** (0.000)
2011	67.34%	236	9,864	73.38%	67.16%	6.22%*** (0.000)
2012	64.08%	193	7,712	72.43%	63.83%	8.60%*** (0.000)
2013	67.04%	166	6,289	71.72%	66.91%	4.81%*** (0.000)
2014	68.04%	97	4,619	74.44%	67.89%	6.55%*** (0.000)
2015	67.15%	104	5,203	74.54%	66.96%	7.58%*** (0.000)
2016	65.88%	93	4,737	71.09%	65.77%	5.32%*** (0.000)
2017	65.69%	75	4,260	72.32%	65.56%	6.76%*** (0.000)
2018	65.90%	65	4,061	72.14%	65.78%	6.36%*** (0.000)
Dec1999-Jun2018	69.40%	994	32,982	74.71%	69.26%	5.46%*** (0.000)

Table A2. 11 – Overall results of the portfolio similarity among fund pairs at the industry level

This table shows, for each year, the overall average portfolio similarity at the industry level and the number of fund pairs within the same fund family and the number of fund pairs in different families, as well as their average overlap. In this table, we present a yearly report of the number of funds during the sample period. The last column shows the results of the mean difference test between both specific averages with the *p*-value in parentheses. We apply the mean difference test for unpaired samples with different variance (in all cases the null hypothesis is rejected in the test of equal variance). In all columns, the annual average is obtained with the monthly portfolio overlap data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Year	Portfolio overlap	#fund pairs (*same fund family*)	#fund pairs (*different fund family*)	Portfolio overlap (*same fund family*)	Portfolio overlap (*different fund family*)	Mean-difference test	
2000	76.66%	282	11,520	86.00%	76.44%	9.55%***	(0.000)
2001	75.64%	341	13,827	81.18%	75.50%	5.67%***	(0.000)
2002	73.18%	354	14,261	76.14%	73.11%	3.02%***	(0.000)
2003	73.69%	340	15,175	77.20%	73.61%	3.59%***	(0.000)
2004	75.70%	337	13,592	80.88%	75.57%	5.31%***	(0.000)
2005	77.48%	391	14,415	81.47%	77.37%	4.09%***	(0.000)
2006	76.98%	421	15,621	78.97%	76.93%	2.04%***	(0.000)
2007	76.65%	474	16,648	76.73%	76.65%	0.08%***	(0.000)
2008	74.85%	468	16,032	78.72%	74.67%	4.05%***	(0.000)
2009	72.20%	422	14,054	76.94%	72.02%	4.91%***	(0.000)
2010	74.03%	255	10,917	78.88%	73.88%	5.00%***	(0.000)
2011	75.00%	236	9,864	79.39%	74.87%	4.52%***	(0.000)
2012	73.76%	193	7,712	80.89%	73.55%	7.33%***	(0.000)
2013	76.07%	166	6,289	79.64%	75.97%	3.66%***	(0.000)
2014	76.99%	97	4,619	81.86%	76.88%	4.98%***	(0.000)
2015	77.38%	104	5,203	83.76%	77.22%	6.54%***	(0.000)
2016	77.44%	93	4,737	82.41%	77.33%	5.07%***	(0.000)
2017	77.52%	75	4,260	84.38%	77.38%	6.99%***	(0.000)
2018	77.38%	65	4,061	83.28%	77.27%	6.01%***	(0.000)
Dec1999-Jun2018	75.60%	994	32,982	79.91%	75.48%	4.42 %***	(0.000)

Table A2. 12 – Family portfolio similarity at the sector level

This table shows the average family portfolio similarity at the sector level and the average family portfolio similarity weighted by total net assets in Euro equity category and weighted by number of Euro equity funds. The average similarity of families that are in the top tercile *(T1)* and the average similarity of families that are in the bottom tercile (*T3*). The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. We apply the mean-difference test for paired samples. In all columns, the annual average is obtained with the monthly portfolio similarity data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock							
Year	Family Overlap	Family overlap (*TNA-weighted*)	Family overlap (*#funds-weighted*)	Family Overlap (*T1*)	Family Overlap (*T3*)	Mean-difference test (*T1-T3*)	
2000	74.84%	78.77%	76.93%	91.86%	56.31%	35.55 %***	(0.000)
2001	73.19%	75.36%	74.12%	90.67%	55.51%	35.16%***	(0.000)
2002	70.19%	72.26%	69.43%	90.48%	49.09%	41.39%***	(0.000)
2003	70.67%	72.02%	70.80%	90.29%	50.11%	40.17%***	(0.000)
2004	74.29%	76.13%	74.38%	91.36%	56.48%	34.88%***	(0.000)
2005	74.09%	74.08%	74.78%	89.05%	57.94%	31.11%***	(0.000)
2006	75.67%	73.88%	75.10%	89.41%	60.37%	29.05%***	(0.000)
2007	73.79%	72.85%	70.95%	89.36%	61.43%	27.92%***	(0.000)
2008	72.32%	71.55%	73.65%	91.23%	55.61%	35.63%***	(0.000)
2009	69.81%	64.91%	71.70%	89.81%	52.84%	36.97%***	(0.000)
2010	73.36%	64.24%	73.21%	90.62%	56.24%	34.39%***	(0.000)
2011	74.36%	62.13%	73.94%	89.41%	58.23%	31.18%***	(0.000)
2012	72.74%	61.19%	72.44%	86.77%	58.36%	28.41%***	(0.000)
2013	71.90%	63.62%	71.95%	83.62%	59.93%	23.69%***	(0.000)
2014	74.47%	72.02%	74.53%	87.78%	61.46%	26.32%***	(0.000)
2015	75.28%	76.10%	74.90%	87.80%	62.22%	25.58%***	(0.000)
2016	72.21%	74.76%	71.80%	85.60%	59.18%	26.42%***	(0.000)
2017	73.44%	75.13%	73.03%	85.98%	61.58%	24.40%***	(0.000)
2018	75.21%	75.61%	74.13%	87.89%	64.55%	23.33%***	(0.000)
Dec1999-Jun2018	73.47%	71.32%	73.25%	89.23%	57.01%	32.22%***	(0.000)

Table A2. 13 – Family portfolio similarity at the industry level

This table shows the average family portfolio similarity at the industry level and the average family portfolio similarity weighted by total net assets in Euro equity category and weighted by number of Euro equity funds. The average similarity of families that are in the top tercile *(T1)* and the average similarity of families that are in the bottom tercile (*T3*). The last column shows the result of a mean-difference test between *T1* and *T3* with the *p*-value in parentheses. We apply the mean-difference test for paired samples. In all columns, the annual average is obtained with the monthly portfolio similarity data. The study period starts in December 1999 and ends in June 2018. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock							
Year	Family Overlap	Family overlap (*TNA-weighted*)	Family overlap (*#funds-weighted*)	Family Overlap (*T1*)	Family Overlap (*T3*)	Mean-difference test (*T1-T3*)	
2000	80.17%	83.90%	82.13%	94.32%	63.38%	30.94%***	(0.000)
2001	78.63%	79.62%	79.30%	94.22%	62.04%	32.18%***	(0.000)
2002	76.03%	77.31%	75.33%	94.23%	56.17%	38.05%***	(0.000)
2003	75.57%	76.65%	75.69%	92.85%	56.27%	36.58%***	(0.000)
2004	79.57%	81.02%	79.36%	93.84%	64.46%	29.37%***	(0.000)
2005	80.59%	79.87%	80.59%	92.65%	67.14%	25.51%***	(0.000)
2006	81.19%	78.55%	79.89%	92.97%	67.86%	25.11%***	(0.000)
2007	79.00%	77.55%	75.81%	93.00%	68.41%	24.59%***	(0.000)
2008	77.27%	76.97%	77.98%	94.31%	62.43%	31.88%***	(0.000)
2009	76.49%	73.17%	77.50%	93.21%	61.82%	31.38%***	(0.000)
2010	79.20%	73.84%	78.77%	94.46%	64.28%	30.18%***	(0.000)
2011	80.57%	72.02%	80.10%	94.28%	65.79%	28.48%***	(0.000)
2012	81.28%	71.48%	80.85%	92.61%	69.79%	22.82%***	(0.000)
2013	80.34%	71.97%	80.06%	91.22%	69.24%	21.98 %***	(0.000)
2014	82.58%	79.57%	82.34%	93.90%	70.31%	23.59 %***	(0.000)
2015	85.07%	85.55%	84.56%	93.73%	75.62%	18.10%***	(0.000)
2016	84.09%	84.82%	83.58%	92.38%	74.84%	17.54%***	(0.000)
2017	85.46%	85.52%	85.12%	93.84%	76.15%	17.68%***	(0.000)
2018	85.71%	85.66%	84.84%	94.96%	77.05%	17.90%***	(0.000)
Dec1999-Jun2018	80.33%	78.52%	80.09%	93.51%	65.84%	27.67%***	(0.000)

Appendix 2.3: Model specifications with independent variables lagged by one month

Table A2. 14 - Portfolio overlap and characteristics of mutual funds

This table shows the results obtained by estimating Equation 2.2 using RE with robust estandar errors from December 1999 to June 2018, where the dependent variable is the *Portfolio Overlap*$_{i,j,t}$ at the stock level and the independent variables are dummy variables. We calculate the percentile rank of each fund-month in each characteristic (*Fund_size*, *Fund_age*, *Fund_#stocks*, *Fund_fees* and *Fund_return*) and we determine the quintile into which mutual funds are. For these characteristics, the model includes four dummy variables: *Same* takes a value equal to 1 when fund *i* and *j* in month *t-1* are in the same quintile; *BothQ1* takes a value equal to 1 when funds *i* and *j* in month *t-1* are in the top quintile; *BothQ5* takes a value equal to 1 when fund *i* and *j* in month *t-1* are in the bottom quintile; Opposite is equal to 1 when in month *t-1*, either fund *i* or fund *j* is in the top quintile and in the other is in the bottom quintile; *Fund_family*$_{i,j,t}$ is equal to 1 when, in month *t-1*, funds *i* and *j* are in the same fund family; and *Time*$_t$ ranges from 1 in the first month to 223 in the last month. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		Coefficient	
	Constant	0.308***	(0.000)
Fund_size	Same	-0.001	(0.306)
	BothQ1	0.020***	(0.000)
	BothQ5	-0.016***	(0.000)
	Opposite	-0.002**	(0.031)
Fund_age	Same	0.005***	(0.003)
	BothQ1	-0.011***	(0.000)
	BothQ5	-0.034***	(0.000)
	Opposite	-0.009	(0.110)
Fund_#stocks	Same	0.011***	(0.000)
	BothQ1	0.004**	(0.028)
	BothQ5	-0.016***	(0.000)
	Opposite	-0.015***	(0.000)
Fund_fees	Same	0.002***	(0.000)
	BothQ1	0.013***	(0.000)
	BothQ5	-0.009***	(0.000)
	Opposite	0.002	(0.299)
Fund_return	Same	0.009***	(0.000)
	BothQ1	-0.008***	(0.000)
	BothQ5	-0.001	(0.646)
	Opposite	-0.009***	(0.000)
Fund_family		0.062***	(0.000)
Time		-0.002***	(0.000)
#Observations		1,073,378	
Wald		1,419.26***	(0.000)
R-squared		5.95%	
VIF		1.24	

Table A2. 15 - The fund family characteristics that enhance portfolio overlap

This table shows the results obtained by estimating Equation 2.4 using Prais-Winsten, GLS, FE and RE with robust estandar errors from December 1999 to June 2018. Where the dependent variable is *Family portfolio overlap*$_{f,t}$ that is the portfolio overlap within fund family *f* in month *t* at the stock level and the independent variables are: *Bank*$_{f,t}$ that takes a value equal to 1 when a fund family depends on a banking or insurance company regarding its governance structure; *Family_size*$_{f,t}$ is the log-normal of the total size of fund family *f* in month *t-1; Bank*$_{f,t}$ *x Family_size*$_{f,t}$ is the interaction between the dummy variable *Bank*$_{f,t}$ and the variable *Family_size*$_{f,t}$ *; Family_age*$_{f,t}$ is the age of fund family *f* in month *t-1* obtained from the inception date of the oldest fund in the family*;* and *Family_%EuroEquity*$_{f,t}$ is the percentage of the assets under management in the Euro equity category with respect to the total size of fund family *f* in month *t-1*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Prais-Winsten	GLS	Prais-Winsten	GLS	FE (*robust standard errors*)	RE (*robust standard errors*)
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	-0.377***	-0.413***	0.754***	0.662***	0.142*	1.119***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.067)	(0.004)
Bank$_{t-1}$	-0.124***	-0.080***	-1.489***	-1.338***		-1.309**
	(0.000)	(0.000)	(0.000)	(0.000)		(0.019)
Family_size$_{t-1}$	0.065***	0.063***	-0.028*	-0.024**	-0.063*	-0.060*
	(0.000)	(0.000)	(0.068)	(0.042)	(0.051)	(0.053)
Bank$_{t-1}$ *x Family_size*$_{t-1}$			0.109***	0.099***	0.102**	0.104**
			(0.000)	(0.000)	(0.029)	(0.016)
Family_age$_{t-1}$	-0.004***	-0.005***	-0.004***	-0.004***	-0.006**	-0.006**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.039)	(0.031)
Family_%EuroEquity$_{t-1}$	0.229***	0.221***	0.286***	0.255***	0.261**	0.267**
	(0.000)	(0.006)	(0.000)	(0.000)	(0.015)	(0.011)
R-squared	12.83%		14.00%		9.73%	9.70%
Wald	161.26***	225.22***	230.35***	280.66***	124.30***	106.40**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman Test					117.70***	
					(0.000)	
#Observations	4,856	4,856	4,856	4,856	4,856	4,856

Table A2. 16 - The fund family characteristics that enhance the manager autonomy

This table shows the results obtained by estimating Equation 2.10 using Prais-Winsten, GLS, FE and RE with robust estandar errors from December 1999 to June 2018. Where the dependent variable is *Intra-family autonomy*$_{f,t}$which is the autonomy level of managers within fund family *f* in month *t* at the stock level and the independent variables are: *Bank*$_{f,t}$ is equal to 1 if a fund family depends on the banking or insurance company according to its governance structure; *Family_size*$_{f,t}$ is the log-normal of total size of fund family *f* in month *t-1; Bank*$_{f,t}$ *x Family_size*$_{f,t}$ is the interaction between the dummy variable *Bank*$_{f,t}$ and the variable *Family_size*$_{f,t}$; *Family_age*$_{f,t}$ is the age of fund family *f* obtained from its start date in month *t-1*; and *Family_%EuroEquity*$_{f,t}$ is the percentage of the value in the Euro equity category with respect to the total size of fund family *f* in month *t-1*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Prais-Winsten	GLS	Prais-Winsten	GLS	FE (*robust standard errors*)	RE (*robust standard errors*)
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	0.898***	0.953***	0.181*	0.193**	0.584**	0.251**
	(0.000)	(0.000)	(0.099)	(0.039)	(0.038)	(0.040)
Bank$_{t-1}$	0.110***	0.126***	0.976***	0.976***		1.113***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.007)
Family_size$_{t-1}$	-0.050***	-0.053***	0.009	0.007	0.055**	0.051**
	(0.000)	(0.000)	(0.306)	(0.320)	(0.027)	(0.031)
Bank$_{t-1}$ *x Family_size*$_{t-1}$			-0.069***	-0.067***	-0.087**	-0.087***
			(0.000)	(0.000)	(0.016)	(0.006)
Family_age$_{t-1}$	0.004***	0.004***	0.004***	0.005***	0.003**	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.163)
Family_%EuroEquity$_{t-1}$	0.047	0.032	0.009	0.033	-0.084	-0.078
	(0.107)	(0.110)	(0.731)	(0.120)	(0.457)	(0.453)
R-squared	12.12%		13.36%		14.62%	14.59%
Wald	299.11***	476.17***	369.25***	589.13***	20.80***	104.20***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman Test					20.06***	
					(0.000)	
#Observations	4,856	4,856	4,856	4,856	4,856	4,856

CHAPTER 3:

FUND TRADING DIVERGENCE AND PERFORMANCE CONTRIBUTION

-"Being different simply means you have something unique to offer the world."-

Scarlett Vespa

Synopsis

Considering that the most distinct trading decisions are crucial to evaluate the ability of fund managers to add value, this chapter aims to examine the trading divergence level among mutual funds and to capture its determinants and its performance consequences. We propose a measure that is more informative than the traditional overlap metrics, providing evidence of a positive and significant trend of fund trading divergence over time, especially after the Global Financial Crisis (GFC) of 2008. Our results also show a negative influence of market stress on the trading divergence level; however, different reactions of fund managers are detected in the successive market shocks of the period analysed. Interestingly, we find that divergent trading implies a significantly greater contribution to subsequent fund performance than do convergent decisions.

3.1 Introduction

Through comparisons between active and passive fund management, mutual fund research has focused on the skills and added value of managers, showing that on average, active funds do not outperform benchmarks (Jensen, 1968; Fama and French, 2010). However, shedding light on the ability of fund managers to add value, other studies document a positive relationship between the value created and trading activity (Wermers, 2000; Dahlquist et al., 2000; Engström, 2004). Along this line, Cremers and Petajisto (2009) find that portfolio holdings that differ from the benchmark weights show a higher performance. More recently, using the information of portfolio holdings and trading decisions, Fulkerson (2013) develops a new measure of the value of active mutual fund management and reveals that most of the skill documented by previous literature arises from correctly trading stocks within industries. Jiang et al. (2014) also find that in actively managed funds, overweighted stocks perform substantially better than underweighted stocks.

The aim of this chapter is to isolate the trading decisions that are distinct regarding those carried out by other funds, that is, to obtain the trading divergence level among funds. Due to the importance of the trading divergence level for examining the value added by managers, we focus on this level in the Spanish market and evaluate the differences in the trading decisions of funds, considering the influence of the stock traded, the type of trading decision (buying, selling or no trading) and the portfolio weight on the total net assets (TNA) of funds.

An important economic principle extended to research on mutual fund managers is that financial agents can obtain excess returns if and only if they manage to stand out from other funds, showing that management skills a competitive advantage (Berk and Van Binsbergen, 2015). In this line, Khorana and Servaes (2007) document that product differentiation strategies are effective in obtaining market share, and thus, the market share is higher in families in which the new fund is more differentiated than the existing offerings. Furthermore, a greater level of difference among funds has a significantly positive influence not only on the family share in the market but also on the financial system. Getmansky et al. (2016), Guo et al. (2016) and Delpini et al. (2018; 2019) document that a significant similarity among funds plays an important role in the transmission of financial difficulties and can make the financial system more fragile.

First, we examine the evolution of the trading divergence level among equity mutual funds from January 2000 to June 2020 in the Spanish industry, and we explore the main breakpoints in its evolution. We hypothesise that the trading divergence level among funds follows a positive pattern, especially within the same family, to reduce costs and to increase market share. We could also expect an increase in the divergence level driven by the desire for greater efficiency in the mutual fund industry.

Second, we study the different determinants of the trading divergence among funds. Specifically, we examine the influence of previous holdings, market stress and stock characteristics. We may expect that those fund pairs that have more similarity in their previous holdings also show a lower divergence level among their trading decisions during the following period. Furthermore, we could also expect that market stress supposes a negative influence on the trading divergence level among funds. A high market stress level implies high levels of uncertainty about the fundamental value of financial assets and information asymmetry in the market (Hakkio and Keeton, 2009); moreover, this information asymmetry is higher for riskier stocks (Easley et al., 1996; Aslan et al., 2011; Martins and Paulo, 2014) and non-domestic stocks (Barron and Ni, 2008), causing fund managers to experience several feelings and emotions, such as fear and panic, that influence their financial decisions (Birâu, 2012). Therefore, due to potential compensation and reputational incentives, fund managers may tend to hold less risky and more familiar stocks in their portfolio and may have more incentives to make decisions similar to those of others (Karunanayake et al., 2010; Khan et al., 2011). In addition, we study whether the trading divergence level is driven by certain stocks, as previous research shows that the trading decisions of fund managers are influenced by stock characteristics. Particularly, the stock characteristics that have attracted greater research attention are the size, the previous volatility and return, and the information level available in the market about them.

Finally, this chapter studies the consequences of trading divergence on subsequent fund performance and thus on industry efficiency. Although previous literature has argued the inability of the active fund to outperform the benchmark, Cremers and Petajisto (2009), Cohen et al. (2010) and Jiang et al. (2014) document that fund managers generate added value through some decisions. We hypothesise that divergent trading decisions have a higher contribution to fund performance than do convergent trading decisions.

In the context of similarity, the correlation among funds' trading has been studied by the previous literature. Kacperczyk and Seru (2012) examine coordination in fund families, calculating the number of positive and negative changes in portfolio holdings by each stock for all funds within a family. Pool et al. (2015) also test whether socially connected fund managers have more similar holdings and trades. However, for several reasons, from a divergence perspective, we study the relationship among the trading decisions of funds. First, we can capture not only the "active" divergence that occurs when the two compared funds trade in the same stock but also the "passive" divergence that occurs when one fund trades in a stock and the other fund does not. No fund will present a trading overlap in stocks that it has not traded; however, it could present a trading divergence depending on whether the other fund has traded that stock. Second, the divergence trading measure proposed in this study allows us to differentiate between the cases in which a fund buys (or sells) a certain stock and another fund does not trade in this stock and the cases in which both funds trade in the opposite direction; however, under the overlap trading methodology, both cases are considered the same.

This chapter is related to the literature that examines the funds' trading decisions, especially the growing literature that examines the similarity level among portfolios. However, this study differs in several aspects. First, we focus on the trading divergence level among funds by proposing a measure that simultaneously takes into account both buying and selling decisions. Hence, our measure is more informative than previous buying overlap and selling overlap metrics. Second, we study the influence of the similarity level of portfolios and stock characteristics on the trading divergence level. Third, we distinguish between the contribution of divergent and convergent trading decisions to fund performance.

This chapter contributes to the literature on the development of the fund industry and on the comparison of behaviour before and after the Global Financial Crisis, GFC, (2008) in the market. This chapter shows a significantly positive pattern in the trading divergence level, especially after the GFC of 2008. In addition, our findings suggest that fund managers do not show the same behaviour for the different market shocks during the sample period.

The findings of the study have several implications for industry regulators because the trading divergence level supposes a significantly positive influence on the fund's performance and thus on the industry efficiency. In addition, according to Delpini et al. (2018; 2019), the trading divergence level could influence the systemic fragility of the financial system. Due to the significantly positive effect of trading divergence on fund performance, this study also has implications for the top management of fund families. Brown and Wu (2014) document that on average; good family performance has a positive effect on the fund flows of its member funds. Therefore, top management within families may be interested in motivating managers to seek investment opportunities and to trade in the other family funds differently. Finally, the findings have implications for fund managers because these managers' reputation and remuneration depend on their performance records (Mason et al., 2016).

The rest of the chapter is organised as follows. Section 2 describes the data and methodology. Section 3 studies the evolution of trading divergence among funds. Section 4 focuses on the determinants of this phenomenon. Section 5 focuses on performance and efficiency consequences, and Section 6 is the conclusion.

3.2 Data and methodology

3.2.1 Data

We analyse the trading divergence among fund pairs in the Spanish equity mutual fund industry from January 2000 to June 2020. Our sample includes funds classified by the Spanish Securities Exchange Commission (*CNMV*) as Euro equity funds, which invest at least 75% of their portfolio holdings in equity assets with a minimum of 60% of the equity allocation in euro zone domiciled companies. The sample is free of survivorship bias, including both surviving and dead funds. ETFs, index funds and funds with less than 2 years of data were excluded. This leads to a final sample of 315 Euro equity mutual funds managed by 114 fund families.

Table 3. 1 – Summary Statistics of the sample

This table shows summary statistics for our sample at five date points: March 2000, March 2005, March 2010, March 2015 and March 2020. Specifically, this table includes the mean, quintile 1 value (Q1), and quintile 5 value (Q5) of each fund characteristic. *#Funds* is the number of funds in our sample; *#Families* is the number of fund families in our sample; *#Families with more than one fund* is the number of fund families that manage more than one fund in our sample; *Fund_size* is the monthly total net assets of funds in million euros; *Fund_age* is the age of funds in years, and we obtain the fund's age from its inception date; *Fund_fees* is the funds' monthly management and deposit fees; *Fund_return* is the funds' annual past gross return; *Fund_moneyflows* is the funds' monthly relative money flows; and *Fund_#stocks* is the number of distinct stocks held by the funds' monthly portfolio holdings.

		March 2000	March 2005	March 2010	March 2015	March 2020
#Funds		159	166	151	95	90
#Families		76	68	66	47	52
#Families_more than one fund		35	31	34	25	23
Fund_size	Mean	95,182	59,947	34,442	94,234	59,343
	Q1	115,824	74,558	33,549	140,799	65,782
	Q5	8,442	6,049	5,119	18,572	8,753
Fund_age	Mean	4	8	11	16	18
	Q1	8	11	16	21	25
	Q5	1	4	7	11	11
Fund_fees	Mean	0.17%	0.15%	0.16%	0.19%	0.14%
	Q1	0.21%	0.19%	0.19%	0.20%	0.17%
	Q5	0.12%	0.12%	0.13%	0.15%	0.11%
Fund_return	Mean	-0.33%	-0.87%	6.51%	3.41%	0.14%
	Q1	2.06%	-0.09%	8.03%	4.04%	1.21%
	Q5	-2.95%	-1.49%	4.69%	2.76%	-1.30%
Fund_moneyflows	Mean	5.04%	5.93%	-0.46%	0.78%	-0.83%
	Q1	11.46%	3.53%	0.31%	3.33%	1.50%
	Q5	-1.02%	-1.96%	-3.28%	-2.92%	-3.26%
Fund_#stocks	Mean	52	44	39	40	41
	Q1	67	55	50	49	49
	Q5	34	31	27	31	30

The *CNMV* database includes monthly portfolio holdings from December 1999 to December 2006 and quarterly holdings from March 2007 to June 2020. When available from the private information source Morningstar, the monthly portfolio holdings are obtained and used to complete the quarterly portfolio holdings from *CNMV*. We use the ISIN codes of both the funds and the portfolio holdings for the merger of the two datasets.[23] The detailed portfolio holdings information allows us to determine the trading decisions made by the mutual funds. The *CNMV* database also includes information about the fund size, the family to which each fund belongs, the fund inception date, the management and deposit fees, and the net asset value (NAV).

Stock information is obtained from DataStream, which provides information about the prices, return and the market capitalization of stocks and considers the main capital operations, such as splits and the payment of dividends.

Table 3.1 reports the summary statistics of the sample. This table shows that due to the severe merging process caused by the strong reorganization of the banking system in the Spanish market during the last decade, both the number of funds (*#Funds*) and the number of fund families (*#Families*) decrease over time. Regarding fund size, Table 3.1 shows that the average fund size (*Fund_size)* decreases after the GFC of 2008 and then recovers, reaching a statistically significantly higher value than before the crisis. However, the average fund size in March 2020 is similar to that in March 2005 because of the significant decline produced in 2020.

Table 3.1 also shows that in March 2015, the fund fees (*Fund_fees)* are higher than the rest of the data points. However, the value of the fees has decreased in recent years, reaching the smallest value in March 2020. In addition, we observe that both fund returns *(Fund_returns)* and fund flows *(Fund_flows)* have shown a negative trend during recent years, showing negative values in March 2020. Finally, we find that the number of stocks within the portfolio (*Fund_#stocks*) decreases slightly over time.

[23] Therefore, we control 100% of the monthly portfolio holdings of the funds in our sample from December 1999 until December 2006 and approximately 83% of the monthly holdings from January 2007 to June 2020.

3.2.2 Methodology

3.2.2.1 Mutual fund trading decisions

Previous studies have documented two approaches to capture mutual fund trading: the change in the portfolio weight of each stock in each mutual fund (Grinblatt and Titman, 1993) and the change in the number of shares (Alexander et al., 2007). We follow the methodology of Alexander et al. (2007) to capture mutual fund trading decisions because this approach is more accurate and is not biased by passive changes in portfolio weights due to price changes during the trading period (Jiang et al., 2007).

For each stock *s*, we first measure the change in the number of this stock's shares held by mutual fund *i* in period *t*.[24] Second, we calculate the amount of each trading decision by multiplying the change in the number of shares by the average market price of stock *s* in month *t*.

3.2.2.2 Mutual fund trading decisions

Once we know the amount of each trading decision of each fund for each stock in each month, we calculate the weight of each trading decision on the fund's TNA. Subsequently, we compare these trading weights on each stock for each fund pair to obtain the level of trading divergence among them.

We propose a measure of the divergence level in which the trading divergence executed among a fund pair is related to its maximum potential trading divergence. This metric includes both the buying and selling decisions of funds, which allows us to capture in a single measure three different cases of divergence: (1) when fund *i* and fund *j* trade in the same direction in stock *s*, that is, when both funds buy or sell stock *s* but with different weights; (2) when fund *i* and fund *j* trade in the opposite direction in stock *s*,

[24] We consider corporate actions, such as stock splits, to obtain the number of shares.

that is, when one fund buys stock s and the other fund sells this stock; and (3) when fund *i* buys (or sells) in stock *s* and fund *j* does not trade in this stock.

Note that the trading overlap measures in the financial literature (e.g., Pool et al., 2005) do not distinguish the case in which a fund buys (or sells) a stock and the other fund does not trade this stock from the case in which a fund buys (or sells) a stock and the other fund trade in the opposite direction. However, the actual trading divergence is higher in the second case.

Based on these considerations, we calculate the actual trading divergence for each fund pair in each month as the sum of all trading comparisons between both funds and calculate the maximum possible divergence as the sum of the maximum divergence between them in buying and selling decisions. If the two funds buy (or both funds sell), the maximum is given by the fund with a higher trading weight in absolute value. If one fund buys and the other sells, the maximum possible divergence is given by the sum of both trading weights in absolute value.

Finally, our divergence measure considers the portfolio weights in the previous month to control that a fund cannot sell a stock if this position is not included in the portfolio holdings. Therefore, we exclude the excess trading of one fund that cannot be made by the other fund due to its previous holding portfolio from both the actual trading divergence and from the maximum possible divergence.

Specifically, the actual trading divergence with respect to the potential trading divergence between fund i and fund j in each month t is computed as follows:

$$TD_{i,j,t} = \frac{\sum_s |t_{i,s,t} - t_{j,s,t}| - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t}}{\sum_s (Max\ |C_{i,j,s,t}| + Max\ |V_{i,j,s,t}|) - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t}} \quad , \tag{3.1}$$

where $t_{i,s,t}$ and $t_{j,s,t}$ is the traiding weight of fund i and fund j, respectively, for the stock s in the month t. This is positive when the fund buys and negative when the fund sells.

$Max\ |C_{i,j,s,t}| = Max\ (|C_{i,s,t}| , |C_{j,s,t}|)$ is the higher weight of the buying decisions between fund i and fund j for the stock s in the month t.

$|C_{i,s,t}| = t_{i,s,t}$ if $t_{i,s,t} > 0$, or $|C_{i,s,t}| = 0$ if $t_{i,s,t} < 0$.

$|C_{j,s,t}| = t_{j,s,t}$ if $t_{j,s,t} > 0$, or $|C_{j,s,t}| = 0$ if $t_{j,s,t} < 0$.

$Max\ |V_{i,j,s,t}| = Max\ (|V_{i,s,t}| , |V_{j,s,t}|)$ is the higher weight in absolute value of selling decisions between fund i and fund j for the stock s in the month t.

$|V_{i,s,t}| = |t_{i,s,t}|$ if $t_{i,s,t} > 0$, or $|V_{i,s,t}| = 0$ if $t_{i,s,t} < 0$.

$|V_{j,s,t}| = |t_{j,s,t}|$ if $t_{j,s,t} < 0$, or $|V_{j,s,t}| = 0$ if $t_{j,s,t} < 0$.

$ExcTD_{i,s,t}$ is the excess trading of fund i for stock s in the month t, which cannot be made by fund j due to its previous stock holding portfolio.

$ExcTD_{i,s,t} = |\ min\left(0\ ,\ \left(t_{i,s,t} + W_{j,s,t-1}\right)\right)|$ if $t_{i,s,t} < 0.$

$ExcTD_{i,s,t} = 0$ if $t_{i,s,t} \geq 0.$

$ExcTD_{j,s,t}$ is the excess trading of fund j for stock s in the month t, which cannot be made by fund i due to its previous stock holding portfolio.

$ExcTD_{j,s,t} = |\ min\left(0\ ,\ \left(t_{j,s,t} + W_{i,s,t-1}\right)\right)|$ if $t_{j,s,t} < 0$.

$ExcTD_{j,s,t} = 0$ if $t_{j,s,t} \geq 0$.

3.3 The evolution of trading divergence among mutual funds

In this section, our aim is to study whether the level of trading divergence is constant over time or not and whether it shows a given trend. We first obtain the trading divergence level among mutual fund pairs of the Spanish Euro-Zone equity mutual fund industry from 2000 to 2020.

Table 3. 2 – Overall results of the trading divergence among fund pairs

This table reports the results of the trading divergence (*TD*) among fund pairs for each year. Section A shows the mean and the standard deviation (St. Dvt.) of the trading divergence level among all fund pairs. Section B shows the number of fund pairs within the same family and the mean and the St. Dvt. of their trading divergence level. Section C shows the number of fund pairs in different fund families and the mean and the St. Dvt. of their trading divergence level. Section D shows the mean and the St. Dvt. difference between the value of fund pairs in the same family and the value of fund pairs in different families. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in the mean difference test between both groups of fund pairs. Note that in this table, we present a yearly report of the number of fund pairs compared during each year, while Table 3.1 presents the total number of funds only at five specific points of the sample period.

	Section A All fund pairs		*Section B. Fund pairs in the same fund family*			*Section C Fund pairs in different fund families*			*Section D Difference (same-different family)*	
Year	Mean TD	St. Dvt. TD	#fund pairs	Mean TD	St. Dvt. TD	#fund pairs	Mean TD	St. Dvt. TD	Mean TD	St. Dvt. TD
2000	95.64%	6.75%	325	80.71%	23.30%	13,879	95.97%	5.43%	-15.27%***	17.87%***
2001	96.49%	6.52%	478	82.62%	23.84%	16,282	96.89%	4.70%	-14.26%***	19.14%***
2002	96.69%	6.24%	363	83.36%	24.64%	14,475	96.99%	4.71%	-13.63%***	19.92%***
2003	96.78%	5.96%	340	84.20%	23.70%	14,622	97.05%	4.57%	-12.85%***	19.14%***
2004	96.61%	6.43%	337	83.52%	24.65%	13,672	96.94%	4.78%	-13.41%***	19.87%***
2005	96.65%	6.15%	391	84.66%	22.96%	14,613	96.98%	4.52%	-12.32%***	18.44%***
2006	96.36%	6.38%	432	84.03%	23.40%	15,352	96.70%	5.27%	-12.67%***	18.13%***
2007	94.88%	6.89%	465	83.19%	21.22%	16,529	95.32%	5.17%	-12.13%***	16.05%***
2008	94.35%	8.04%	476	84.31%	21.96%	16,244	94.81%	6.37%	-10.50%***	15.59%***
2009	95.28%	7.22%	436	84.52%	21.71%	14,492	95.68%	5.63%	-11.16%***	16.08%***
2010	96.37%	6.12%	267	86.64%	21.65%	11,458	96.68%	4.52%	-10.04%***	17.13%***
2011	96.73%	6.07%	239	86.71%	23.53%	9,727	97.02%	4.30%	-10.31%***	19.23%***
2012	96.47%	6.49%	193	87.90%	22.72%	7,764	96.72%	5.11%	- 8.82%***	17.61%***
2013	96.82%	5.78%	167	88.75%	21.05%	6,171	97.04%	4.53%	- 8.29%***	16.52%***
2014	96.45%	5.92%	98	88.33%	22.12%	4,625	96.63%	4.83%	- 8.30%***	17.30%***
2015	96.88%	5.23%	104	90.61%	16.57%	4,655	97.04%	4.48%	- 6.43%***	12.08%***
2016	97.49%	4.46%	100	92.42%	13.49%	4,909	97.60%	3.97%	- 5.18%***	9.52%***
2017	97.74%	4.70%	89	91.98%	14.50%	4,753	97.85%	4.19%	- 5.88%***	10.31%***
2018	97.88%	4.37%	73	92.56%	13.43%	4,732	97.97%	3.95%	- 5.42%***	9.48%***
2019	97.70%	4.51%	60	93.33%	11.19%	4,311	97.78%	4.25%	- 4.45%***	6.94%***
2020	97.55%	4.19%	62	94.31%	8.62%	4,077	97.61%	4.02%	- 3.30%***	4.60%***
2000-2020	96.56%	6.37%	1,190	87.08%	22.68%	35,521	96.82%	4.93%	-9.74%***	17.75%***

Table 3.2 presents the average of the divergence level of all fund pairs as well as these averages split according to whether the fund pairs belong to the same fund family or not. We find that the trading divergence level is lower among fund pairs within the same family. This result is consistent with the findings of previous literature that show a higher portfolio overlap among fund pairs within the same family than among fund pairs in different fund families (Chen et al., 2004; Elton et al., 2007). Pomorski (2009) also shows that when funds belonging to the same family trade the same stock in the same direction, this stock outperforms.

The development of the mutual fund industry in recent decades has increased competition in the industry. Fund families could have incentives to offer different funds to increase their market share (Gavazza, 2011). Similarly, due to personal promotion and recognition concerns in a competitive environment, fund managers may also have incentives to generate added value in the management of their funds. In addition, the GFC of 2008 is included in our sample period. This crisis caused an intense reorganization of the Spanish banking system (Montes, 2014), and this reorganization was also translated to fund and fund family mergers (Neal and García-Iglesias, 2013). Therefore, the consolidation of the industry and the GFC provided incentives to increase the trading divergence among funds in an attempt to achieve a higher fund diversification and a higher efficiency level in the mutual fund industry.[25] In addition, Delpini et al. (2019) conclude that the GFC stimulated the decrease in the similarity level among portfolios.

Therefore, our first hypothesis in this study is as follows:

3.1H: The trading divergence level among mutual fund pairs increases over time.

[25] According to DeYoung et al. (2009), the larger and more diversified financial services firms are more likely to come out of the restructuring periods in the financial market.

To test this hypothesis, we use a dynamic panel-data model. Specifically, we apply the generalised method of moments (GMM) method of Arellano and Bower (1995) and Blundell and Bond (1998) on a quarterly basis as follows: [26]

$$TD_{i,j,t} = \alpha_{i,j,t} + \gamma_{i,t} TD_{i,j,t-1} + \beta_1 Time_t + \beta_2 Fund\_family_{i,j,t} + \beta_3 Size\_\ Difference_{i,j,t} + \\ + \beta_4 Age\_Difference_{i,j,t} + \beta_5 Fees\_Difference_{i,j,t} + \\ + \beta_6 Return\_Difference_{i,j,t} + \beta_7 \#Stocks\_Difference_{i,j,t} + \\ + \beta_8 MoneyFlows\_Difference_{i,j,t} + \varepsilon_{i,j,t} \quad , \tag{3.2}$$

where $TD_{i,j,t}$ and $TD_{i,j,t-1}$ are the average trading divergence between funds *i* and *j* in quarter *t* and *t-1*, respectively. $Time_t$ ranges from 1 in the first quarter to 82 in the last quarter. $Fund\_family_{i,j,t}$ is equal to 1 if funds *i* and *j* in quarter *t* belong to the same mutual fund family and equal 0 otherwise. $Size\_Difference_{i,j,t}$, $Age\_\ Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences among the sizes, ages, fees, returns related to the last twelve months, number of stocks held in portfolios and the relative money flows of funds *i* and *j* in quarter *t*.

This model allows us to study the relationship between trading divergence and the *Time* variable that captures the trend of this divergence during the sample period. For robustness reasons, the model includes six control variables for the differences among the characteristics of funds in each fund pair.

Fund_family: We include this variable to control whether a fund pair belongs to the same family. The inclusion of this control variable is explained by the fact that, as we

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[26] The dynamic model has also been carried out on a yearly basis. However, the dynamic model has not been applied on a monthly basis as a consequence of non-adequate degrees of freedom due to the relative relationship between the number of individuals (in our study, the number of fund pairs) and the number of time periods (Roodman, 2009). In this situation, previous literature proposed grouping data in longer periods of time (for example, the grouping of monthly data into quarterly data), reducing thus the number of time periods (Pesaran et al., 1989; Lee et al., 1990). For robustness purposes, we also apply the fixed effects (FE) model in monthly, quarterly, and annual computations.

can observe in Table 3.2, the trading divergence level is lower among fund pairs within the same fund family than across families, in line with the findings of previous studies.

Size_Difference: We include the difference among the sizes of funds in each pair to control for its potential effect on the trading divergence level. The previous literature finds differences among the trading characteristics of large and small funds, although the findings of several studies run in the opposite direction. To reinforce the idea of differences among funds depending on their sizes, Busse et al. (2021) document that to avoid incurring higher trading costs, larger funds trade less frequently and hold more liquid stocks and larger stocks than do smaller funds. However, Pástor et al. (2020) find that larger funds are better diversified and that they trade more.

Age_Difference: We consider including the difference of age among fund pairs because previous literature points out that the flow-performance relation is stronger for younger funds than for older funds (Chevalier and Ellison, 1997). Therefore, this age difference may have an influence on the trading divergence level among funds.

Fees_Difference: According to previous studies, fund fees also influence the expected level of fund trading. Malhotra and McLeod (1997), Livingston and O'Neal (1996) and Rabarison (2016) show a significantly positive relationship between fees and fund trading volume. Consequently, we hypothesise that the greater (lower) the difference in fees among the pair of funds is, the greater (lower) the difference among their trading volumes.

Return_Difference: Previous studies document a significant relationship between the fund's past return and trading behaviour. Sirri and Tufano (1998) and Del Guercio and Tkac (2002) show that mutual fund investors disproportionately allocate more capital to funds with the highest recent returns. Given this, managers of funds with worse past returns may have more incentives than managers of funds with better past returns to seek new opportunities that allow the fund to improve its results (Carpenter, 2000; Chen, 2009). For that reason, we consider that the greater the difference in past returns among the pairs of funds is, the greater the difference in incentives to seek new investment opportunities, which could influence the trading divergence among them.

#Stocks_Difference: We approximate the level of diversification of a fund with the number of stocks within its portfolio. According to Anderson (2013), high-frequency traders tend to hold less diversified portfolios. Several researchers document an opposite result for these relationships (Pástor et al., 2020). Thus, we consider that the fund diversification level may influence the fund trading level.

MoneyFlows_Difference: We consider that two funds with very different money flows may show a higher trading divergence because a fund attracting positive money flows will tend to make buying decisions, while a fund suffering large money outflows will tend to make selling decisions. In this line, Dubofsky (2010) documents a significantly positive relationship between the fund trading level and the fund flows and argues that an excessive trading level in mutual funds is a consequence of large positive flows.

Given the previous discussion regarding the funds' different trading behaviour depending on the funds' characteristics, we could presume that the greater the difference among fund characteristics is, the greater the probability that the trading divergence among them will be high.

Section A of Table 3.3 presents the results of Equation 3.2 for all fund pairs during the whole sample period (January 2000-June 2020). The results show that the coefficient of the *Time* variable is significantly positive at the 5% level. Therefore, we find that the trading divergence increases over time, although the values are in a narrow range.[27] This result is also observed in Figure 3.1.

Note that the values of the trading divergence level are high since the methodology of this study not only captures the "active" divergence that occurs when both compared funds trade in a certain stock (both trade in the same direction or in the opposite directions) but also the "passive" divergence that occurs when a fund trades in a certain stock and the other fund does not trade in this stock.

Table 3. 3 – The evolution of the trading divergence and characteristics of mutual funds

This table shows the results obtained from Equation 3.2 with the dynamic model on a quarterly basis. Section A shows the coefficients and *p*-values for the whole sample period (January 2000-June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t*, and the independent variables are the following: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1;* $Time_t$ ranges from 1 in the first quarter of our sample period to 82 in the last quarter; $Fund\_family_{i,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* belong to the same fund family and it is equal to 0, otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$, and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in quarter *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Section A *Period 2000-2020*	*Section B* *Sub-period:2000-2009*	*Section C* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.8693*** (0.000)	0.9406*** (0.000)	0.8626*** (0.000)
TD_{t-1}	0.0812*** (0.000)	0.0735*** (0.000)	0.0481*** (0.000)
Time	0.0001** (0.030)	-0.0012*** (0.000)	0.0006*** (0.000)
Fund_family	-0.1204*** (0.000)	-0.1488*** (0.000)	-0.0380*** (0.000)
Size_Difference	-0.0002 (0.884)	0.0007*** (0.003)	0.0005** (0.036)
Age_Difference	0.0230*** (0.000)	-0.0460*** (0.000)	0.0566*** (0.000)
Fees_Difference	-0.0455 (0.844)	-0.7563 (0.178)	0.3631 (0.110)
Return_Difference	-0.0040*** (0.000)	0.0083*** (0.000)	-0.0098*** (0.000)
#Stocks_Difference	0.0002*** (0.000)	0.0002*** (0.000)	0.0001*** (0.002)
MoneyFlows_Difference	0.0009* (0.080)	0.0050*** (0.000)	-0.0062*** (0.000)
Wald	1,383.5*** (0.000)	2,419.5*** (0.000)	322.39*** (0.000)
VIF	1.02	1.03	1.03

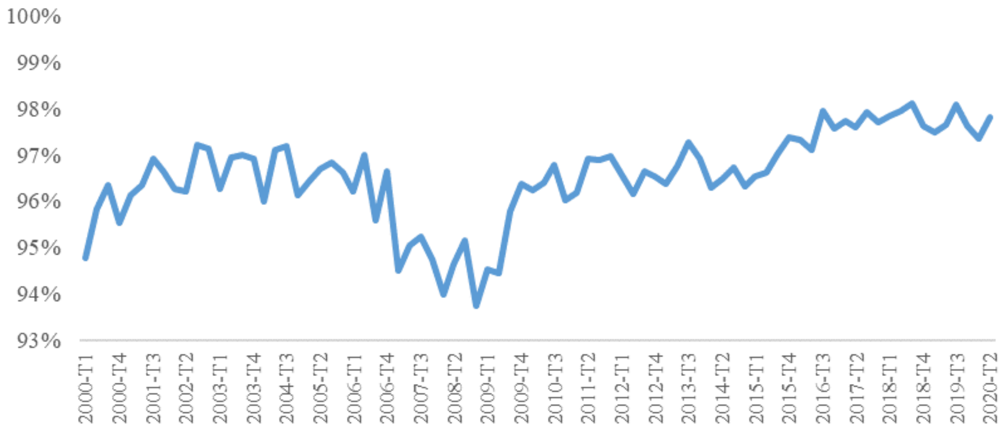
[1] Model was estimated with Robust Standard Errors.
[2] Variance Inflation Factors (VIF) values are widely acceptable in the literature.

[27] The dynamic model on a quarterly and annual basis and the FE model on a monthly, quarterly and annual basis provide similar findings for the *Time* variable and for the control variables, showing thus the robustness in our findings (see Appendix 3.1 for more details).

Although the results show that the trading divergence increases over the sample period, Figure 3.1 also shows a different pattern before and after the GFC (2008). We apply the Bai-Perron test to find structural breaks in the level of trading divergence, and we find that 2009 is the main breakpoint in the pattern of trading divergence.

Figure 3. 1 – Evolution of the trading divergence level for all fund pairs

This figure represents the evolution of the trading divergence level for all fund pairs from January 2000 to June 2020. The value is computed quarterly based on the average of their months.



According to the results of the Bai-Perron test, we split the whole sample period into two sub-periods: sub-period 1 comprises the period from January 2000 to December 2009, and sub-period 2 comprises the period from January 2010 to June 2020. Section B and Section C of Table 3.3 show the results for each sub-period. The evidence suggests that in the sub-period 2000-2009, the trading divergence tends to decrease, while the sub-period 2010-2020 presents an increasing divergence evolution, in line with the findings of Delpini et al. (2019).

Regarding the control variables, we find that the *Fund_family* and *#Stocks_Difference* variables are significantly negative and positive, respectively, in the whole period and when the period is split it into the two sub-periods. Therefore, we find a lower trading divergence in fund pairs when the pairs are within the same family (as previously shown in Table 3.2) and when the difference in the numbers of stocks held in their portfolios is low. We also find that in the two sub-periods, the trading divergence level is lower in fund pairs with similar size. In addition, the results show significant opposite results between the sub-periods for the rest of the control variables *(Age_Difference, Return_Difference and MoneyFlows_Difference),* which does not allow clear conclusions about the influence of these variables. Finally, the difference in fund fees does not seem to show a significant influence on the trading divergence level among funds for either the whole period or the sub-periods.

3.4 Determinants of the trading divergence among mutual funds

3.4.1 Management and external market determinants

This section aims to identify the determinants that may influence the trading divergence among mutual funds. Specifically, we study to what extent the trading divergence between two mutual funds is explained by (1) the previous holding of both funds and (2) by the level of market stress.

Portfolio overlap: We consider that funds that have a high (low) portfolio overlap in their previous holdings may show less (more) trading divergence in the subsequent period. In this sense, previous studies have documented a similar investment style/objective and common access to the same information and resources as the main cause of portfolio overlap among any fund pair (e.g., see Elton et al., 2007; Pool et al., 2015) and the high correlation among their performance (Brown and Wu, 2016). Therefore, our second hypothesis is as follows:

3.2H: Previous portfolio overlap negatively influences the level of trading divergence among mutual funds.

Market stress: The trading behaviour of fund managers may differ under different market conditions, as documented in the literature. Raddatz and Schmukler (2012) find that both investors and fund managers react to periods of market stress with substantial adjustments in their decisions and pro-cyclical behaviour, reducing their exposure in riskier countries. Furthermore, several studies argue that investment agents prefer to take risks on more visible stocks (Covrig et al., 2001) and on more familiar stocks (Garlappi et al., 2007; Epstein and Schneider, 2008) and that this preference could be enhanced with a higher stress in the market. Therefore, moments of high stress in the market may incite fund managers to buy less risky and more familiar stocks and to sell risky stocks; thus, this common trading objective may result in a lower trading divergence level during these periods.

Similarly, Karunanayake et al. (2010) and Khan et al. (2011) argue that the cost and time of processing information are higher in market stress periods, increasing the incentives of fund managers to make decisions similar to those made by others. Kodres and Pritsker (2002) also affirm that negative news and financial stress tend to generate contagion and imitation among fund managers. In addition, social comparisons (Karau and Williams, 1993) and the influence of the performance records of managers on their compensation (Kempf et al., 2009; Maug and Naik, 2011) may evoke a conformity goal of not differing from others in periods of higher market stress.

Consequently, we could expect a significantly negative relationship between the trading divergence level and market stress. Our third hypothesis is as follows:

3.3H: Market stress negatively influences the level of trading divergence among mutual funds.

To examine the determinants of the level of trading divergence (TD), we apply the dynamic generalized method of moments (GMM) model of Arellano and Bower (1995) and Blundell and Bond (1998) on a quarterly basis as follows:[28]

$$\begin{aligned} TD_{i,j,t} = {} & \alpha_{i,j,t} + \gamma_{i,j,t}TD_{i,j,t-1} + \beta_1 Portfolio\_Overlap_{i,j,t-1} + \beta_2 Market\ Stress_t + \\ & + \beta_3 Fund\_family_{i,j,t} + \beta_4 Size\_Difference_{i,j,t} + \beta_5 Age\_Difference_{i,j,t} + \\ & + \beta_6 Fees\_Difference_{i,j,t} + \beta_7 Return\_Difference_{i,j,t} + \\ & + \beta_8 \#Stocks\_Difference_{i,j,t} + \beta_9 MoneyFlows\_Difference_{i,j,t} + \varepsilon_{i,j,t}, \end{aligned} \quad (3.3)$$

where $Portfolio\_Overlap_{i,j,t-1}$ is the average portfolio overlap between funds i and j in quarter t-1.[29] $Market\ Stress_t$: is the level of equity market stress measured with the Spanish Financial Market Stress Indicator (FMSI)[30] of CNMV. The rest of the control variables are defined in Equation 3.2.

Table 3.4 presents the results of Equation 3.3 for the 2000-2009 sub-period and the 2010-2020 sub-period. The findings show that the previous portfolio overlap of a fund pair significantly influences its subsequent trading divergence and that the fund pairs with a higher (or lower) previous portfolio overlap show a lower (or higher) divergence level among their following trading decisions, as expected according to 3.2H. In addition, the results show that the coefficient of the market stress variable is significantly negative in both sub-periods, highlighting that market stress negatively influences the level of divergence among funds trading decisions. This finding is in line with the studies showing

[28] We apply Equation 3.3 to each sub-period (2000-2009 and 2010-2020) because we find different patterns in the trading divergence level between both periods, as documented in the previous section. In addition, we apply Equation 3.3 for monthly, quarterly and annual frequency, and we use both the dynamic and FE model, as in Equation 3.2 (see Appendix 3.2 for more details).

[29] Following the methodology used by Elton et al. (2007) and Pool et al. (2015), we obtain the portfolio overlap.

[30] The FMSI was introduced by Cambón and Estévez (2016) and is used in several studies, such as Kremer (2016). FMSI is similar to the “Composite Indicator of Systemic Stress” that Holló et al. (2012) proposed for the euro area as a whole. This indicator represents a real-time measure of systemic risk and tries to quantify stress in the Spanish financial system. Specifically, to capture the stress in the equity market, the index comprises three individual stress indicators, namely, volatility, liquidity and sudden asset price movements that are common in a period of financial crisis.

that in periods of high market stress, there is a higher likelihood of convergence as well as a greater incentive for managers to make decisions similar to those of others (Karunanayake et al., 2010; Khan et al., 2011), as stated in 3.3H.

Table 3. 4 – Determinants of the trading divergence among mutual funds

This table shows the results obtained from Equation 3.3 with the dynamic model on a quarterly basis. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the subperiod comprising January 2010 to June 2020. The dependent variable, $TD_{I,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t* and the independent variables are as follows: $TD_{I,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1; Market Stress*$_t$ is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); $Portfolio\_Overlap_{i,j,t-1}$ is the portfolio overlap of funds *i* and *j* in quarter *t-1*; $Fund\_family_{I,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* are within the same fund family and it is equals 0, otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$, and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in quarter *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *Sub-period:2000-2009*	*Section B* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9197*** (0.000)	0.9471*** (0.000)
TD_{t-1}	0.0584*** (0.000)	0.0316*** (0.000)
Market Strees	-0.0919*** (0.000)	-0.0010** (0.034)
$Portfolio\_Overlap_{t-1}$	-0.1058*** (0.000)	-0.0196*** (0.000)
Fund_family	-0.1308*** (0.000)	-0.0376*** (0.000)
Size_Difference	0.0004** (0.039)	0.0001*** (0.000)
Age_Difference	0.0350*** (0.000)	-0.0139*** (0.000)
Fees_Difference	-0.3774 (0.480)	0.1866 (0.559)
Return_Difference	0.0005 (0.709)	-0.0093*** (0.000)
#Stocks_Difference	0.0001*** (0.000)	0.0001*** (0.000)
MoneyFlows_Difference	0.0028*** (0.000)	-0.0073*** (0.000)
Wald	3,561.63*** (0.000)	503.71*** (0.000)
VIF	1.06	1.05

[1] Equation was estimated with Robust Standard Errors.
[2] Variance Inflation Factors (VIF) values are widely acceptable in the literature.

The findings of the control variables are consistent with the results obtained in Equation 3.2, that is, there is a lower trading divergence among fund pairs that are within the same fund family, have a smaller difference in their size, and have a smaller difference in the number of stocks held in their portfolios.

3.4.2 Trading divergence considering the previous fund holdings

In the previous section, we find that trading divergence is affected by the previous holdings of the funds analysed. However, fund managers could have the same perception of stock behaviour in the market, as the managers consider the information and recommendations from analysts.[31] Consequently, in their portfolio holdings, they will tend to have an exposure consistent with that perception, and thus, considering their initial position, they will buy, sell or refrain from trading to adjust the stock weight in the portfolio. Hence, funds with different initial positions in portfolio holdings for certain stocks could show different trading decisions (which could lead to a trading divergence) to achieve a similar weight[32] according to the analysts' recommendations. For that reason, the trading divergence obtained in Equation 3.1 may be overvalued. In this section, we approach a more accurate trading divergence measure by excluding the contribution to divergence caused by trading decisions that led to similar final portfolio weights.

First, we determine the difference in the portfolio weight in each stock *s* for each fund pair in both the previous period *t-1* and the current period *t* (see Equations 3.4 and 3.5). Second, we calculate the variation between the holding divergence (HD) in the current period and that observed in the previous period.

$$HD_{i,j,s,t} = |w_{i,s,t} - w_{j,s,t}| \tag{3.4}$$

$$HD_{i,j,s,t-1} = |w_{i,s,t-1} - w_{j,s,t-1}| \tag{3.5}$$

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[31]The impact of the analysts' recommendations on the trading decisions of fund managers has been documented by many studies, even after controlling for other trading determinants (Jegadeesh et al., 2004; Chen and Cheng, 2006; Barber et al., 2007). More recently, Frank and Kert (2013) show that fund managers attribute high information value to consensus forecast revisions and that thus, mutual funds significantly increase (decrease) their holdings in stocks when any of the consensus forecast measures increases (decreases) within the quarter prior to the observation period.

[32] For illustrative proposes, the portfolio weights of the funds *i* and *j* in the stock *s* at the beginning of month *t* are equal to 1.5% and 6%, respectively. During the period *t*, the fund *i* buys in the stock *s*, and the weight of this buying decision is equal to 1.5%. However, the fund *j* sells in the stock *s*, and the weight of this selling decision is equal to 2.5%. Finally, at the end of month *t*, the portfolio weights of funds *i* and *j* in the stock *s* are equal to 3% and 3.5%, respectively. Therefore, both funds trade in stock *s* in opposite direction, but these trading decisions result in a more similar portfolio weight in this stock.

Once we have calculated both holding divergences, we try to capture the portion of false trading divergence (FTD) in each fund pair for each stock *s* in each month *t*.

$$FTD_{i,j,s,t} = max\,(0, HD_{i,j,s,t} - HD_{i,j,s,t-1}) \tag{3.6}$$

Then, we calculate a more accurate trading divergence measure (TD*) between fund *i* and fund *j* in each month *t* as follows:

$$TD^*_{i,j,t} = \frac{\sum_s |t_{i,s\,t} - t_{j,s,t}| - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t} - \sum_s FTD_{i,j,s,t}}{\sum_s (Max\,|C_{i,j,s,t}| + Max\,|V_{i,j,s,t}|) - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t}} \tag{3.7}$$

Note that we conduct the following analyses in the chapter with this more accurate trading divergence measure (*TD**). Appendix 3.3 shows the results obtained by using TD*. We find similar results for its evolution (Figure A3.1 and Table A3.10) and for the influence of market stress (Table A3.11) as those found with the original measure. However, Table A3.10 and Table A3.11 shows that the use of TD* leads to the loss of significance of the *Fund_family* variable, which means that there are no significant differences among the fund pairs in the same family and those in different families. This could be explained by the fact that the probability that trading decisions will lead to similar positions in portfolios is greater among funds that belong to different families, since, as previously documented, mutual funds in the same family already show a higher previous holding overlap.

3.4.3 Trading divergence patterns in market shocks

In the previous section, we find that the level of market stress is a determinant that has a significantly negative influence on the trading divergence level among mutual funds. However, it is interesting to analyse in more detail the reaction of the fund managers in shock moments in which market stress shoots up and then to compare these reactions across the different shocks within the sample period.

Specifically, for our sample period, in terms of market stress, we identified three important shocks, occurring in (1) January–March 2008, (2) March–April 2011 and (3) March–April 2020, in which the level of market stress showed increases equal to 197%, 107% and 180%, respectively. These shocks coincided with the outbreaks of the GFC (2008), the European debt crisis (2011) and the COVID-19 crisis.

Regarding the GFC (2008), most studies about mutual funds focus on the role of institutional investors in propagating the crisis. These studies document a common pattern of investors who liquidated their fund positions by selling stocks that turned "toxic" and illiquid because they faced liquidity needs (Manconi et al., 2012). Regarding the sovereign debt crisis of the Eurozone (2011), although it mainly affected government bonds and monetary funds, equity funds were also influenced by the derived consequences that were observed in the return of stocks in the European market. Bhanot et al. (2014) find evidence of spillovers from the bond yield to Eurozone financial stock returns. In this line, Gallagher et al. (2020) show that managers rebalanced and adjusted their portfolio risk to avoid information-sensitive European risks and to especially avoid holding stocks from European countries with higher credit risk.

Concerning the COVID-19 crisis, recent studies document the preliminary results of the initial impact of this pandemic crisis on financial systems an increase in systematic risk and market volatility due to policy interventions (Zaremba et al., 2020; Zhang et al., 2020) and the stock market contagion (Akhtaruzzaman et al., 2020). For the mutual fund industry, Mirza et al. (2020) and Rizvi et al. (2020) document a transition from riskier to relatively safer stocks and a clear switch to the non-cyclical sector investment due to the reactions of industries to sudden COVID-related news announcements (Goodell and Huynh, 2020). Regarding the impact on the performance and efficiency of mutual funds, Pástor and Vorsatz (2020) find that most active funds underperform passive benchmarks during the COVID-19 pandemic.

For several reasons, we could expect to find different reactions from equity fund managers to the market shocks of 2008 and 2020. First, the different situations of the financial system in both moments could have led managers to react in different ways. Spatt (2020) documents that at the beginning of 2008, the financial system was infected, as financial institutions often held excessive exposure to mortgage-related instruments that had declined substantially in value. However, at the beginning of the COVID-19 crisis, the financial system was strong. Second, both crises also have a completely different origin: a financial origin in the 2008 crisis and a sanitary one in the 2020 crisis. Third, the greater transparency and investor protection required in financial markets with the several reforms and measures of recent years and the higher experience and learning of fund managers who have faced other past market shocks may imply that they currently show a different behaviour. Greenwood and Nagel (2009) and Seru et al. (2010) document that negative prior experiences in the market influence investor behaviour through the learning process. Finally, in the GFC, fund managers showed a common tendency to sell toxic products, as Manconi et al. (2012) document, while in the COVID-19 crisis, they may consider this moment a chance to seek new investment opportunities (Spatt, 2020).

Regarding the European sovereign debt crisis, although its cause was linked to the GFC in 2008, this crisis did not show the same impact in all countries or on all institutional investors (Gallagher et al., 2020). Therefore, we might think that not all managers reacted in the same way and that their reaction depended on their exposure to the countries and assets with the worst credit ratings.

We first study the reaction of fund managers in terms of the trading divergence level in the periods of the three market shocks mentioned above. Specifically, we compare the average of the trading divergence level before and during the shock period in each of them, applying the mean difference test. Second, we compare the results of this test across the three shocks.

Table 3. 5 – Trading divergence patterns in the different economic crises

This table shows the results of the comparison between the different market stress shocks in terms of the trading divergence (TD^*) level among fund pairs. Panel A shows the results of the shock in the GFC (2008), Panel B shows the results of the shock in the European debt crisis (2011), and Panel C shows the results of the shock in the COVID-19 crisis (2020). The first column includes the specific period of the shock. The second and third columns show the mean and the standard deviation (St. Dvt.) of the trading divergence level in each period. The fourth and fifth columns show the differences in the mean and St. Dvt between the stock period and the previous period. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in the mean difference test.

Panel A: GFC (2008)				
			Difference Shock period-Previous period	
	Mean TD^*	St. Dvt. TD^*	Mean TD^*	St. Dvt. TD^*
Shock period: January – March 2008	69.33%	21.45%		
- 3 months: October - December 2007	73.55%	19.60%	-4.22%*** (0.000)	1.85%*** (0.000)
- 6 months: July - December 2007	72.47%	19.96%	-3.14%*** (0.000)	1.49%*** (0.000)
- 9 months: April - December 2007	73.02%	19.45%	-3.69%*** (0.000)	2.00%*** (0.000)
- 12 months: January - December 2007	73.13%	19.25%	-3.80%*** (0.000)	2.20%*** (0.000)

Panel B: The European debt crisis (2011)				
			Difference Shock period-Previous period	
	Mean TD^*	St. Dvt. TD^*	Mean TD^*	St. Dvt. TD^*
Shock period: July - August 2011	81.31%	17.25%		
- 3 months: April - June 2011	78.46%	18.30%	2.85%*** (0.000)	-1.05%*** (0.000)
- 6 months: January - June 2011	78.45%	17.62%	2.86%*** (0.000)	-0.37%*** (0.000)
- 9 months: October 2010 - June 2011	77.78%	17.96%	3.53%*** (0.000)	-0.70%*** (0.000)
- 12 months: July 2010 - June 2011	77.43%	18.27%	3.89%*** (0.000)	-1.02%*** (0.000)

Panel C: The COVID-19 crisis (2020)				
			Difference Shock period-Previous period	
	Mean TD^*	St. Dvt. TD^*	Mean TD^*	St. Dvt. TD^*
Shock period: March - April 2020	83.12%	15.49%		
- 3 months: December - February 2020	82.39%	17.72%	0.73%*** (0.000)	-2.23%*** (0.000)
- 6 months: September - February 2020	82.90%	17.37%	0.23%*** (0.000)	-1.88%*** (0.000)
- 9 months: June 2019 - February 2020	82.88%	17.31%	0.24%*** (0.000)	-1.82%*** (0.000)
- 12 months: March 2019 - February 2020	82.38%	17.58%	0.74%*** (0.000)	-2.08%*** (0.000)

Table 3.5 shows the results of the comparison among the trading divergence patterns in the different crises. In the shock of 2008, we find that the trading divergence level decreases significantly compared to the level of divergence in the pre-crisis shock. In addition, the results show that during the market shock period, the dispersion in the level of trading divergence among the least and most divergent funds is higher because although in general, the level of divergence decreased, the fund pairs that showed less previous divergence mainly explained this decrease.

However, in the market shock of 2020, we observe that the trading divergence level slightly increases compared to the level in previous months and that the dispersion decreases due to the divergence of previously least divergent (or most divergent) fund pairs increases (or decreases). Previous researchers document that in periods with high market stress, there is a higher level of uncertainty about stocks (Hakkio and Keeton, 2009; Martins and Paulo, 2014) and a greater incentive for fund managers to make decisions similar to those of others (Patev and Kanaryan, 2003; Karunanayake et al., 2010; Khan et al., 2011). Therefore, among the funds with a lower previous divergence, the effect of a higher level of uncertainty may be predominant. In the search for new investment opportunities in line with the behaviour documented by Spatt (2020), this effect may cause an increase in the trading divergence level among those fund pairs. Furthermore, this could explain the difference of this shock with the 2008 shock, in which the trend of funds was to undo toxic positions, while in 2020, there seems to be a trend of seeking opportunities. The fund pairs with the highest level of prior trading divergence may show behaviour towards the market during this shock period, as in 2008.

Regarding the Eurozone crisis, during the marked stress shock period, as during the 2020 crisis, we observe a general increase in the level of trading divergence, which could be related to the rebalancing of portfolio holdings. Gallagher et al. (2020) document a tendency to remove positions exposed to the European riskiest countries with the worst credit rating and to bet on other investment alternatives. However, the results of the 2011 shock should be considered with caution since it was still a period of recovery from the global crisis.

3.4.4 The influence of stock characteristics on the trading divergence at the stock level

We next examine whether the trading divergence level is driven by stock characteristics. This analysis could be interesting for fund managers, for the top management of families, for investors and for regulators, as it could help them to identify the stocks with which managers could provide value added to fund management in the industry.

Previous literature shows that mutual funds have a preference for certain stocks and that the trading decisions of fund managers depend on the stock information available for these stocks. Falkenteins (1996) finds that mutual funds show an aversion to small stocks with low idiosyncratic volatility and little information. Similarly, Aggarwal et al. (2005) document that funds tend to invest in large firms that have better accounting quality. Brands et al. (2006) find that active managers exhibit preferences for stocks exhibiting high-price variance, large market capitalization, greater levels of analyst coverage and lower variability in analysts' earnings forecasts. Gompers and Metrick (2001) also study institutional investors' demand for stocks and find that these investors invest in stocks, which are larger, liquid and have had relatively low returns in the previous year. In contrast to these results, Otten and Bams (2002) reveal a fund preference for small stocks, and Covrig et al. (2006) find similarities and differences in the stock preferences of domestic and foreign fund managers. Nevertheless, the authors show that both manager groups prefer stocks with high return on equity and low return variability.

Some studies propose that institutional investors tend to converge in buying large stocks because these investors follow common market signals (Lin and Swanson, 2003; Sias, 2004; Lu et al., 2012). However, other studies indicate that convergence is more pronounced in small stocks because fund managers may receive lower and bounded information from these stocks (Huang et al., 2010; Liao et al., 2011).

Following the measure proposed in this study, we aggregate the trading divergence of all fund pairs by each stock *s* in each month *t* as shown in Equation 3.8:

$$TD*_{s,t} = \frac{\sum_{i,j|i<j} \left(\sum_s |t_{i,s\,t} - t_{j,s,t}| - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t} - FTD_{i,j,s,t}\right)}{\sum_{i,j|i<j} \left(\sum_s (Max\,|C_{i,j,s,t}| + Max\,|V_{i,j,s,t}|) - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t}\right)} \qquad (3.8)$$

Then, to examine the stock characteristics that influence the level of trading divergence at the stock level, we apply the FE model on a quarterly basis as follows: [33]

$$TD*_{\mathrm{s,t}} = \alpha_{s,t} + \beta_1 Stock\_return_{s,t} + \beta_2 Stock\_volatility_{s,t} + \beta_3 Stock\_size_{s,t} +$$

$$+ \beta_4 Stock\_popularity_{s,t} + \varepsilon_{s,t}\,, \qquad (3.9)$$

where $TD*_{\mathrm{s,t}}$ is the average trading divergence level among funds for stock *s* in quarter *t* and the independent variables are as follows: $Stock\_return_{s,t}$ is the return of stock *s* in quarter *t* related to the last twelve months in absolute value. $Stock\_volatility_{s,t}$ is the volatility of stock *s* in quarter *t* and is measured as the standard deviation of its return during the last twelve months. $Stock\_size_{s,t}$ is the market capitalization of stock *s* in quarter *t*. $Stock\_popularity_{s,t}$ is the popularity level of stock *s* in quarter *t* and is measured with the relation between the number of funds that trade the stock and the number of funds existing in that quarter in the sample.

[33] The selection of the model is supported by the Hausman test, which suggests the use of FE instead of Random effects (RE). Robust standard errors are used in the estimation. For robustness purposes, we also apply the FE model in monthly and annual computations. The dynamic model has not been applied in Equation 3.9 because the Sargan test (1958) shows over-identifying restrictions. Note that to be overidentified just means that there are more instruments than endogenous variables. In this case, the literature recommends the use of static panel data models (see Appendix 3.4 for more details).

Table 3. 6 – Stock characteristics and trading divergence among mutual funds

This table shows the results obtained from Equation 3.9 with the FE model on a quarterly basis. Section A shows the results for all fund pairs. Section B shows the results for fund pairs within the same family. Section C shows the results for fund pairs in different fund families. The dependent variable, $TD^*_{s,t}$ is the trading divergence level among funds for stock *s* in quarter *t,* and the independent variables are as follows*:* $Stock\_return_{s,t}$ is the absolute value of the yearly past return of stock *s* in quarter *t; * $Stock\_volatility_{s,t}$ is the volatility of stock *s* in quarter *t* and is measured as the standard deviation of its return during the last year; $Stock\_size_{s,t}$ is the market capitalization of stock *s* in quarter *t*; and $Stock\_popularity_{s,t}$ is the popularity level of stock *s* in quarter *t* and is measured with the percentage of funds that trade in the stock *s* within our sample. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *All fund pairs*		*Section B* *Fund pairs in the same fund family*		*Section C* *Fund pairs in different fund families*	
	Coefficient	(*p*-value)	Coefficient	(*p*-value)	Coefficient	(*p*-value)
Constant	0.9459***	(0.000)	0.9358***	(0.000)	0.9537***	(0.000)
Stock_return	0.0022	(0.406)	-0.0029**	(0.039)	0.0038**	(0.015)
Stock_volatility	-0.0234	(0.231)	-0.0846***	(0.002)	-0.0036	(0.812)
Stock_Size	-0.0029***	(0.001)	0.0059*	(0.084)	-0.0035***	(0.000)
Stock_popularity	-0.4469***	(0.000)	-0.8770***	(0.000)	-0.4223***	(0.000)
F	162.7***	(0.000)	111.37***	(0.000)	143.75***	(0.000)
R^2	12.03%		15.30%		22.59%	
Hauman Test	243.48***	(0.000)	13.43***	(0.009)	731.17***	(0.000)

Table 3.6 shows the influence of the stock characteristics on the trading divergence level in that stock among fund pairs. The influence of the previous return is not statistically significant when considering all fund pairs. However, if we focus on within (or across) families, we observe a lower (or higher) divergence level in the stocks with a extreme previous performance (both very positive and very negative previous performance). This result suggests that within a family, the top management who influences managers' trading decisions may have a common opinion about stocks with outstanding performance, which results in similar trading decisions in these stocks among their funds. However, across families, the existence of extreme positive (or negative) performance leads to a higher divergence because each family can see investment opportunities in different stocks. On the other hand, most managers could have the same interest in the remaining undistinguished stocks regardless of the fund family to which the funds belong.

Stock volatility has a negative influence on the trading divergence level, but this effect is only statistically significant for fund pairs belonging to the same family. This finding provides evidence about the internal control of the risk management level within families and how this internal control results in a lower divergence trading level in the more volatile stocks among their funds. In the analysis of all fund pairs or of the fund pairs in different families, we also find a lower trading divergence level in larger stocks, which could be explained by the fact that the information available on these stocks is greater (Lin and Swanson, 2003; Sias, 2004; Lu et al., 2012). However, we find a lower level of trading divergence in small stocks within families, shedding light on the fact that fund managers could have a greater autonomy to make decisions about large companies, while the trading decisions for small companies are more influenced by the guidelines from the family's top management (i.e., investment directors). Finally, we find a lower level of trading divergence in stocks with a higher level of popularity in the market, regardless of whether analysing funds from the same family or from different families.

3.5 Performance consequences of the divergent trading

In the previous sections, we study the evolution and determinants of the trading divergence level among funds. In this section, we examine its consequences for fund performance. First, we study the influence of the trading divergence level on the subsequent fund performance. Second, we approximate the average contribution of divergent and convergent trading decisions to fund performance.

3.5.1 The influence of trading divergence on fund performance

Previous literature examines the abilities of active funds to outperform the benchmark and the value added of the managers' trading decisions. Some studies show that active funds do not outperform the benchmark (Jensen, 1968; Fama and French, 2010); however, recent studies document superior skills in certain trading decisions. Cremers and Petajisto (2009) document that an active fund manager can attempt to outperform the benchmark only by taking positions that are different from the benchmark. They find strong evidence for performance persistence for funds with the highest active share. Jiang et al. (2014) also demonstrate superior abilities in active fund management because managers overweight (or underweight) the stocks that show better (or worst) performance than the benchmark.

Similarly, Cohen et al. (2010) find that the best ideas of active managers outperform the market and the other stocks in their portfolios. In addition, Alexander et al. (2007) and Andreu et al. (2017) find that trading decisions based on valuation criteria have a significantly positive influence on fund performance. We hypothesise that the most distinct trading decisions of a fund manager and thus, the most divergent decisions with respect to the remaining funds are based on valuation criteria since his (or her) position, reputation and compensation depend on his or her fund's performance records (Mason et al., 2016). Consequently, we could expect a significantly positive relationship between the trading divergence level and the subsequent fund performance, and our fourth hypothesis is as follows:

3.4H: The trading divergence level positively influences subsequent fund performance.

To test this hypothesis, we first obtain the average divergence level of each fund *i* in each month *t* with respect to the rest of the funds $\left(TD*_{i,t}\right)$.

$$TD*_{i,t} = \overline{TD*_{i,j,t}} \tag{3.10}$$

Then, we run the following FE model on a quarterly basis as follows:[34]

[34] The selection of the model is supported by the Hausman test, which suggests the use of FE instead of RE. Robust standard errors are used in the estimation. For robustness purposes, we also apply the FE model in monthly and annual computations (see Appendix 3.5 for more details).

$$Fund\_Performance_{i,t+n} = \alpha_{i,t} + \beta_1 TD^*_{i,t} + \beta_2 Fund\_size_{i,t} + \beta_3 Fund\_age_{i,t} +$$

$$+ \beta_4 Fund\_fees_{i,t} + \beta_5 Fund\_\#stocks_{i,t} + \beta_6 Fund\_flows_{i,t} + \varepsilon_{i,t}\,, \quad (3.11)$$

where $Fund\_Performance_{i,t+n}$ represents the alpha of fund *i* in quarter *t+n* and is measured through the capital asset pricing model (CAPM), the Fama and French three-factor model and the Carhart four-factor model, with n ∈ {3,6,12} months. $TD^*_{i,t}$ is the average trading divergence level of fund *i* in quarter *t*, as defined in Equation 3.10. *Fund_size, Fund_age, Fund_fees, Fund_#stocks, Fund_flows* are the size, age, fees, number of stocks held in portfolios and relative money flows of fund *i* in quarter *t*, respectively.

Table 3.7 shows a significantly positive relationship between the subsequent fund performance and the trading divergence level. Therefore, our results provide evidence that funds that make the most divergent trading decisions in the industry outperform their counterparts, even after controlling for their characteristics. We could think that some funds only trade in stocks that seem to involve an investment opportunity but that also suppose a relatively high risk level. Consequently, compared to other funds, these funds that trade in those stocks are supposed to make more divergent trading decisions.

Regarding the control variables, in general terms, we observe that fund age, fund fees and fund money flows have a significantly positive influence on fund performance. Our findings support the findings of previous studies, which document a positive influence of the fund experience and that higher fees can result in higher gross returns (Ferreira et al., 2013) and reflect the investors' ability to predict future fund performance (i.e., the "smart money" effect first documented by Gruber 1996 and Zheng 1999). In addition, in line with the previous literature documenting that fund size erodes its performance (Kacperczyk and Seru, 2007; Pástor et al., 2015), Table 3.7 shows a significantly negative influence of the size variable. Finally, the number of stocks in portfolio holdings does not seem to have a significant influence on fund performance.

Table 3. 7 – The trading divergence and the subsequent fund performance

This table shows the results obtained from Equation 3.11 on a quartely basis. Section A shows the results obtained with the fund alpha of the CAPM. Section B shows the results obtained with the fund alpha of the Fama and French three-factor model. Section C shows the results obtained with the fund alpha of the Carhart four-factor model. We estimate the alphas by using rolling windows of 60 (*t+3*), 120 (*t+6*) and 240 (*t+12*) daily data. The dependent variable is the subsequent performance of the fund *i* in quarter *t*, and the independent variables are as follows: $TD^*_{i,t}$ is the average of the trading divergence level of fund *i* in quarter *t*; $Fund\_size_{i,t}$ is the average of the relativised size of fund *i* in quarter *t; $Fund\_age_{i,t}$* is the average of the relativised age of fund *i* in quarter *t*; $Fund\_fees_{i,t}$ is the average fees of fund *i* in quarter *t*; $Fund\_\#stocks_{i,t}$ is the average number of stocks held by fund *i* in quarter *t*; and $Fund\_flows_{i,t}$ is the average relative money flows fund *i* in the year *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$Fund\_Performance_{i,t}$								
	Section A: CAPM			*Section B: 3Factors*			*Section C: 4Factors*		
	t+3	*t+6*	*t+12*	*t+3*	*t+6*	*t+12*	*t+3*	*t+6*	*t+12*
Constant	-0.0009***	-0.0007***	-0.0005***	-0.0006***	-0.0007***	-0.0007***	-0.0005***	-0.0007***	-0.0006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TD	0.0008***	0.0006***	0.0005***	0.0004***	0.0005***	0.0006***	0.0003***	0.0005***	0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund_size	-0.0001***	-0.0001***	-0.0001**	-0.0001***	-0.0001**	-0.0001	-0.0001***	-0.0001**	-0.0001
	(0.002)	(0.004)	(0.028)	(0.006)	(0.024)	(0.230)	(0.003)	(0.027)	(0.261)
Fund_age	0.0001	0.0001*	0.0001**	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0001**
	(0.107)	(0.054)	(0.017)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.019)
Fund_fees	0.0542**	0.0453**	0.0026	0.0346*	0.0305*	0.0105	0.0337*	0.0267*	0.0021
	(0.020)	(0.022)	(0.880)	(0.067)	(0.054)	(0.540)	(0.072)	(0.093)	(0.903)
Fund_#stocks	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.244)	(0.913)	(0.515)	(0.628)	(0.445)	(0.226)	(0.617)	(0.312)	(0.155)
Fund_flows	0.001	0.0001**	0.0001***	0.0001	0.0001***	0.0001**	0.0001	0.0001**	0.0001***
	(0.167)	(0.010)	(0.003)	(0.316)	(0.003)	(0.010)	(0.275)	(0.010)	(0.005)
F	19.20***	14.01***	12.11***	9.11***	13.52***	13.79***	6.86***	13.15***	13.19***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	1.41%	1.85%	2.61%	1.52%	2.20%	3.09%	2.24%	2.07%	3.01%
Hausman test	17.19***	43.01***	81.18***	54.08***	13.52***	52.26***	60.81***	58.75***	49.44***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

3.5.2 The contribution of divergent trading decisions to fund performance

According to Equation 3.7, we compare the contribution of the actual trading divergence and the contribution of the actual trading convergence of funds to their performance. Then, our fifth hypothesis is as follows:

3.5H: The contribution of divergent trading decisions to fund performance is significantly higher than that of convergent trading decisions.

First, we obtain the actual trading divergence (ATD^*) and the actual trading convergence (ATC^*) between fund i and fund j in each month t as follows:

$$ATD^*_{i,j,s,t} \begin{cases} = \sum_s (t_{i,s,t} - t_{j,s,t}) - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t} - \sum_s FTD_{i,j,s,t} & \text{if } (t_{i,s,t} - t_{j,s,t})>0 \\ = \sum_s (t_{i,s,t} - t_{j,s,t}) + \sum_s ExcTD_{i,s,t} + \sum_s ExcTD_{j,s,t} + \sum_s FTD_{i,j,s,t} & \text{if } (t_{i,s,t} - t_{j,s,t})<0 \end{cases} \tag{3.12}$$

$$ATC^*_{i,j,s,t} = min\ (PTD_{i,j,s,t} - ATD^*_{i,j.s,t}\ ;\ t_{i,s,t}) \tag{3.13}$$

where $ATD^*_{i,j,s,t}$ is the numerator of Equation 3.7 and represents the more accurate actual trading divergence between funds i and j in stock s and month t, controlling the sign of the trading divergence for each fund within each pair.[35] $ATC^*_{i,j,s,t}$ is the actual trading convergence between funds i and j in stock s and month t. This measure is calculated as the difference between the potential trading divergence *(PTD)* that is represented for the denominator in Equation 3.7 and the ATD^* for each fund pair in each stock s, controlling that this difference is not greater than the trading weight of fund i in stock s.

Second, for each fund pair in each month, we obtain the contribution of the actual trading divergence (C_ATD) and the contribution of the actual trading convergence *(C_ATC)* to their fund performance, multiplying the ATD^* and the ATC^* of the fund pair

[35] Note that in a fund pair, one fund could buy in a certain stock, while the other fund could sell in this stock. Whether the subsequent performance of this stock is positive, the contribution of this trading divergence to the performance will be positive for the buying fund and negative for the selling fund.

in each stock by the stock alpha. Then, we sum all of these multiplications (see Equations 3.14 and 3.15).

$$C\_ATD^{*}_{i,j,t+n} = \sum_{s} (ATD^{*}_{i,j,s,t} \,.\, \alpha_{s,t+n}) \qquad \forall\ j \neq i \tag{3.14}$$

$$C\_ATC^{*}_{i,j,t+n} = \sum_{s} (ATC^{*}_{i,j,s,t} \,.\, \alpha_{s,t+n}) \qquad \forall\ j \neq i \tag{3.15}$$

where $C\_ATD^{*}_{i,t+n}$ is the contribution of the actual trading divergence between funds i and j in month $t+n$. $C\_ATC^{*}_{i,t}$ is the contribution of the actual trading convergence between funds i and j in month $t+n$. $\alpha_{s,t+n}$ is the subsequent alpha of stock s in month $t+n$.[36]

Third, for each fund in each month, we obtain the C_ATD^{*} and the C_ATC^{*} as the mean of all comparisons of a given fund with the rest of the funds (see Equations 3.16 and 3.17).

$$C\_ATD^{*}_{i,t+n} = \overline{C\_ATD^{*}_{i,j,t+n}} \tag{3.16}$$

$$C\_ATC^{*}_{i,t+n} = \overline{C\_ATC^{*}_{i,j,t+n}} \tag{3.17}$$

where $C\_ATD^{*}_{i,t+n}$ is the average contribution of the actual trading divergence of fund i in month $t+n$. $C\_ATC^{*}_{i,t}$ is the average contribution of the actual trading convergence of fund i in month $t+n$.

Finally, we compare the values of C_ATD^{*} and C_ATC^{*} through the mean difference test. Table 3.8 shows that the contribution of trading divergence to fund performance is significantly higher than the contribution of trading convergence, as stated in 3.5H. The results show a significantly positive difference of up to 0.15% in the annual performance. This outstanding conclusion provides evidence that fund managers who seek distinct trading strategies are more prone to offer added value to their shareholders.

[36] For robustness purposes, similarly to Equation 3.11, in this analysis, we also consider the alpha with the CAPM, the Fama and French three-factor model, and the Carhart four-factor model, with n ∈ {3,6,12} months.

Table 3. 8 – Stock characteristics and trading divergence among mutual funds

This table reports the results of the average contribution of the actual trading divergence level (*C_ATD)* and the average of the contribution of the actual trading convergence level (*C_ATC*) to the fund performance in annual computation and the difference between both values *(C_ATD – C_ATC).* Panel A shows the results obtained with the stock alpha of the capital asset pricing model (CAPM). Panel B shows the results obtained with the stock alpha of the Fama and French three-factor model. Panel C shows the results obtained with the stock alpha of the Carhart four-factor model. We estimate the alphas by using rolling windows of 60 (*t+3*), 120 (*t+6*) and 240 (*t+12*) daily data. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in the mean difference test.

Panel A: CAPM			
	t+3	*t+6*	*t+12*
C_ATD	0.0216%	0.0168%	0.0102%
C_ATC	-0.0075%	-0.0694%	-0.0089%
C_ATD – C_ATC	0.0291%** (0.023)	0.0862%*** (0.000)	0.0192%*** (0.003)
Panel B: 3Factors			
	t+3	*t+6*	*t+12*
C_ATD	0.0370%	0.0136%	0.0083%
C_ATC	-0.1161%	-0.0022%	-0.0094%
C_ATD – C_ATC	0.1531%** (0.000)	0.0158%*** (0.000)	0.0177%*** (0.002)
Panel C: 4Factors			
	t+3	*t+6*	*t+12*
C_ATD	0.0126%	0.0086%	0.0136%
C_ATC	-0.1120%	-0.0197%	-0.0020%
C_ATD – C_ATC	0.1245%*** (0.000)	0.0283%*** (0.000)	0.0155%** (0.012)

3.6 Conclusions

In this chapter, we link the strand of the literature that analyses the ability of mutual fund managers to add value to their shareholders and the research topic focused on the divergence among the managers' trading decisions. Specifically, we capture to what extent the trading of a fund differs with respect to that for the rest of the funds in any period and how these divergent decisions contribute to fund performance, considering that this distinct trading may be an important source of the value added by fund managers.

We find that funds that belong to the same family present lower levels of divergent trading. However, the higher similarity among funds of the same family documented by the previous research and our evidence of a lower trading divergence among funds with a higher previous portfolio overlap lead us to control the potential influence of the previous holdings, obtaining thus a more accurate value of the trading divergence level. Even when controlling this effect, we find an increase in distinct trading among funds, especially after the GFC of 2008.

Our analyses also reveal that the level of trading divergence is lower in periods with high market stress. This finding is in line with previous studies indicating that managers tend to reduce risk and invest in popular stocks in critical situations. Nevertheless, we find different reactions in terms of the trading divergence across the different market shocks that have occurred during the period analysed. This result could be explained by the different origins and strength levels of the financial system in each crisis and the learning process of managers from past negative market experiences.

Our findings also indicate that the trading divergence level is driven by certain stock characteristics. Specifically, we find a lower trading divergence in small stocks with an extreme performance and risk among funds within the same family. These results suggest an internal influence of the top management of families on certain investment opportunities and the existence of internal risk control within families. In addition, in line with documenting that managers show a higher interest in visible and well-known stocks, we find a lower trading divergence level in stocks with a higher level of popularity.

Finally, our study shows that funds with higher levels of trading divergence obtain significantly higher performance. This noteworthy evidence is confirmed when we compare the performance contribution of divergent trading decisions with the convergent trading's performance contribution, revealing that fund managers generate added value with their distinct trading decisions. These findings are interesting for fund families and managers and should increase their willingness to seek new investment opportunities to add value in portfolio management.

3. References

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Appendix 3.1: Robustness analyses of the results of the evolution of the trading divergence among mutual funds

Table A3. 1 – The evolution of the trading divergence and characteristics of mutual funds (dynamic model on a yearly basis)

This table shows the results obtained from Equation 3.2 with the dynamic model on a yearly basis. Section A shows the coefficients and *p*-values for the whole sample period (January 2000-June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in year *t*, and the independent variables are the following: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in year *t-1; Time*$_t$ ranges from 1 in the first year of our sample period to 21 in the last year; *Fund_family*$_{i,j,t}$ is equal to 1 when funds *i* and *j* in year *t* belong to the same fund family and it is equal to 0, otherwise; *Size_Difference*$_{i,j,t}$, *Age_Difference*$_{i,j,t}$, *Fees_Difference*$_{i,j,t}$, *Return_Difference*$_{i,j,t}$, *#Stocks_Difference*$_{i,j,t}$, and *MoneyFlows_Difference*$_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in year *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Section A *Period 2000-2020*	*Section B* *Sub-period:2000-2009*	*Section C* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.4915*** (0.000)	0.5186*** (0.000)	0.6640*** (0.000)
TD_{t-1}	0.4750*** (0.000)	0.4752*** (0.000)	0.2698*** (0.000)
Time	0.0001 (0.638)	-0.0024*** (0.000)	0.0015*** (0.000)
Fund_family	-0.0722*** (0.000)	-0.0933*** (0.000)	-0.0300*** (0.002)
Size_Difference	-0.0002** (0.014)	-0.0003*** (0.005)	0.0004** (0.023)
Age_Difference	0.0222*** (0.000)	-0.0047 (0.114)	0.0492*** (0.000)
Fees_Difference	-0.6547 (0.105)	-2.2763** (0.016)	-0.5864 (0.133)
Return_Difference	0.0056*** (0.003)	0.0249*** (0.000)	-0.0161*** (0.000)
#Stocks_Difference	-0.0050*** (0.001)	0.0002*** (0.000)	0.0001*** (0.002)
MoneyFlows_Difference	0.0002*** (0.000)	0.0088*** (0.000)	-0.0078** (0.016)
Wald	2,348.89*** (0.000)	4,595.21*** (0.000)	441.13*** (0.000)

Table A3. 2 – The evolution of the trading divergence and characteristics of mutual funds (FE on a monthly basis)

This table shows the results obtained from Equation 3.2 with the FE model on a monthly basis. Section A shows the coefficients and *p*-values for the whole sample period (January 2000-June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in month *t*, and the independent variables are the following: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in month *t-1; Time*$_t$ ranges from 1 in the first month of our sample period to 246 in the last month; $Fund\_family_{i,j,t}$ is equal to 1 when funds *i* and *j* in month *t* belong to the same fund family and it is equal to 0 otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in month *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Section A *Period 2000-2020*	*Section B* *Sub-period:2000-2009*	*Section C* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9633*** (0.000)	0.9881*** (0.000)	0.9384*** (0.000)
Time	0.0001*** (0.000)	-0.0002*** (0.000)	0.0001*** (0.000)
Fund_family	-0.1031*** (0.000)	-0.1285*** (0.000)	-0.0659*** (0.000)
Size_Difference	-0.0003*** (0.000)	-0.0003*** (0.000)	-0.0003*** (0.003)
Age_Difference	0.0027** (0.020)	-0.0248*** (0.000)	0.0235*** (0.000)
Fees_Difference	-3.6112*** (0.000)	2.7024*** (0.000)	-0.6148*** (0.000)
Return_Difference	0.0080*** (0.000)	0.0013 (0.177)	-0.0008 (0.482)
#Stocks_Difference	0.0002*** (0.000)	0.0002*** (0.000)	0.0000 (0.420)
MoneyFlows_Difference	.0.0011*** (0.001)	0.0012*** (0.000)	-0.0086*** (0.000)
Wald	103.7*** (0.000)	143.31*** (0.000)	89.66*** (0.000)

Table A3. 3 – The evolution of the trading divergence and characteristics of mutual funds (FE on a quarterly basis)

This table shows the results obtained from Equation 3.2 with the FE model on a quarterly basis. Section A shows the coefficients and *p*-values for the whole sample period (January 2000-June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t*, and the independent variables are the following: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1; $Time_t$* ranges from 1 in the first quarter of our sample period to 82 in the last quarter; $Fund\_family_{i,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* belong to the same fund family and it is equal to 0, otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in quarter *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Section A *Period 2000-2020*	*Section B* *Sub-period:2000-2009*	*Section C* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9559*** (0.000)	0.9889*** (0.000)	0.9330*** (0.000)
Time	0.0001*** (0.000)	-0.0008*** (0.000)	0.0005*** (0.000)
Fund_family	-0.0966*** (0.000)	-0.1197*** (0.000)	-0.0632*** (0.000)
Size_Difference	-0.0004*** (0.000)	-0.0002** (0.013)	-0.0004*** (0.002)
Age_Difference	0.0036*** (0.001)	-0.0223*** (0.000)	0.0260*** (0.000)
Fees_Difference	-0.0084 (0.952)	0.7988** (0.018)	0.4871*** (0.000)
Return_Difference	0.0057*** (0.000)	0.0026** (0.015)	-0.0045*** (0.000)
#Stocks_Difference	0.0002*** (0.000)	0.0002*** (0.000)	0.0000* (0.055)
MoneyFlows_Difference	-0.0007 (0.126)	0.0041*** (0.000)	-0.0085*** (0.000)
Wald	71.89*** (0.000)	261.55*** (0.000)	97.86*** (0.000)

Table A3. 4 – The evolution of the trading divergence and characteristics of mutual funds (FE on a yearly basis)

This table shows the results obtained from Equation 3.2 with the FE model on a yearly basis. Section A shows the coefficients and *p*-values for the whole sample period (January 2000-June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{I,j,t}$ is the trading divergence among funds *i* and *j* in year *t*, and the independent variables are the following: $TD_{I,j,t-1}$ is the trading divergence among funds *i* and *j* in year *t-1; Time*$_t$ ranges from 1 in the first year of our sample period to 21 in the last year; $Fund\_family_{I,j,t}$ is equal to 1 when funds *i* and *j* in year *t* belong to the same fund family and it is equal to 0, otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ And $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in year *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Section A *Period 2000-2020*	*Section B* *Sub-period:2000-2009*	*Section C* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9547*** (0.000)	0.9906*** (0.000)	0.9379*** (0.000)
Time	0.0004*** (0.000)	-0.0033*** (0.000)	0.0016*** (0.000)
Fund_family	-0.0930*** (0.000)	-0.1121*** (0.000)	-0.0616*** (0.000)
Size_Difference	-0.0004 (0.884)	-0.0002*** (0.005)	-0.0004*** (0.009)
Age_Difference	0.0037*** (0.000)	-0.0216*** (0.000)	0.0211*** (0.000)
Fees_Difference	0.2757 (0.345)	-1.6621*** (0.003)	-0.4656* (0.096)
Return_Difference	0.0137*** (0.000)	0.0056*** (0.001)	-0.0079*** (0.000)
#Stocks_Difference	0.0002*** (0.000)	0.0002*** (0.000)	0.0000** (0.038)
MoneyFlows_Difference	-0.0011 (0.254)	0.0068*** (0.000)	-0.0071*** (0.004)
Wald	76.22*** (0.000)	269.72*** (0.000)	74.67*** (0.000)

Appendix 3.2: Robustness analyses of the results of the determinants of the trading divergence among mutual funds

Table A3. 5 – Determinants of the trading divergence among mutual funds (dynamic model on a yearly basis)

This table shows the results obtained from Equation 3.3 with the dynamic model on a yearly basis. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the subperiod comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in year *t* and the independent variables are as follows: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in year *t-1; Market Stress$_t$* is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); $Portfolio\_Overlap_{i,j,t-1}$ is the portfolio overlap of funds *i* and *j* in year *t-1; * $Fund\_family_{I,j,t}$ is equal to 1 when funds *i* and *j* in year *t* are within the same fund family and equals 0 otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in year *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *Sub-period:2000-2009* Coefficient (*p*-value)	*Section B* *Sub-period:2010-2020* Coefficient (*p*-value)
Constant	0.5533*** (0.000)	0.7790*** (0.000)
TD_{t-1}	0.4309*** (0.000)	0.2180*** (0.000)
Market Strees	-0.0071*** (0.000)	-0.0054*** (0.000)
$Portfolio\_Overlap_{t-1}$	-0.0880*** (0.000)	-0.0855*** (0.000)
Fund_family	-0.0942*** (0.000)	-0.0313*** (0.001)
Size_Difference	-0.0006*** (0.000)	0.0005*** (0.002)
Age_Difference	0.0341*** (0.000)	0.0002 (0.966)
Fees_Difference	-2.2659*** (0.008)	-1.2975*** (0.000)
Return_Difference	0.0101*** (0.000)	-0.0184*** (0.000)
#Stocks_Difference	0.0001*** (0.000)	0.0001*** (0.000)
MoneyFlows_Difference	0.0022 (0.151)	-0.0130*** (0.000)
Wald	4,327.21*** (0.000)	562.68*** (0.000)

Table A3. 6 – Determinants of the trading divergence among mutual funds (FE model on a monthly basis)

This table shows the results obtained from Equation 3.3 with the EF model on a monthly basis. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the subperiod comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in month *t* and the independent variables are as follows: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in month *t-1; Market Stress*$_t$ is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); *Portfolio_Overlap*$_{i,j,t-1}$ is the portfolio overlap of funds *i* and *j* in month *t-1; Fund_family*$_{I,j,t}$ is equal to 1 when funds *i* and *j* in month *t* are within the same fund family and equals 0 otherwise; *Size_Difference*$_{i,j,t}$, *Age_Difference*$_{i,j,t}$, *Fees_Difference*$_{i,j,t}$, *Return_Difference*$_{i,j,t}$, *#Stocks_Difference*$_{i,j,t}$ and *MoneyFlows_Difference*$_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in month *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *Sub-period:2000-2009* Coefficient (*p*-value)	*Section B* *Sub-period:2010-2020* Coefficient (*p*-value)
Constant	0.9867*** (0.000)	0.9954*** (0.000)
Market Strees	-0.0150*** (0.000)	-0.0022*** (0.000)
Portfolio_Overlap$_{t-1}$	-0.0873*** (0.000)	-0.0734*** (0.000)
Fund_family	-0.1289*** (0.000)	-0.0584*** (0.000)
Size_Difference	-0.0004*** (0.000)	-0.0002* (0.098)
Age_Difference	0.0107*** (0.000)	-0.0158*** (0.000)
Fees_Difference	-4.8217*** (0.000)	-0.9773*** (0.000)
Return_Difference	-0.0015* (0.085)	-0.0023** (0.039)
#Stocks_Difference	0.0001*** (0.000)	0.0000* (0.081)
MoneyFlows_Difference	-0.0016*** (0.000)	-0.0091*** (0.000)
Wald	327.79*** (0.000)	99.86*** (0.000)

Table A3. 7 – Determinants of the trading divergence among mutual funds (FE model on a quarterly basis)

This table shows the results obtained from Equation 3.3 with the EF model on a quarterly basis. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the subperiod comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t* and the independent variables are as follows: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1; Market Stress$_t$* is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); $Portfolio\_Overlap_{i,j,t-1}$ is the portfolio overlap of funds *i* and *j* in quarter *t-1; $Fund\_family_{I,j,t}$* is equal to 1 when funds *i* and *j* in quarter *t* are within the same fund family and equals 0 otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in quarter *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *Sub-period:2000-2009* Coefficient (*p*-value)	*Section B* *Sub-period:2010-2020* Coefficient (*p*-value)
Constant	0.9800*** (0.000)	0.9948*** (0.000)
Market Strees	-0.0196*** (0.000)	-0.0013*** (0.009)
Portfolio_Overlap$_{t-1}$	-0.0995*** (0.000)	-0.0716*** (0.000)
Fund_family	-0.1207*** (0.000)	-0.0570*** (0.000)
Size_Difference	-0.0002*** (0.002)	-0.0003** (0.024)
Age_Difference	0.0238*** (0.000)	-0.0214*** (0.000)
Fees_Difference	1.5274*** (0.000)	0.0091 (0.948)
Return_Difference	-0.0023** (0.024)	-0.0068*** (0.000)
#Stocks_Difference	0.0001*** (0.000)	0.0000*** (0.000)
MoneyFlows_Difference	0.0001 (0.843)	-0.0094*** (0.000)
Wald	483.84*** (0.000)	112.12*** (0.000)

Table A3. 8 – Determinants of the trading divergence among mutual funds (FE model on a yearly basis)

This table shows the results obtained from Equation 3.3 with the EF model on a yearly basis. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the subperiod comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in year *t* and the independent variables are as follows: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in year *t-1; Market Stress$_t$* is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); *Portfolio_Overlap$_{i,j,t-1}$* is the portfolio holding overlap of funds *i* and *j* in year *t-1; Fund_family$_{I,j,t}$* is equal to 1 when funds *i* and *j* in year *t* are within the same fund family, and it is equals 0 otherwise; *Size_Difference$_{i,j,t}$*, *Age_Difference$_{i,j,t}$*, *Fees_Difference$_{i,j,t}$*, *Return_Difference$_{i,j,t}$*, *#Stocks_Difference$_{i,j,t}$* and *MoneyFlows_Difference$_{i,j,t}$* are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in year *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *Sub-period:2000-2009* Coefficient (*p*-value)	*Section B* *Sub-period:2010-2020* Coefficient (*p*-value)
Constant	0.9855*** (0.000)	1.0002*** (0.000)
Market Strees	-0.0234*** (0.000)	-0.0049*** (0.000)
Portfolio_Overlap$_{t-1}$	-0.1124*** (0.000)	-0.0925*** (0.000)
Fund_family	-0.1123*** (0.000)	-0.0544*** (0.000)
Size_Difference	-0.0003*** (0.000)	-0.0003** (0.012)
Age_Difference	0.0244*** (0.000)	-0.0168*** (0.000)
Fees_Difference	-0.0234 (0.962)	-1.2307*** (0.000)
Return_Difference	-0.0019 (0.224)	-0.0147*** (0.000)
#Stocks_Difference	0.0001*** (0.000)	0.0001*** (0.000)
MoneyFlows_Difference	-0.0079*** (0.000)	-0.0122*** (0.000)
Wald	432.16*** (0.000)	123.85*** (0.000)

Appendix 3.3: Results of the trading divergence measure (TD*) that takes into account the initial positions

Table A3. 9 – Overall results of the TD* among fund pairs

This table reports the results of the *TD** among fund pairs for each year. Section A shows the mean and the standard deviation (St. Dvt.) of the trading divergence level among all fund pairs. Section B shows the number of fund pairs within the same family and the mean and the St. Dvt. of their trading divergence level. Section C shows the number of fund pairs in different fund families and the mean and the St. Dvt. of their trading divergence level. Section D shows the mean and the St. Dvt. difference between the value of fund pairs in the same family and the value of fund pairs in different families. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in the mean difference test between both groups of fund pairs. Note that in this table, we present a yearly report of the number of fund pairs compared during each year, while Table 3.1 presents the total number of funds only at five specific points of the sample period.

	Section A All fund pairs		*Section B. Fund pairs in the same fund family*			*Section C Fund pairs in different fund families*			*Section D Difference (same-different family)*	
Year	Mean TD	St. Dvt. TD	#fund pairs	Mean TD	St. Dvt. TD	#fund pairs	Mean TD	St. Dvt. TD	Mean TD	St. Dvt. TD
2000	76.74%	17.84%	325	65.55%	28.27%	13,879	76.99%	17.46%	-11.44%***	10.82%***
2001	76.80%	19.17%	478	68.32%	28.23%	16,282	77.04%	18.79%	- 8.72%***	9.44%***
2002	76.89%	19.06%	363	68.89%	28.11%	14,475	77.07%	18.77%	- 8.19%***	9.35%***
2003	76.99%	19.01%	340	69.10%	27.34%	14,622	77.16%	18.75%	- 8.05%***	8.59%***
2004	77.34%	18.17%	337	68.75%	27.11%	13,672	77.56%	17.83%	- 8.81%***	9.28%***
2005	77.50%	18.13%	391	68.96%	26.30%	14,613	77.73%	17.80%	- 8.77%***	8.50%***
2006	77.63%	18.12%	432	69.06%	26.54%	15,352	77.86%	17.78%	- 8.80%***	8.76%***
2007	73.13%	19.25%	465	67.03%	24.83%	16,529	73.37%	18.97%	- 6.34%***	5.87%***
2008	69.40%	21.12%	476	65.42%	26.42%	16,244	69.59%	20.82%	- 4.17%***	5.60%***
2009	74.72%	19.47%	436	69.45%	25.94%	14,492	74.92%	19.15%	- 5.47%***	6.79%***
2010	76.86%	18.03%	267	72.17%	24.59%	11,458	77.01%	17.76%	- 4.84%***	6.83%***
2011	78.35%	18.08%	239	72.34%	26.56%	9,727	78.53%	17.74%	- 6.19%***	8.82%***
2012	76.95%	19.32%	193	73.83%	25.41%	7,764	77.04%	19.11%	- 3.21%***	6.30%***
2013	81.52%	17.18%	167	76.59%	25.09%	6,171	81.66%	16.90%	- 5.07%***	8.20%***
2014	81.64%	15.83%	98	76.47%	24.34%	4,625	81.76%	15.56%	- 5.29%***	8.77%***
2015	80.33%	16.73%	104	76.66%	22.07%	4,655	80.42%	16.57%	- 3.75%***	5.51%***
2016	81.29%	16.93%	100	78.80%	19.81%	4,909	81.34%	16.86%	- 2.54%***	2.95%***
2017	84.49%	15.85%	89	81.12%	19.57%	4,753	84.56%	15.76%	- 3.44%***	3.31%***
2018	84.60%	15.16%	73	80.47%	19.34%	4,732	84.68%	15.06%	- 4.21%***	4.28%***
2019	82.43%	17.53%	60	79.04%	18.10%	4,311	82.50%	17.52%	- 3.46%***	0.58%***
2020	82.86%	16.54%	62	79.29%	18.56%	4,077	82.94%	16.49%	- 3.64%***	2.07%***
2000-2020	77.40%	18.59%	1,190	69.82%	26.52%	35,521	77.61%	18.29%	-7.78%***	8.23%***

Table A3. 10 – The evolution of the TD* and the characteristics of mutual funds

This table shows the results of Equation 3.2 using the *TD**. Section A shows the coefficients and *p*-values for the whole sample period (January 2000-June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t*, and the independent variables are the following: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1; $Time_t$* ranges from 1 in the first quarter of our sample period to 82 in the last quarter; $Fund\_family_{i,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* belong to the same fund family and it is equals 0 otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in quarter *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Section A *Period 2000-2020*	*Section B* *Sub-period:2000-2009*	*Section C* *Sub-period:2010-2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.6192*** (0.000)	0.7686*** (0.000)	0.7330*** (0.000)
TD_{t-1}	0.0922*** (0.000)	0.0963*** (0.000)	0.3465*** (0.000)
Time	0.0002*** (0.000)	-0.0039*** (0.000)	0.0005*** (0.000)
Fund_family	-0.0043 (0.648)	-0.0004 (0.968)	0.0002 (0.988)
Size_Difference	0.0004 (0.305)	0.0018*** (0.001)	0.0046*** (0.000)
Age_Difference	0.1196*** (0.000)	-0.0524*** (0.000)	-0.0232 (0.216)
Fees_Difference	3.4764*** (0.000)	1.3253 (0.260)	5.6024*** (0.000)
Return_Difference	0.0067** (0.019)	0.0299*** (0.000)	-0.0193*** (0.001)
#Stocks_Difference	0.0527*** (0.000)	0.0573*** (0.000)	0.0650*** (0.000)
MoneyFlows_Difference	0.0008* (0.080)	0.0008*** (0.000)	-0.0003*** (0.000)
Wald	6,298.27*** (0.000)	8,865.85*** (0.000)	637.56*** (0.000)
VIF	1.02	1.03	1.03

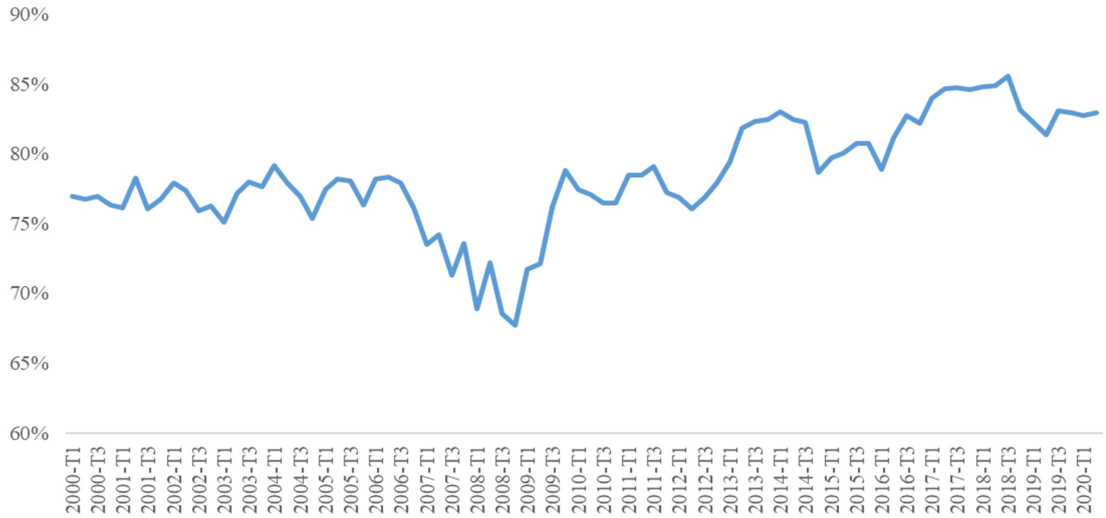
Table A3. 11 – Determinants of the of the TD*

This table shows the results of Equation 3.3 using the TD*. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the subperiod comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t* and the independent variables are as follows: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1; Market Stress*$_t$ is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); $Fund\_family_{I,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* are within the same fund family and it is equals 0 otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in quarter *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *Sub-period:2000-2009* Coefficient (*p*-value)	*Section B* *Sub-period:2010-2020* Coefficient (*p*-value)
Constant	0.6095*** (0.000)	0.8068*** (0.000)
TD_{t-1}	0.0823*** (0.000)	0.0298*** (0.000)
Market Strees	-0.9746*** (0.000)	-0.0328*** (0.000)
Fund_family	-0.0164 (0.139)	0.0060 (0.719)
Size_Difference	0.0014** (0.011)	0.0041*** (0.000)
Age_Difference	0.1795*** (0.000)	-0.0788*** (0.000)
Fees_Difference	-2.9030** (0.014)	4.8370 *** (0.000)
Return_Difference	0.0323*** (0.000)	-0.0208*** (0.000)
#Stocks_Difference	0.0515*** (0.000)	0.0600*** (0.000)
MoneyFlows_Difference	0.0006*** (0.000)	0.0002*** (0.000)
Wald	1,365.53*** (0.000)	961.88*** (0.000)
VIF	1.06	1.05

Figure A3. 1 – Evolution of the of the TD* for all fund pairs

This figure represents the evolution of the more accurate trading divergence level for all fund pairs from January 2000 to June 2020. The value is computed quarterly based on the average of their months.



Appendix 3.4: Robustness analyses of the influence of the stock characteristics on the trading divergence among mutual funds

Table A3. 12 – Stock characteristics and trading divergence among mutual funds (FE model on a monthly basis)

This table shows the results obtained from Equation 3.9 with the FE model on a monthly basis. Section A shows the results for all fund pairs. Section B shows the results for fund pairs within the same family. Section C shows the results for fund pairs in different fund families. The dependent variable, $TD^*_{s,t}$ is the trading divergence level among funds for stock *s* in month *t*, and the independent variables are as follows*:* $Stock\_return_{s,t}$ is the absolute value of the yearly past return of stock *s* in month *t;* $Stock\_volatility_{s,t}$ is the volatility of stock *s* in month *t* and is measured as the standard deviation of its return during the last year; $Stock\_size_{s,t}$ is the market capitalization of stock *s* in month *t*; and $Stock\_popularity_{s,t}$ is the popularity level of stock *s* in month *t* and is measured with the percentage of funds that trade in the stock *s* within our sample. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *All fund pairs*	*Section B* *Fund pairs in* *the same fund family*	*Section C* *Fund pairs in* *different fund families*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9299*** (0.000)	0.9181*** (0.000)	0.9368*** (0.000)
Stock_return	0.0029 (0.225)	-0.0046** (0.014)	0.0048** (0.029)
Stock_volatility	-0.0086 (0.637)	-0.0818*** (0.001)	0.0028 (0.861)
Stock_Size	-0.0039*** (0.001)	0.0059* (0.052)	-0.0044*** (0.000)
Stock_popularity	-0.3393*** (0.000)	-0.7246*** (0.000)	-0.3167*** (0.000)
F	133.12*** (0.000)	102.13*** (0.000)	109.62*** (0.000)
R^2	11.24%	13.75%	11.42%
Hauman Test	243.48*** (0.000)	69.10*** (0.009)	1879.17*** (0.000)

Table A3. 13 – Stock characteristics and trading divergence among mutual funds (FE model on a yearly basis)

This table shows the results obtained from Equation 3.9 with the FE model on a yearly basis. Section A shows the results for all fund pairs. Section B shows the results for fund pairs within the same family. Section C shows the results for fund pairs in different fund families. The dependent variable, $TD^*_{s,t}$ is the trading divergence level among funds for stock *s* in year *t*, and the independent variables are as follows: $Stock\_return_{s,t}$ is the absolute value of the yearly past return of stock *s* in year *t*; $Stock\_volatility_{s,t}$ is the volatility of stock *s* in year *t* and is measured as the standard deviation of its return during the last year; $Stock\_size_{s,t}$ is the market capitalization of stock *s* in year *t*; and $Stock\_popularity_{s,t}$ is the popularity level of stock *s* in year *t* and is measured with the percentage of funds that trade in the stock *s* within our sample. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Section A *All fund pairs*		*Section B* *Fund pairs in the same fund family*		*Section C* *Fund pairs in different fund families*	
	Coefficient	(*p*-value)	Coefficient	(*p*-value)	Coefficient	(*p*-value)
Constant	0.9537***	(0.000)	0.9464***	(0.000)	0.9656***	(0.000)
Stock_return	0.0038	(0.105)	0.0037	(0.390)	0.0064**	(0.011)
Stock_volatility	-0.0036	(0.812)	-0.1015***	(0.003)	-0.0117	(0.435)
Stock_Size	-0.0035***	(0.005)	0.0054	(0.179)	-0.0026**	(0.021)
Stock_popularity	-0.4223***	(0.000)	-0.9430***	(0.000)	-0.5110***	(0.000)
F	143.75***	(0.000)	103.11***	(0.000)	152.27***	(0.000)
R^2	12.59%		18.34%		26.55%	
Hauman Test	731.17***	(0.000)	5.99***	(0.009)	337.20***	(0.000)

Appendix 3.5: Robustness analyses of the influence of the trading divergence on subsequent fund performance

Table A3. 14 – The trading divergence and the subsequent fund performance (on a monthly basis)

This table shows the results obtained from Equation 3.11 on a monthly basis. Section A, Section B and Section C show the results obtained with the fund alpha of the CAPM, with the alpha of the three-factor model, and with the four-factor model, respectively. We estimate the alphas by using rolling windows of 60 (*t+3*), 120 (*t+6*) and 240 (*t+12*) daily data. The dependent variable is the subsequent performance of the fund *i* in month *t*, and the independent variables are as follows: $TD^*_{i,t}$ is the average of the trading divergence level of fund *i* in month *t*; $Fund\_size_{i,t}$ is the average of the relativised size of fund *i* in month *t; * $Fund\_age_{i,t}$ is the average of the relativised age of fund *i* in month *t*; $Fund\_fees_{i,t}$ is the average fees of fund *i* in month *t*. $Fund\_\#stocks_{i,t}$ is the average number of stocks held by fund *i* in month *t;* and $Fund\_flows_{i,t}$ is the average relative money flows fund *i* in month *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

	Fund_Performance								
	Section A : CAPM			*Section B: 3Factors*			*Section C: 4Factors*		
	t+3	*t+6*	*t+12*	*t+3*	*t+6*	*t+12*	*t+3*	*t+6*	*t+12*
Constant	-0.0005***	-0.0004***	-0.0003***	-0.0005***	-0.0003***	-0.0004***	-0.0005***	-0.0005***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TD	0.0004***	0.0003***	0.0002***	0.0003***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund_size	-0.0001**	-0.0001**	-0.0001	-0.0001*	-0.0001	-0.0001	-0.0001**	-0.0001	-0.0001
	(0.014)	(0.044)	(0.166)	(0.090)	(0.240)	(0.519)	(0.041)	(0.167)	(0.541)
Fund_age	0.0001	0.0001**	0.0002***	0.0002***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.199)	(0.019)	(0.007)	(0.001)	(0.008)	(0.001)	(0.001)	(0.000)	(0.004)
Fund_fees	0.0351*	0.0305*	-0.0036	0.0257*	0.0253***	0.0050	0.0263*	0.0198*	0.0001
	(0.059)	(0.056)	(0.777)	(0.095)	(0.007)	(0.701)	(0.082)	(0.088)	(0.999)
Fund_#stocks	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.294)	(0.956)	(0.445)	(0.717)	(0.592)	(0.248)	(0.753)	(0.251)	(0.134)
Fund_flows	0.0001	0.0001*	0.0001**	0.0001	0.0001*	0.0001**	0.0001	0.0001*	0.0001**
	(0.373)	(0.060)	(0.018)	(0.599)	(0.073)	(0.039)	(0.484)	(0.082)	(0.019)
F	12.34***	8.06***	7.26***	8.20***	8.97***	7.39***	6.16***	8.81***	6.81***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	1.40%	1.54%	1.51%	2.02%	2.80%	1.59%	2.74%	1.23%	1.43%
	40.84***	232.00***	72.13***	87.43***	23.40***	66.59***	98.51***	88.58***	57.01***
Hausman test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table A3. 15 – The trading divergence and the subsequent fund performance (on a yearly basis)

This table shows the results obtained from Equation 3.11 on a yearly basis. Section A, Section B and Section C show the results obtained with the fund alpha of the CAPM, with the alpha of the three-factor model, and with the four-factor model, respectively. We estimate the alphas by using rolling windows of 60 (*t+3*), 120 (*t+6*) and 240 (*t+12*) daily data. The dependent variable is the subsequent performance of the fund *i* in year *t*, and the independent variables are as follows: $TD^*_{i,t}$ is the average of the trading divergence level of fund *i* in year *t*; $Fund\_size_{i,t}$ is the average of the relativised size of fund *i* in year *t;* $Fund\_age_{i,t}$ is the average of the relativised age of fund *i* in year *t*; $Fund\_fees_{i,t}$ is the average fees of fund *i* in year *t*; $Fund\_\#stocks_{i,t}$ is the average number of stocks held by fund *i* in year *t;* and $Fund\_flows_{i,t}$ is the average relative money flows fund *i* in the year *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Fund_Performance								
	Section A : CAPM			*Section B: 3Factors*			*Section C: 4Factors*		
	t+3	*t+6*	*t+12*	*t+3*	*t+6*	*t+12*	*t+3*	*t+6*	*t+12*
Constant	-0.0012***	-0.0010***	-0.0008***	-0.0009***	-0.0009***	-0.0009***	-0.0007***	-0.0008***	-0.0008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TD	0.0011***	0.0009***	0.0007***	0.0006***	0.0007***	0.0008***	0.0004***	0.0006***	0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund_size	-0.0001***	-0.0001***	-0.0001**	-0.0001***	-0.0001***	-0.0001	-0.0001***	-0.0001***	-0.0001
	(0.002)	(0.000)	(0.025)	(0.005)	(0.001)	(0.202)	(0.005)	(0.001)	(0.217)
Fund_age	0.0001	0.0001	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.600)	(0.155)	(0.005)	(0.003)	(0.000)	(0.003)	(0.002)	(0.001)	(0.005)
Fund_fees	0.1381**	0.0932*	0.0409	0.1080*	0.0653	0.0432	0.0937	0.0466	0.0250
	(0.046)	(0.062)	(0.303)	(0.073)	(0.126)	(0.229)	(0.123)	(0.253)	(0.471)
Fund_#stocks	0.0001	0.0001	0.0001	0.0001	0.0001	-0.0001	0.0001	0.0001	-0.0001
	(0.335)	(0.739)	(0.545)	(0.973)	(0.569)	(0.191)	(0.917)	(0.301)	(0.122)
Fund_flows	0.0004***	0.0003**	0.0003**	0.0002*	0.0002**	0.0003**	0.0002	0.0002**	0.0003**
	(0.008)	(0.045)	(0.033)	(0.079)	(0.038)	(0.029)	(0.169)	(0.025)	(0.026)
F	27.36***	17.81***	13.55***	13.29***	16.27***	15.02***	8.02***	13.55***	14.39***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	6.43%	5.73%	5.16%	3.52%	5.40%	5.37%	2.54%	4.95%	5.50%
Hausman test	76.84***	66.68***	54.02***	70.30***	58.14***	20.67***	78.42***	60.26***	21.41***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

FINAL CONCLUSIONS

Here, I summarise the main conclusions and contributions of the thesis. The main reasons why I have investigated several abilities of fund managers: the importance of mutual funds in the financial system and their economic and social impacts on individual investors due to the great amount of money managed in this industry, and the essential role of managers in managing fund portfolios. The thesis is also motivated by the lack of empirical studies that focus on the learning process in the mutual fund industry and by the aim of exploring the consequences of the similarity level among portfolios and the divergence level among managers' trading decisions in the Spanish market.

In Chapter 1, we identify the important trading decisions of funds based on the hypothesis that not all decisions have the same importance in terms of the performance and risk of a fund and thus, the same impact on its learning process. In this chapter, we argue that important trading decisions simultaneously have a relatively high importance with respect to a fund's total net assets (TNA), a significantly higher importance with respect to other trading decisions made by the fund, and a significantly higher importance with respect to other trading decisions of the other funds in the same stock.

We analyse the evolution of the percentage of important trading decisions that result in a significantly negative impact on fund performance as a metric of the funds' learning process from their important past errors. This chapter provides evidence of a significant decreasing trend in the percentage of funds' important trading errors over the sample period that indicates the level of learning process in the mutual fund industry over time.

Then, we examine the learning ability of each fund family with respect to the remaining families. The findings show that a large number of fund families drives this learning process, by showing a significant decrease in the percentage of the important errors of their member funds equal to or greater than the industry average.

Furthermore, we study whether two important characteristics of the Spanish fund families influence the learning process: the family size and their dependence on banking and insurance groups. In general terms, we do not find evidence of a significant influence by these characteristics in the learning of mutual funds.

The findings of this chapter have several implications for individual investors, fund managers, supervisors, and the overall efficiency of the fund industry. The decrease in important errors by the fund's management could encourage investors to allocate their savings to this industry due to greater confidence in professional management. In addition, this process may have a positive influence on the compensation of fund managers and the overall efficiency of the industry. Further, this study could be interesting for supervisors who ensure investor protection and promote good practices in the fund industry.

In addition, given that individual investors could hold more than one mutual fund in order to reduce the level of idiosyncratic risk, another important topic is the similarity level among portfolio holdings. The literature has shown that individual investors will concentrate all their investments in a financial company because of the switching costs. Specifically, this behaviour and the demand spillover effects are common in the mutual fund industry. Therefore, Chapter 2 focuses on the similarity level among mutual funds and the manager's autonomy in the portfolio allocation within families.

The findings show that the fund concentration in a single family has a significantly negative impact on the potential diversification. Furthermore, the results show that the potential diversification is definitely lower for individual investors who concentrate all of their fund investments in larger families, which belong to a bank-holding group and do not have wide experience in the fund market. Furthermore, in this chapter, we find less autonomy for managers in the portfolio allocation within the fund families with these characteristics.

In this chapter, we also analyse the consequences of the similarity level among portfolios and the manager’s autonomy on the individual investors’ return. The findings show that a greater similarity among funds not only causes fund families to offer less diversification to individual investors but also has a significantly negative effect on their returns, while the influence of autonomy for managers is significantly positive.

The implications of this chapter are also especially interesting in the Spanish mutual fund industry because of its high concentration level and its dependence on the banking sector. According to the findings of this chapter, fund families with a higher market share show a higher portfolio overlap among their funds.

The results obtained in Chapter 2 about the economic implication of the great similarity among mutual funds and the autonomy of managers in the portfolio allocation for individual investors lead us to focus on the divergence level among the funds' trading decisions and the ability to add value through their distinct decisions.

Chapter 3 presents a measure that captures to what extent the trading of a fund in any period differs from the rest of the funds. In accordance with the results obtained in Chapter 2, we find a lower level of trading divergence among fund pairs belonging to the same family than those from different families. We also observe that the decisions of the funds are more different from each other over time, especially since the GFC of 2008 at which time the severe mutual fund merging process began that caused the strong reorganization of the Spanish banking system.

In Chapter 3, we study the determinants of the divergence level in trading. Concretely, we show that the trading divergence is influenced by the previous holdings;

a fact that leads us to control for the initial positions in the divergence measure. With this control, the trading divergence in fund pairs of the same family is not significantly different compared to the trading divergence in fund pairs of different families. This loss of statistical significance is logical because pairs in the same family start from more similar positions according to the results in Chapter 2. Despite this control of the previous holdings, we find that the level of market stress has a significantly negative influence on the level of trading divergence among funds. Therefore, the likelihood that a fund will make more distinct trading decisions in relation to the rest of funds is lower in market stress periods. This relation could be driven mainly by the common aim of managers to hold less risky stocks and invest in more popular stocks during critical market circumstances. However, Chapter 3 also shows that the behaviour of fund managers in terms of the level of trading divergence is not the same across the different market shocks in the sample period. The natural origin of each shock and the learning in portfolio management could have an important role in this finding.

This chapter also presents the influence of the stock characteristics on the level of trading divergence. The results provide evidence on a greater similarity among trading decisions in the smallest stocks with extreme behaviour in terms of the past return and volatility within families. This finding indicates an internal influence at the family level on the decisions in those stocks, which could be an investment opportunity but also imply a high risk level. However, the outlook of investment opportunities may be different across families due to their individual investment and risk policies for portfolio management.

Finally, in line with the results of Chapter 2 about the significantly negative influence of the greater similarity among portfolios and the low autonomy of managers on the investors' returns, this chapter shows that a high level of trading divergence results in a high fund performance. Furthermore, Chapter 3 also shows that mutual funds have the ability to add more value through their distinctive trading decisions due to the higher performance contribution of divergent trading decisions compared to convergent decisions. This chapter has important implications for fund managers, for the top-management of the families, and for regulators because of this significantly positive relationship. Due to the significantly positive influence of the trading divergence on fund performance that is encouraged by the top management of fund families, managers may increase their interest in seeking investment opportunities and trading differently with respect to other fund.

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RESUMEN Y CONCLUSIONES
(SUMMARY IN SPANISH)

Tal y como recoge el Real Decreto 99/2011, de 28 de enero, por el que se regulan las enseñanzas oficiales de Doctorado, las tesis doctorales que quieran optar a la Mención Internacional deben incluir los principales contenidos de la misma en dos lenguas oficiales para la comunicación científica.

Dado que el indioma de redacción de la tesis es el inglés, a continuación, se presenta un resumen de la tesis doctoral desarrollada en español, con el objetivo de que la misma pueda ser considerada para la obtención de la Mención de Internacional.

MOTIVACIÓN

Los gestores de fondos de inversión toman sus decisiones en base a la información que obtienen de diversas fuentes internas y externas, entra las cuales, se puede destacar la experiencia, el proceso de aprendizaje, la interacción social, las directrices recibidas desde la sociedad gestora (familia de fondos) de la que formen parte, así como la estrategia que se sigue dentro de la misma. Estos agentes financieros deciden los títulos en los que invierten y su importancia dentro de las carteras, procurando un nivel de diversificación óptimo.

Por tanto, los partícipes se benefician de la diversificación de la cartera de forma automática, independientemente de la cantidad invertida. Esta diversificación intrínseca hace que, en general, invertir en uno fondos sea más seguro que invertir en un título individual. Además, los partícipes podrían buscar una mayor diversificación, invirtiendo en diferentes fondos, sin embargo, diferente no es siempre lo mismo que diverso. En este sentido, el nivel de similitud entre las carteras es un aspecto importante dentro de la industria de fondos de inversión, así como la autonomía de los gestores en la selección de títulos y su habilidad para generar valor añadido con sus decisiones más divergentes en la industria.

Esta Tesis Doctoral consta de tres capítulos empíricos sobre tres importantes habilidades de los gestores de fondos: aprendizaje, autonomía y gestión divergente. Además, se incluye una introducción sobre la industria española de fondos de inversión, en la cual se muestran algunas estadísticas relacionadas con su evolución y se hace referencia a sus características específicas más importantes.

En el primer capítulo, se estudia el proceso de aprendizaje en la gestión de carteras. Este capítulo se basa en la hipótesis de que, se aprende de los errores cuando las consecuencias duelen y, por lo tanto, los gestores aprenden de los errores, especialmente, cuando estos errores tienen graves consecuencias en el rendimiento del fondo. Este estudio está motivado por la falta de investigación sobre el proceso de aprendizaje en la gestión de carteras con respecto a la gestión empresarial. Este mayor nivel de investigación sobre el aprendizaje en el ámbito corporativo podría explicarse porque las consecuencias de un error importante en una empresa podrían ser drásticas e incluso suponer su cierre, mientras que, desde la perspectiva de gestión de carteras, las consecuencias de un error importante pueden ser relevantes, pero menos drásticas o definitivas debido a su mayor diversificación. Sin embargo, el proceso de aprendizaje en la industria de fondos de inversión merece que se le preste atención desde el ámbito de la investigación porque la eficiencia de este mercado tiene importantes implicaciones sociales y económicas.

El capítulo dos examina el nivel de similitud entre las carteras de los fondos de inversión y sus implicaciones para los inversores individuales en términos de diversificación y rentabilidad. De acuerdo con la literatura, los inversores individuales tienden a concentrar sus diferentes fondos en la misma familia. Esto podría explicarse por el coste económico y tiempo invertido que implica un cambio de proveedor (*switching cost*). Este proceso mental por parte de los inversores justifica el interés de estudiar el nivel de similitud entre las carteras de los fondos de inversión, especialmente, entre aquellos fondos que pertenecen a la misma familia. Cabe resaltar que, esta tendencia por parte de los partícipes a concentrar sus inversiones en fondos de la misma familia es especialmente interesante en la industria española debido a su alta concentración y dependencia a los grupos bancarios y aseguradoras. También, se estudian las características de las familias de fondos con un mayor nivel de similitud entre sus carteras. Finalmente, en cada familia de fondos, se analiza la autonomía de los gestores cuando seleccionan títulos dentro de cada industria, así como sus implicaciones económicas.

El tercer capítulo se centra en el nivel de divergencia entre las decisiones de gestión de los fondos de inversión, controlando las posiciones previas en las carteras. Este capítulo se justifica por el objetivo de vincular los estudios recientes sobre la habilidad de los gestores para generar valor añadido y los estudios que analizan la diversidad existente entre los fondos. En particular, este capítulo estudia hasta qué punto las decisiones de compra y venta de los distintos fondos difieren entre ellas y cómo este nivel de divergencia contribuye a la performance de la cartera. La hipótesis a contratar se basa en la idea de que las decisiones de compra y venta más diferentes de los gestores de fondos pueden ser una fuente importante de valor añadido.

INTRODUCCIÓN: LA INDUSTRIA ESPAÑOLA DE FONDOS DE INVERSIÓN

A continuación, se muestran datos evolutivos del volumen patrimonial gestionado, el número de partícipes y el número de fondos existentes en la industria española de fondo de inversión, con el objetivo de analizar su desarrollo tanto desde la perspectiva de la demanda como de la oferta.

Según los datos de la Asociación de Instituciones de Inversión Colectiva (INVERCO), la industria de fondos de inversión gestionaba un patrimonio de 206.166 millones de euros en diciembre de 1999, mientras que, en junio de 2020, esta cantidad fue aproximadamente superior en 55.000 millones de euros, alcanzándose un total de 260.895 millones de euros. Aunque estas cifras reflejan un extraordinario crecimiento, se debe tener en cuenta que la evolución del sector no se ha producido de forma sostenida en el tiempo, ya que se ha visto afectada en varias ocasiones por las crisis financieras. Los datos muestran el fuerte impacto negativo de la crisis financiera global de 2008 y la crisis de deuda soberana europea, el cual provoco una importante disminución en la cantidad gestionada de 49% de diciembre de 2007 a diciembre de 2012. La industria comenzó a recuperarse a partir del año 2013, aunque no fue hasta 2017 cuando se alcanzaron cifras similares a las que se mostraban antes de la crisis de 2008. El extraordinario crecimiento de la industria de fondos de inversión durante los últimos años se ha visto motivado por la recuperación de la confianza de los inversores en el asesoramiento profesional, y por la bajada de los tipos de interés que ha generado una situación de incertidumbre entre los ahorradores e inversores. Estos han dejado de encontrar un atractivo en los depósitos bancarios y como consecuencia, han empezado a migrar sus ahorros hacía otros instrumentos financieros y en especial, hacía los fondos de inversión. Sin embargo, la crisis provocada por la COVID-19 también ha implicado un ligero descenso en el patrimonio gestionado. Concretamente, el importe total de los activos gestionados en la industria de fondos disminuyo alrededor de un 6% entre diciembre de 2019 y junio de 2020. Por lo tanto, se pone de manifiesto la importante vulnerabilidad de la demanda en esta industria a la situación económica.

La evolución del número de inversores también muestra un patrón similar a la evolución del patrimonio gestionado por los fondos. En diciembre de 1999, esta industria tenía aproximadamente 8 millones de inversores, mientras que, en junio de 2020, esta cifra ascendía a 11,2 millones de inversores. El número de inversores nos permite comprender el gran impacto económico y social que tiene la industria de fondos en España y, por tanto, la gran importancia que tiene la eficiencia en la gestión de los fondos, porque de ello depende, el ahorro de una parte importante de la población española.

El crecimiento del número de fondos en el mercado muestra la evolución de la oferta del sector. Se observa un crecimiento notable en el número de fondos españoles desde 1999 hasta 2009. Sin embargo, desde entonces, la tendencia ha sido negativa. Esta observación podría relacionarse con el proceso de restructuración bancaría del sistema financiero español durante la última década. Con este proceso, se tenía como objetivo mejorar la eficiencia del mercado e implico un número importante de fusiones de fondos y sociedades gestoras.

Centrándonos en la oferta en la industria de fondos, si bien la evolución y el crecimiento de esta industria son notables y los partícipes pueden seleccionar entre una amplia gama de fondos y familias, la industria española se caracteriza por estar muy concentrada. En este sentido, los datos muestran que, en junio de 2020, las cinco mayores gestoras de España controlan el 62% de los activos totales invertidos en esta industria por el 71% de los partícipes. Esta evidencia sobre el nivel alto de concentración es todavía más pronunciada cuando se consideran las dos gestoras más grandes que controlan aproximadamente el 34% del patrimonio total.

Como reflejan los datos, este mercado se encuentra lejos del paradigma de la competencia perfecta y así, las familias de fondos disfrutan de un alto poder de mercado en el sector de los fondos de inversión. En esta línea, Losada (2015) argumenta que los partícipes no disfrutan de la información perfecta sobre los fondos de inversión que se ofrecen en el mercado. Estos se enfrentan a altos costes económicos y tiempo invertido en la búsqueda de información cuando cambian de proveedor, lo que les lleva a concentrar sus inversiones de fondos en una sola familia. Otro aspecto importante a resaltar, en la oferta de fondos de inversión, es la alta dependencia del sector a los grupos bancarios y aseguradoras. Aunque la importancia relativa de las familias de fondos independientes sigue una tendencia positiva, el peso de este tipo de gestoras es todavía pequeño en comparación con otras industrias europeas.

Capítulo 1: Aprendes cuando duele: evidencia en la industria de fondos de inversión.

Introducción

El comportamiento de los gestores ha sido un tópico que ha atraído la atención de los investigadores desde distintos puntos de vista. Así, el objetivo de este estudio es mostrar eficiencia empírica sobre el proceso de aprendizaje en la gestión de fondos de inversión a partir de los errores importantes derivados de decisiones importantes. En este estudio, dentro del ámbito de la gestión de fondos de inversión, se considera una decisión importante a aquella compra o venta de un título realizada en un mes concreto que representa simultáneamente una alta importancia relativa en relación con: (1) el tamaño del fondo calculado con el valor total neto de los activos gestionado, (2) el resto de decisiones de gestión del mismo fondo con otros activos diferentes en el mismo mes y (3) las decisiones de gestión tomadas por el resto de fondos con el mismo título en el mismo mes. Posteriormente, esta decisión importante en la gestión de carteras será un error importante si tiene un impacto significativamente negativo en el rendimiento posterior del fondo.

Estrechamente relacionado con la práctica de la toma de decisiones, el aprendizaje es el proceso mediante el cual la información se convierte en conocimiento, y permite la constitución progresiva de un conjunto de técnicas y conocimientos que ayudan a mejorar la eficiencia, tal y como se establece en el concepto de “aprender haciendo”, que fue inicialmente estudiado por Arrow (1962). En este sentido, la literatura previa ha identificado tres niveles de aprendizaje: aprendizaje a nivel de individuo, aprendizaje a nivel de grupo y aprendizaje a nivel de organización (Crossan et al., 1999). Concretamente, el aprendizaje a nivel de organización ha generado un gran interés entre profesionales y académicos en el entorno económico y empresarial, ya que se le considera un activo estratégico para las organizaciones, en el que se basan las ventajas competitivas sostenibles en el tiempo (March, 1991; Adams y Lamont, 2003; Hatch y Dyer, 2004).

En lo que tiene que ver con la gestión de fondos de inversión, los investigadores defienden que tanto el proceso de toma de decisiones, como el proceso de aprendizaje no son específicos de un gestor. En esta línea, Chen et al. (2004), Nanda et al. (2004) y Cici et al. (2018) consideran que la sociedad gestora (familia de fondos), como entidad en sí, influye de forma significativa en la gestión de sus fondos. También, Jones y Shanken (2005) y Brown y Wu (2016) encuentra que el hecho de pertenecer a una familia de fondos genera la oportunidad de disfrutar de un aprendizaje global, algo que no es posible cuando los gestores trabajan de forma independiente. Asi como Sevcenko y Ethiraj (2018) documentan que el aprendizaje individual genera externalidades positivas a nivel de familia de fondos.

Respecto a la medida de aprendizaje, números trabajos han estudiado este proceso como la reducción de los sesgos cognitivos identificados en la literatura sobre finanzas conductuales (Dhar y Zhu, 2006; Campbell, 2006; Nicolosi et al., 2009; Seru et al., 2009; Koestner et al., 2017). Estos autores identifican la experiencia como la principal fuente aprendizaje, medida tanto por el número de años de experiencia como por el número de operaciones acumuladas en los mercados financieros. De manera similar, Offerman y Sonnemans (1998) y Kempf et al. (2017) analizan la importancia del concepto “aprender haciendo” y muestran que la experiencia está asociada a una mejor capacidad de gestión.

Centrándonos en la habilidad de aprendizaje a nivel de organización, Crossan y Bapuji (2003) utilizan la medida tradicional de aprendizaje relacionada con las llamadas curvas de aprendizaje, donde el aprendizaje interno de una organización es una función en el tiempo. En este capítulo, el proceso de aprendizaje se mide a través de la evolución del porcentaje de errores importantes en la gestión de los fondos de inversión. Este enfoque es consistente con el aprendizaje motivado principalmente por los errores del pasado, siguiendo los estudios de Zhao (2011) y Marsick y Watkins (2015) y teniendo presente que, no todas las decisiones en la gestión de carteras tienen la misma contribución a la rentabilidad del fondo y, por tanto, la misma influencia en el proceso de aprendizaje. Según Zhao (2011) y Marsick y Watkins (2015), existe una relación positiva entre el sentimiento negativo causado por cometer errores y la motivación para aprender de estos errores.

Por tanto, el primer capítulo de la tesis contribuye a la literatura de varias maneras. En primer lugar, se analiza el proceso de aprendizaje en la gestión profesional de fondos de inversión, en lugar de analizarse en el comportamiento de los inversores individuales, ampliamente estudiado en la literatura. En segundo lugar, se contribuye a la literatura con el análisis del proceso de aprendizaje basado en el supuesto de que no todas las decisiones tienen la misma importancia relativa y contribución a la rentabilidad del fondo y, así, la misma influencia en este proceso. Se considera que el aprendizaje está motivado principalmente por lo errores pasados que tienen consecuencias graves. En tercer lugar, se analiza el proceso de aprendizaje a nivel de industria y familia de fondos, siguiendo el enfoque de aprendizaje a nivel organizacional que defiende que la capacidad de aprendizaje dentro de una organización o entidad no es específica de un individuo.

Datos y metodología

En este capítulo, se analiza el proceso de aprendizaje en los fondos de inversión clasificados, según la vocación inversora, en la categoría renta variable euro en la industria española, en el periodo de tiempo comprendido entre enero 2000 y junio 2014.

Cabe destacar que la industria española representa un marco interesante para el objetivo principal de este estudio por diferentes razones. En primer lugar, la industria española de fondos de inversión es una de las industrias europeas más importantes en términos de número de fondos registrados, situándose en el quinto lugar del ranking (EFAMA, 2018), lo que pone de manifiesto la importancia de las consecuencias económicas de los análisis realizados. En segundo lugar, esta industria se caracteriza por una alta concentración dado que las 10 sociedades gestoras de fondos de inversión más grandes gestionan más del 75% del patrimonio total (Inverco, 2018) así como por una alta dependencia a la banca. En tercer lugar, el gran auge de los fondos de inversión españoles tuvo lugar durante la década de los noventa, por lo tanto, el periodo analizado coincide con la etapa de madurez, evitando así posibles efectos de las etapas de expansión y crecimiento que pudieran afectar al proceso de aprendizaje (Penrose, 1959; Autio et al., 2000).

La muestra está compuesta por un total de 292 fondos de inversión gestionados por 101 sociedades gestoras: 145 fondos de inversión Renta Variable Domestica y 147 de Renta Variable Euro. Resaltar que, en este estudio, se han controlado las adquisiciones y fusiones de los fondos de la muestra. Además, no se ha exigido que los fondos hayan nacido durante el periodo temporal analizado, así como tampoco que estos permanezcan vivos al final del periodo de análisis, por lo tanto, la base de datos está libre de sesgo de supervivencia.

La información de las carteras de los fondos de inversión se ha obtenido de la Comisión Nacional del Mercado de Valores (CNMV) y de Morningstar. La fusión de la información procedente de ambas bases de datos permite que se controlen todas las carteras trimestrales y más del 80% de las carteras mensuales. Concretamente, se analizan 20.572 decisiones de gestión a partir de los datos extraídos de las carteras de los fondos de inversión.

En relación con la metodología aplicada, se realizan tres análisis: (1) análisis del proceso de aprendizaje a nivel de industria, (2) análisis del proceso de aprendizaje a nivel de familia de fondos y (3) análisis de la influencia de las características de las familias en su nivel de aprendizaje.

Centrándonos en el análisis a nivel de industria, en primer lugar, se identifican las decisiones de compra y venta de activos siguiendo el enfoque de cambio en el número de títulos (Alexander et al., 2007). La comparación entre dos carteras mensuales consecutivas de un fondo, junto con la información bursátil de los títulos proporcionada por Datastream permite obtener el número de títulos comprados o vendidos por el fondo de inversión durante ese periodo. Una vez que se conoce el número de títulos que han sido comprados o vendidos, se calcula el importe económico de cada decisión, multiplicando el cambio en el número de acciones por su precio medio en el mercado, durante el mes correspondiente.

En segundo lugar, se calcula la importancia relativa de cada decisión de compra y venta, dividiendo la cuantía de la misma entre el patrimonio total del fondo, y posteriormente, se identifican las compras y ventas importantes, aplicando tres filtros independientes. Estos filtros se basan en tres condiciones necesarias para que una decisión sea considerada como compra o venta importante en la gestión de los fondos de inversión. Con el primer filtro, se considera que decisión de compra o venta es importante cuando su importancia relativa es significativamente alta. Con el segundo filtro, se asume que una decisión es importante cuando su importancia relativa es significativamente mayor a la importancia relativa del resto de decisiones tomadas por el mismo fondo con el resto de títulos durante el mismo mes. En el tercer filtro, se considera que una decisión es importante si su importancia relativa es significativamente mayor a la de las decisiones tomadas por el resto de fondos con el mismo título en el mismo mes. Finalmente, se considera que una compra o venta se encuentra definitivamente entre las decisiones importantes, cuando esta supera los tres filtros explicados de forma simultánea.

En tercer lugar, una vez que se han identificados las decisiones importantes, se procede a identificar los errores importantes, es decir, esas decisiones importantes que tienen un impacto significativamente negativo en la rentabilidad posterior del fondo. Para ello, se calcula el impacto económico de cada decisión, multiplicando su importancia relativa por el alfa de Jensen del título correspondiente. Con el objetivo de dar robustez a los resultados obtenidos, se aplica este tercer paso con el alfa calculada a partir de 60, 120 y 240 datos diarios. El objetivo es observar si los resultados son similares en el corto plazo (alfa a 3 meses) y en el medio y largo plazo (alfas a 6 y 12 meses). Se selecciona, el 20% de las decisiones importantes con el impacto económico más negativo en la rentabilidad del fondo: el 10% de las compras importantes y el 10% de las ventas importantes. No obstante, se aplica también deciles y cuartiles en la identificación de estos errores importantes por motivos de robustez.

Finalmente, se calcula el porcentaje anual de errores importantes para cada fondo en cada año, dividiendo el número de errores en compras y ventas entre el número de compras y ventas totales, respectivamente, y se analiza la evolución de este porcentaje, aplicando el modelo dinámico de datos de panel (Arellano y Bover, 1995; Blundell y Bond, 1998) con tendencia. Además, para verificar la robustez de los resultados, incluimos cinco variables de control sobre las características de los fondos de inversión y la situación del mercado: tamaño del fondo, antigüedad del fondo, número de títulos en la cartera, índice de rotación y rentabilidad del *benchmark.*

En el segundo análisis a nivel de familia de fondos, se parte del porcentaje de errores importantes obtenido en el primer análisis a nivel de industria y se aplica el mismo modelo, incluyendo adicionalmente una variable dummy (*Familia*) que toma valor 1 cuando el fondo está gestionado por la familia en cuestión. De esta manera, esta variable dummy tiene el mismo valor en todos los fondos gestionados por esta familia. En este modelo, también se incluye la interacción entre la variable dummy *Familia* y la variable *Tiempo* la cual captura la tendencia del porcentaje de errores importantes a lo largo del tiempo. Esta interacción nos permite comparar el nivel de aprendizaje de cada familia de fondos con respecto al nivel global de aprendizaje en la industria.

En el tercer análisis, se pretende determinar si existen diferencias significativas entre el nivel de aprendizaje de las diez familias de fondos más grandes registradas en España y el nivel de aprendizaje del resto de familias. En la misma línea, se analiza si existen diferencias significativas entre familias independientes y dependientes de grupos bancarios o aseguradoras. Para alcanzar ambos objetivos, se estima el modelo utilizado en los dos primeros análisis, pero en este caso, se incluye una variable dummy que permite distinguir entre las diez familias de fondos más grandes y el resto de familias, para el primer objetivo y entre las familias independientes y dependientes, para el segundo objetivo.

Resultados empíricos y conclusiones alcanzadas

El primer análisis en este capítulo muestra que el porcentaje de errores importantes en la gestión de los fondos de inversión renta variable euro registrados en la industria española disminuye significativamente con el tiempo. Estos errores importantes son consecuencias de importantes decisiones de compra o venta que cumplen los tres filtros, explicados en el apartado de metodología, cuyo impacto en la rentabilidad posterior del fondo es significativamente negativo. Se concluye que esta tendencia decreciente en el porcentaje de errores importantes muestra la capacidad general de la industria de fondos de inversión para aprender de los errores cometidos en el pasado. Los resultados de este estudio siguieren que, detrás de los errores hay una fuente de aprendizaje que lleva a los gestores de fondos de inversión a cometer menos errores a lo largo del tiempo, y apoyan la hipótesis de que cuanto más negativo es el impacto de los errores, mayor es la motivación para aprender y evitar cometer los mismos errores en el futuro, es decir, "se aprende cuando algo duele". Este resultado es consistente tanto cuando se calcula el efecto de las decisiones a corto plazo (alfa de Jensen a 3 meses) como cuando se calcula a medio y largo plazo (alfas de Jensen a 6 y 12 meses).

La variable dependiente retardada permite controlar el posible sesgo de endogeneidad en el modelo y su influencia positiva y significativa indica que cada fondo presenta patrones individuales en sus decisiones de gestión que tienden a persistir en el tiempo y como consecuencia, algunos fondos son más propensos a cometer errores. De esta manera, los fondos que cometen el mayor número de errores en el pasado son también los que cometen el mayor número de errores en el futuro.

En relación con las variables de control, el tamaño y la edad del fondo no muestran una clara influencia en el porcentaje de errores importantes, sin embargo, los resultados indican que los fondos más diversificados, es decir, aquellos con un mayor número de títulos en sus carteras, y con índices de rotación más bajos cometen menos errores importantes. Con respecto al resultado de número de títulos, este se podría explicar porque, en general, las decisiones de gestión en las carteras más diversificadas tienden a representar un valor relativamente menor y, por lo tanto, la probabilidad de cometer errores importantes también es menor. En la misma línea, el resultado sobre el índice de rotación podría explicarse porque cuando este es bajo, se toman menos decisiones y así, la probabilidad de cometer un error también es menor. Finalmente, se encuentra una relación negativa entre el porcentaje de errores y la rentabilidad de mercado. De esta manera, se muestra evidencia de que es más probable que se cometan errores importantes en los mercados bajistas que en los alcistas.

En el segundo análisis, los resultados indican que el nivel de aprendizaje del 70% (o más del 60%) de las familias de fondos es mayor o similar al nivel de aprendizaje global en la industria española de fondos renta variable nacional (fondos renta variable euro). Por lo tanto, se muestra evidencia empírica de que el proceso de aprendizaje documentado en el primer análisis está impulsado por un número importante de familias de fondos de inversión.

En el tercer análisis, en el cual se analiza el papel del tamaño de la familia de fondos, así como el papel de la dependencia a grupos bancarios o aseguradoras en el proceso de aprendizaje, los resultados obtenidos muestran que ninguna de estas características tiene una influencia significativa en el aprendizaje de la familia.

Capítulo 2: Diversificación y autonomía en las familias de fondos: implicaciones para los inversores

Introducción

El desarrollo de la industria de fondos de inversión ha implicado un aumento importante en el número de inversores individuales que participan en los mercados financieros, delegando la gestión de sus ahorros a los gestores de fondos de inversión. Esto se ve reflejado en los 15,6 mil millones de euros gestionados por 60.000 fondos en la industria europea de fondos de inversión (EFAMA, 2018).

La diversificación es una de las principales ventajas que ofrecen los fondos de inversión a los inversores individuales (Markowitz, 1952; Sharpe, 1964; Statman, 2004; y Goetzmann y Kumar, 2008, entre otros). Sin embargo, Moreno y Rodríguez (2013) indican que los fondos de inversión no están siempre bien diversificados y, por lo tanto, los inversores deben invertir en más de un fondo para reducir el riesgo idiosincrático en las carteras. Además, en lo que se refiere a la selección de los fondos de inversión, la literatura encuentra que los inversores primero selecionan la entidad financiera (familia de fondos), y posteriormente, eligen los diferentes fondos dentro de la familia selecionada (Massa 2003). En esta línea, Gerker et al. (1996) y Massa (2003) encuentran que es más probable que, los inversores que han invertido previamente en una familia de fondos seleccionan un fondo de inversión de esta misma familia, en futuras decisiones de inversión a que lo seleccionan aquellos inversores que no han invertido anteriormente. Esto puede estar explicado por el hecho de que los inversores pueden mover sus ahorros entre diferentes fondos de inversión dentro de la misma familia de fondos a un menor coste que entre distintas familias, invirtiendo menos esfuerzos en el proceso de búsqueda y selección.

En lo que se refiere al proceso de toma de decisiones en la gestión de carteras, estudios recientes encuentran que las decisiones de los gestores de los fondos de inversión están influenciadas por diferentes factores internos como: las experiencias pasadas (Menkhoff et al., 2006; Kempf et al., 2017), la propia intuición (Brown y Davies, 2017) o en nivel de familiaridad o preferencia hacía determinados títulos (Pool et al., 2015), y factores externos, entre los cuales cabe destacar: la información obtenida a través de la interacción social (Pool et al., 2015); las recomendaciones de expertos y analistas financieros (Brown et al., 2014); el nivel de competencia y cooperación con otros gestores (Kempf y Ruenzi, 2008; Simutin, 2013; Evans et al., 2020) y la estrategia interna de la familia (Kacperczyk y Seru, 2012; Sevcenko y Ethiraj, 2018).

Centrándonos en la gestión interna dentro de cada familia de fondos, diferentes estudios ponen de manifiesto la importancia de maximizar el uso de los recursos internos, coordinando internamente las decisiones de los gestores, así como la importancia de la reputación global a nivel de familia de fondos que depende de la gestión de todos sus fondos.

En esta línea, Elton et al. (2007) encuentran que los rendimientos de los fondos dentro de una familia tienden a estar altamente correlacionados y argumentan que esta mayor correlación se debe principalmente a los títulos comunes que se mantienen en las carteras. Además, la posible existencia de directrices por parte de los altos directivos también puede conducir a posiciones similares en las carteras de los fondos e implicar una reducción de la autonomía de los gestores en las decisiones de compra y venta de títulos (Kacperczyk y Seru, 2012).

En esta línea, el objetivo de este capítulo es analizar si la concentración de fondos dentro de la misma familia influye en la diversificación de los inversores individuales. En el primer análisis de este capítulo, se analiza el nivel de similitud entre las carteras de los fondos de inversión renta variable euro en la industria española, distinguiendo entre parejas de fondos en las cuales ambos fondos pertenecen la misma familia y parejas de fondos en las cuales cada fondo pertenece a una familia diferente. Posteriormente, se estudian las características de las parejas de fondos que muestran un mayor nivel de similitud entre sus carteras.

En el segundo análisis, el capítulo se centra en el nivel de similitud entre carteras dentro de cada familia. De esta manera, se obtiene el nivel de similitud entre los diferentes fondos dentro de cada familia, y se contrasta si hay familias con un nivel de similitud entre sus fondos significativamente mayor al de otras familias con el objetivo de estudiar la existencia de heterogeneidad entre las diferentes familias en términos de diversificación.

En el tercer análisis, se propone una medida para captar la autonomía que tiene los gestores dentro de cada familia en el proceso de selección de títulos pertenecientes a una industria concreta. Posteriormente, de la misma manera que se procede con el nivel de similitud entre carteras, se estudia si hay familias con un nivel de autonomía significativamente mayor, así como las características de estas familias.

Finalmente, se analiza si el nivel de similitud entre los distintos fondos de inversión, y en nivel de autonomía en la selección de títulos dentro de una industria específica son factores determinantes de la rentabilidad que obtienen los inversores que concentrar su selección de fondos de inversión en una sola familia.

Datos y metodología

Se estudia el nivel de similitud entre las carteras de los fondos de inversión clasificados en la categoría renta variable euro, en la industria española, desde diciembre de 1999 a junio de 2018. Varios trabajos se han centrado en analizar el nivel de similitud entre carteras en el mercado estadounidense. En esta línea, Elton et al. (2007) y Evans et al. (2020) examinan el nivel de similitud entre los fondos de inversión en EE.UU. desde 1998 hasta 2002 y desde 1990 hasta 2015, respectivamente. También, Pool et al. (2015) estudian el nivel de similitud entre las carteras de los fondos ofertados en EE.UU., gestionados por profesionales que viven en la misa zona o barrio dentro de la misma ciudad. Sin embargo, el estudio desarrollado en este capítulo es el primero que analiza la similitud entre carteras en el mercado español, que se caracteriza por una alta concentración y dependencia al sector bancario (Ferreira y Ramos, 2009; Ferreira et al., 2013). Según los datos reportados por INVERCO, las diez y cinco familias de fondos más grandes gestionan el 75% y 40% del patrimonio, respectivamente. Por otro lado, el 87% de los fondos están gestionados por familias que pertenecen a un grupo bancario o aseguradora. Se han excluido los fondos ETFs y fondos indexados, y se ha exigido que el fondo tenga un mínimo de 24 observaciones mensuales. De esta manera, la muestra está compuesta por un total de 276 fondos gestionados por 108 familias de fondos.

Las carteras mensuales de los fondos, se obtiene de la base de datos de la Comisión Nacional del Mercado de Valores (CNMV) y de Morningstar. En la CNMV, se han obtenido las carteras mensuales desde 1999 hasta 2006 y las carteras mensuales trimestrales desde enero de 2007 hasta junio de 2018 que se complementan con las carteras mensuales disponible en Morningstar, analizando así un total de 24.561 posiciones de cartera. En la CNMV, también se obtiene información sobre las características de los fondos y sociedades gestoras (familias de fondos). En este estudio, se distingue entre las gestoras dependientes y las gestoras independientes.

En lo que se refiere a la metodología utilizada, el nivel de similitud entre los diferentes fondos se obtiene a través de la medida utilizada por Elton et al. (2007) y Pool et al. (2015). Se obtiene el nivel de similitud tanto a nivel de título como a nivel de sector e industria de acuerdo a la clasificación industrial (ICB) de PTSE Russel, obtenida en Datastream.

En el primer análisis, se analizan las características de las parejas de fondos con carteras similares. Se utiliza un modelo en el que se contrasta si las parejas de fondos que mantienen carteras más similares, son también más similares en términos de tamaño, edad, número de títulos, comisiones y rentabilidad pasada. Además, en este modelo, también se contrasta si el nivel de similitud entre carteras es significativamente mayor entre las parejas de fondos dentro de la misma familia y las parejas en las cuales cada uno de los fondos pertenece a una familia diferente.

En el segundo análisis, se obtiene el nivel de similitud entre carteras dentro de cada familia de fondos, y se estudia si hay familias con mayor nivel de similitud entre sus fondos, aplicando tanto el test paramétrico de diferencia de medias como el test no paramétrico de Kruskal-Wallis, por motivos de robustez.

En el tercer análisis, se obtiene el nivel de autonomía dentro de cada familia. Se propone una medida de autonomía con un doble enfoque, que se basa en la intuición de que, el exceso de similitud a nivel de industria sobre el nivel de similitud a nivel de título capta la autonomía de los gestores en la selección de títulos específicos dentro de cada industria. En el primer enfoque, para obtener el nivel de autonomía en cada familia, se consideran todas las comparaciones de sus fondos, independientemente si estos se comparan con fondos de la misma familia o con fondos en otras familias. Sin embargo, en el segundo enfoque, solo se consideran las parejas de fondos en las que ambos fondos pertenecen a la misma familia. Posteriormente, también se utilizan el test paramétrico de diferencia de medias y el test no paramétrico de Kruskal-Wallis para contrastar si el nivel de autonomía en la selección de títulos es significativamente mayor en algunas familias, considerando ambos enfoques.

Finalmente, se analiza si el nivel de similitud entre carteras y el nivel de autonomía son determinantes de la rentabilidad que obtienen los inversores individuales y, por lo tanto, si los partícipes que concentrar todas sus inversiones en fondos dentro de la misma familia podrían obtener mejores resultados en determinadas familias, en función de ambos factores.

Resultados empíricos y conclusiones alcanzadas

Los resultados del análisis del nivel de similitud entre carteras muestran que las parejas de fondos, en las que ambos fondos pertenecen a la misma familia mantienen carteras más similares que las parejas de fondos en diferentes familias. Especialmente, el nivel de similitud es significativamente mayor entre las carteras de los fondos grandes. Sin embargo, en las parejas de fondos pequeños o con tamaños muy diferentes la parte común entre sus carteras es significativamente menor. Este resultado está en línea con la hipótesis de que los gestores de fondos grandes tienen habilidades comunes, así como un acceso común a un mayor nivel de información.

En relación con la edad de los fondos, los resultados muestran que el grado de similitud entre carteras es significativamente mayor entre las parejas de fondos con edades similares. Sin embargo, no se observa este resultado entre los fondos más antiguos o con una menor experiencia en el mercado. Por un lado, se podría pensar que los fondos más antiguos tienen la experiencia suficiente para poder desarrollar su propia estrategia de gestión de carteras. Por otro lado, los fondos más jóvenes que suelen enfrentarse al reto de aumentar su participación en el mercado, podrían tener mayores incentivos a ofrecer carteras lo más diferentes posibles al resto, siguiendo una estrategia de diferenciación de producto, en línea con los estudios de Mamaysky y Spiegel (2002), Massa (2003) y Khorana y Servaes (2012).

También, los resultados muestran que la parte común entre carteras es significativamente mayor en las parejas de fondos más diversificados que aplican comisiones de gestión más altas. Con respecto al número de títulos en la cartera, este resultado está en línea con el estudio de Kacperczyk et al. (2005). Estos autores documentan que los gestores de los fondos más diversificados mantienen posiciones más similares a la cartera global del mercado, sin embargo, los gestores de los fondos más concentrados siguen estilos de inversión más distintivos. En relación con las comisiones, el resultado obtenido podría estar explicado por la relación positiva, documentada por la literatura, entre los gastos de gestión y el esfuerzo realizado en la búsqueda de información, para tomar las decisiones de gestión en consecuencia.

Finalmente, los resultados muestran que el nivel de similitud entre carteras es significativamente mayor en las parejas de fondos que han tenidos una rentabilidad similar durante el último año. No obstante, no se observa este resultado cuando la rentabilidad ha sido muy positiva o muy negativa. Esta observación confirma nuestra hipótesis de que las reacciones de los gestores de fondos ante un nivel extremo de rentabilidad (muy positivo o muy negativo) pueden ser significativamente diferentes, y, en consecuencia, las posiciones entre sus carteras.

Una vez que se ha analizado el nivel de similitud en las posiciones de las carteras, distinguiendo entre parejas de fondos en la misma familia y parejas de fondos en distintas familias, y se muestra evidencia de que la concentración de fondos en una sola familia tiene una influencia negativa y significativa en el nivel de diversificación de los inversores. Posteriormente, este capítulo se centra en la diversificación entre fondos dentro de cada familia. Se tiene como objetivo explorar la heterogeneidad entre las familias de fondos en términos de diversificación. En esta línea, Evans et al. (2020) contribuye a la literatura sobre la heterogeneidad de estrategias de gestión entre las distintas familias de fondos, mostrando evidencia sobre la coexistencia de estrategias competitivas y cooperativas.

En este estudio, se contrasta la hipótesis nula que establece que no existen diferencias significativas en este fenómeno entre las diferentes familias. Los resultados muestran que, en promedio, en nivel de similitud entre carteras en las familias que se posicionan en tercil superior asciende a 55.55%, sin embargo, este porcentaje es igual a 15.67% en las familias pertenecientes al tercil inferior. De esta manera, la diferencia entre los valores de similitud de las familias que se posicionan en el tercil superior frente a las que están en el tercil inferior es igual a 39.89%, estadísticamente significativa al 1%. Por tanto, se muestra evidencia de que hay familias en las que el nivel de similitud entre carteras es significativamente superior con respecto a otras familias.

Este resultado lleva al análisis de las características de las familias en las que el nivel de similitud entre carteras es significativamente mayor. Para alcanzar este objetivo se aplican diferentes modelos por motivos de robustez. En este sentido, se obtiene que los resultados son consistentes y muestran un mayor nivel de similitud entre carteras en las familias grandes que pertenecen a un grupo bancario o aseguradora. En relación con la experiencia de la familia de fondos en el mercado, los resultados muestran evidencia de una mayor similitud en las familias de fondos con menos experiencia en el mercado. Finalmente, en este análisis, se documenta que la diversificación entre fondos es significativamente inferior en aquellas familias con una mayor cantidad de dinero gestionado en la categoría de fondos renta variable euro.

No obstante, en este capítulo, no solo se analiza la heterogeneidad entre familias de fondos en términos de diversificación. También, se analiza si hay familias de fondos en las cuales, el nivel de la autonomía en la selección de títulos dentro de una industria específica es significativamente mayor. Los resultados muestran que los gestores de fondos disfrutan de una mayor autonomía en la selección de títulos dentro de las familias de fondos antiguas de menor tamaño que no dependen del sector bancario.

Finalmente, se documenta que el nivel de similitud entre carteras tiene una influencia negativa y significativa en la rentabilidad que obtienen los inversores cuando concentran la selección de fondos en una misma familia. Sin embargo, los inversores parecen beneficiarse de una mayor autonomía en la selección de títulos. Estos resultados son especialmente interesantes en la industria española, ya que las familias grandes que dependen del sector bancario gestionan más de 40% de los fondos, y son estas las que precisamente muestran un mayor nivel de similitud entre sus fondos y una menor autonomía, lo que influye de forma negativa y significativa en la rentabilidad que obtienen los inversores. Para terminar, cabe resaltar la tendencia negativa de este fenómeno a lo largo del tiempo, lo que podría traducirse en una mejora de la eficiencia del sector. Según lo documentado por la literatura, una alta similitud entre carteras es señal de una industria con alto riesgo sistémico, y, en consecuencia, de una alta posibilidad de contagio y propagación de los shocks de mercado.

Capítulo 3: Nivel de divergencia entre las decisiones de gestión de los fondos de inversión y su contribución a la performance de la cartera.

Introducción

La habilidad de los gestores de fondos de inversión para generar valor añadido a la rentabilidad del fondo es un elemento de gran interés, tanto desde el punto de vista académico como desde el punto de vista profesional. La literatura previa ha analizado el valor añadido generado por los gestores, comparando el desempeño de la gestión pasiva y la gestión activa. Sin embargo, existe una cierta controversia sobre los resultados obtenidos. Por un lado, hay estudios que muestran que los fondos que siguen una gestión activa no superan a sus índices de referencia (*benchmark*) (Jensen, 1968; Fama y French, 2010). Por otro lado, varios estudios documentan que las posiciones de las carteras que más se diferencias de las posiciones mantenidas por el *benchmark* llevan asociada una rentabilidad significativamente mayor (Wermers, 2000; Dahlquist et al., 2000; Engström, 2004; Cremers y Petajisto, 2009; Fulkerson, 2013; Jiang et al., 2014).

El objetivo de este capítulo es identificar aquellas decisiones de compra y venta más diferentes en la gestión de un fondo de inversión con respecto a las decisiones tomadas por otros fondos, teniendo en cuenta los títulos negociados, el tipo de decisión (compra, venta o mantener posición) y su importancia relativa calculada sobre el tamaño total del fondo. De esta manera, se obtiene en qué medida las decisiones de gestión de los fondos de inversión se diferencia entre sí. También, se tiene como objetivo analizar la contribución de estas decisiones divergentes a la performance del fondo.

Uno de los principios económicos más importante, extendido a la gestión de carteras, establece que los gestores pueden obtener un exceso de rentabilidad, si, y solo si, logran diferenciarse del resto de fondos, utilizando las habilidades de gestión como una ventaja competitiva. Además, Khorana y Servaes (2007) documentan que las estrategias de diferenciación contribuyen a obtener una mayor participación en el mercado. Por tanto, se considera que tanto los gestores como las familias de fondos tiene incentivos para ofrecer una gestión diferente que genere valor añadido. Además, un mayor nivel de divergencia entre las decisiones de gestión también podría tener una influencia positiva en el sistema financiero. En esta línea, Getmansky et al. (2016), Guo et al. (2016) y Delpini et al. (2018; 2019) documentan que una similitud significativa entre las carteras de los fondos de inversión juega un papel importante en la transmisión de las dificultades financieras, y puede implicar que el sistema financiero sea más frágil.

En este capítulo, en primer lugar, se analiza la evolución del nivel de divergencia entre las decisiones de gestión de los fondos de inversión españoles, clasificados en la categoría renta variable euro, durante el periodo transcurrido entre enero de 2000 y junio de 2020. El desarrollo de la industria de fondos de inversión en las últimas décadas ha implicado un aumento en el nivel de competencia (Gavazza, 2011). De esta manera, las familias y gestores de fondos podrían verse más motivados a ofrecer una gestión más divergente en este entorno más competitivo, con el objetivo de aumentar su participación en el mercado y promocionar en sus puestos de trabajo, respectivamente. Además, la crisis financiera global de 2008 implico un proceso de fusiones y adquisiciones de fondos de inversión sin precedentes, lo que también ha podido influir en este fenómeno, provocando un aumento en el nivel de divergencia entre los distintos fondos. Por todo ello, cabría esperar una tendencia positiva en el nivel de divergencia en la gestión de los fondos de inversión.

En segundo lugar, este capítulo se centra en el análisis de los factores internos de gestión y los factores externos a nivel del mercado financiero que tienen una influencia significativa en este fenómeno. Concretamente, se examina la influencia de las posiciones previas mantenidas en las carteras, el nivel de estrés en el mercado de renta variable y las características de los títulos. En lo que se refiere a las posiciones previas en las carteras, se espera que las parejas que presentan un mayor nivel de similitud entre sus carteras previas, también muestren un nivel de divergencia más bajo entre sus decisiones de gestión, durante el periodo posterior.

Respecto al nivel de estrés en el mercado, cabe destacar que la literatura previa ha documentado que el comportamiento de los agentes financieros puede variar en función de las condiciones de mercado. En este sentido, Hakkio y Keeton (2009) argumentan que un nivel de estrés alto en el mercado implica altos niveles de incertidumbre sobre los valores fundamentales de los activos financieros, así como, una importante asimetría de información en el mercado, provocando sentimientos de miedo y pánico en los agentes financieros. Especialmente, este nivel alto de incertidumbre y asimetría se encuentra en los títulos extranjeros más arriesgados (Aslan et al., 2011; Martins y Paulo, 2014; Barron y Ni, 2008). De esta manera, la preferencia a asumir riesgos en los títulos más conocidos con los que se está más familiarizado, la cual ha sido documentada por varios estudios (Covrig et al., 2001; Garlappi et al., 2007; Epstein y Schneider, 2008), podría acentuarse en momentos de estrés en el mercado (Birâu, 2012). En esta línea, Raddatz y Schmukler (2012) encuentran que, tanto los inversores como los gestores de fondos de inversión reaccionan a los periodos de estrés con ajustes importantes en sus decisiones, y con un comportamiento procíclico, reduciendo así sus exposiciones a países y títulos de mayor riesgo. De esta manera, los momentos de alto estrés en el mercado pueden incitar a todos los gestores a comprar títulos menos arriesgados y más conocidos, y así, este objetivo común de gestión resultar en un nivel bajo de divergencia entre las decisiones de gestión de los fondos. Además, Karunanayake et al. (2010) y Khan et al. (2011) argumentan que el coste económico y el tiempo invertido en la búsqueda y procesamiento de la información son mayores en los periodos de estrés alto en el mercado, lo que podría aumentar los incentivos de los gestores para tomar decisiones similares a otros. Por tanto, se podría esperar que el nivel de estrés en el mercado tenga una influencia significativa y negativa en el nivel de divergencia entre las decisiones de gestión de los fondos.

Finalmente, dado que la literatura previa ha documentado que los gestores tienen preferencias hacía ciertos títulos con determinadas características, y así, estas características afectan a sus decisiones, se analiza la influencia de las mismas en este fenómeno. Aggarwal et al. (2005) documentan que los fondos de inversión tienden a invertir en títulos grandes con valores fundamentales altos. En la misma línea, Gompers y Metrick (2001) y Brands et al. (2006) encuentran que los gestores de fondos de inversión tienden a invertir en títulos grandes, líquidos y volátiles que han tenido rendimientos bajos durante el último año. Sin embargo, Otten y Bams (2002) y Covrig et al. (2006) encuentran una mayor preferencia por títulos poco volátiles con un rendimiento pasado alto. Además, algunos estudios encuentran que los inversores institucionales tienden a converger en las compras de títulos grandes, siguiendo las señales comunes del mercado (Lin y Swanson, 2003; Sias, 2004; Lu et al., 2012). Mientras otros autores como Huang et al. (2010) y Liao et al. (2011), indican que la convergencia es más pronunciada en títulos pequeños, justificando que los gestores de los fondos reciben información sobre estos títulos más limitada y precisa al mismo tiempo.

En tercer lugar, en este capítulo, se estudian las implicaciones económicas de las decisiones distintivas de los fondos de inversión. Concretamente, la hipótesis contrastada es que las decisiones divergentes tienen una contribución en el rendimiento del fondo significativamente mayor que la que tienen las decisiones convergentes, siguiendo los estudios de Cremers y Petajisto (2009), Cohen et al. (2010) y Jiang et al. (2014). Estos autores encuentran que los gestores de carteras generan valor añadido con las decisiones que más les separan del índice de referencia.

El tercer capítulo de la tesis contribuye a la literatura de varias maneras. Por un lado, este estudio está relacionado con la literatura previa que analiza el nivel de similitud entre los fondos de inversión, sin embargo, se propone una medida de divergencia en la que se incluyen las decisiones de compra y venta de forma conjunta a diferencia de la metodología utilizada en estudios anteriores. También, se analiza la influencia de las posiciones previas en las carteras y las características de los títulos en este fenómeno. Además, se finaliza el capítulo distinguiendo entre la contribución económica de las decisiones divergentes y la contribución de las decisiones convergentes a la performance de la cartera.

Por otro lado, este capítulo contribuye a la literatura sobre el desarrollo de la industria de fondos de inversión, la comparación del comportamiento de los gestores de fondos de inversión entre los periodos pre-crisis y post-crisis y el análisis de la reacción a los shocks de mercado por parte de los mismos.

Datos y metodología

En este capítulo, se analiza el nivel de divergencia en las decisiones de gestión entre las parejas de fondos españoles, clasificados en la categoría renta variable euro, desde enero de 2000 hasta junio de 2020. No se ha exigido que los fondos hayan nacido durante el periodo analizado, así como tampoco que permanezcan vivos al final de periodo. De esta manera, la muestra está libre de sesgo de supervivencia. Además, se han excluido los fondos ETFs, los fondos indexados y aquellos fondos con menos de 24 carteras mensuales. Esto conduce a que la muestra final este compuesta por 315 fondos de inversión renta variable euro gestionados por 114 familias de fondos.

De la base de datos de la CNMV, se obtienen las carteras mensuales de todos los fondos de la muestra reportadas desde diciembre de 1999 hasta diciembre de 2006 y las carteras trimestrales desde enero de 2007 hasta junio de 2020. Adicionalmente, durante este segundo tramo, las carteras trimestrales se completan con las carteras mensuales de Morningstar, cuando están disponibles en esta base de datos. Se usa en código ISIN para la fusión de la información procedentes de ambas bases de datos. También, de la CNMV, se ha obtenido información sobre el tamaño de los fondos, la entidad gestora (familia de fondos) con su correspondiente número de registro en cada momento, fecha de inicio del fondo, las comisiones de gestión y depósito y el valor liquidativo.

En Datastream, se ha obtenido información sobre el precio, rentabilidad y capitalización bursátil de los títulos en las carteras de los fondos. Cabe resaltar que se han controlado las principales operaciones de capital como splits, contrasplis y pago de dividendos.

Centrándonos en la metodología aplicada en este capítulo, en primer lugar, se determina el importe de cada decisión comercial de la misma forma que en el primer capítulo, es decir, multiplicando el cambio en el número de títulos durante un periodo y el precio medio del título en ese periodo. Posteriormente, se calcula el peso de cada decisión con respecto al tamaño del fondo medido con el valor total neto de los activos gestionados. Finalmente, se comparan estos pesos para cada título en cada pareja de fondos y en cada mes, para obtener así, el nivel de divergencia de gestión entre ambos fondos en ese mes.

Se propone una medida para captar en qué medida se diferencia las decisiones de gestión entre los distintos fondos de inversión, en la cual la divergencia realizada se relativiza con respecto a la divergencia máxima posible entre cada pareja de fondos en cada periodo. Esta medida incluye decisiones de compra y venta de forma conjunta en una sola medida, lo que permite identificar tres casos de divergencia: (1) cuando dos fondos operan en la misma dirección en un título, es decir, los dos compran o los dos venden, aunque el peso de las decisiones sea diferente; (2) cuando los dos fondos toman decisiones opuestas en un título, es decir, uno compra y otro vende; (3) cuando un fondo compra o vende un título y el otro fondo no negocia con este título. Además, en esta medida, se tienen en cuenta los pesos de los títulos en las carteras previas de los fondos, con el objetivo de controlar los casos en los que un fondo no puede vender en un título porque no lo tiene en la cartera.

En el primer análisis, el objetivo es analizar si el nivel de divergencia entre las decisiones de gestión de los fondos de inversión es constante en el tiempo o si, por el contrario, muestra una tendencia determinada. Se aplica el modelo dinámico GMM, de Arellano y Bover (1995) y Blundell y Bond (1998) con tendencia, en el cual se incluyen las características de los fondos (tamaño, edad, comisiones, rentabilidad pasada, número de títulos en la cartera y flujos monetarios), controlando así, los posibles efectos de las mismas en este fenómeno. Además, se aplica el test de Bai-Perron con el objetivo de identificar los puntos de corte en la evolución del nivel de divergencia.

En el segundo análisis, se analiza la influencia de las posiciones en las carteras previas, el estrés de mercado y las características de los títulos. En los dos primeros casos, se aplica el mismo modelo que en el primer análisis, incluyendo el nivel de similitud entre las carteras de los fondos al final de periodo previo, calculado con la medida utilizada por Elton et al. (2007) y Pool et al. (2015) y el nivel de estrés en el mercado renta variable, obtenido en la CNMV, el cual fue introducido por Cambón y Estévez (2016). Los resultados obtenidos en este análisis sobre el impacto de las posiciones previas llevan a que, en la medida propuesta, se controlen las posiciones iniciales y las posiciones finales, excluyendo el nivel de divergencia procedentes de decisiones divergentes que llevan a posiciones finales más similares. En el tercer caso, se obtiene el nivel de divergencia a nivel de título y se analiza la influencia de sus características (rentabilidad, volatilidad, tamaño y nivel de popularidad en el mercado).

En el tercer análisis, se distingue entre la aportación económica de las decisiones convergentes y decisiones divergentes a la performance del fondo, así como también, se analiza la influencia de este fenómeno en la performance de la cartera.

Resultados empíricos y conclusiones alcanzadas

Los resultados obtenidos en el primer análisis llevado a cabo en este capítulo nos permiten concluir la existencia de una tendencia global negativa en la evolución del nivel de divergencia de gestión entre los diferentes fondos. No obstante, a pesar de que se encuentra esta evolución global negativa, se observa un punto de inflexión en la tendencia en el año 2008, lo que podría relacionarse con el inicio del importante proceso de reestructuración bancaria. De esta manera, hasta el año 2008 el nivel de divergencia sigue una tendencia positiva que posteriormente, se revierte. En lo que se refiere a las características de los fondos y variables de control, en ambos sub-periodos en los que se divide el periodo global de análisis (teniendo en cuenta el punto de inflexión mencionado), se observa una menor divergencia entre las decisiones de gestión en las parejas de fondos pertenecientes a la misma familia con respecto a las parejas de fondos, en las cuales cada fondo pertenece a una familia distinta. Este resultado está en línea con los resultados del capítulo 2 sobre el nivel de similitud entre carteras. También, en ambos sub-periodos, se observa un menor nivel de divergencia de gestión entre parejas de fondos con un tamaño y un número de títulos en cartera similares. Sin embargo, los resultados muestran resultados opuestos entre los dos sub-periodos para el resto de características (edad, rentabilidad pasada y flujos monetarios), por lo que no se pueden obtener conclusiones claras sobre la influencia de las mismas en este fenómeno. Por último, la diferencia en las comisiones parece no mostrar una influencia significativa en el nivel de divergencia de gestión entre las parejas de fondos, resultado consistente en ambos sub-periodos.

En el segundo análisis abordado en este capítulo, se observa que aquellas parejas de fondos de inversión que muestran un menor nivel de similitud entre sus carteras previas son los que cometen decisiones de compra y venta más diferentes. También, se encuentra que el nivel de estrés de mercado tiene una influencia negativa y significativa en este fenómeno. De manera que, en momentos de alto estrés, los gestores de fondos de inversión tienden a converger más en sus decisiones de compra y venta que en momentos de bajo estrés. El primer hallazgo sobre la influencia de las carteras lleva a que se proceda a controlar las posiciones previas y finales en las carteras, en cada periodo y así, excluir el nivel de divergencia que, en realidad, implica converger en posiciones. No obstante, a pesar del control en este sentido, el resultado relacionado con el nivel de estrés es consistente, manteniendo su influencia negativa y significativa.

En relación con la influencia de la situación del mercado, además de estudiarse el efecto del estrés de mercado en este fenómeno, se analiza la reacción de los gestores de los fondos de inversión, en términos de divergencia de gestión, a los distintos shocks de mercado que tienen lugar durante el periodo de análisis. Concretamente, los tres shocks de mercado más importantes coinciden con el inicio de la crisis económica de 2008 (enero-marzo 2008), la crisis de deuda soberana de 2011 (marzo-abril 2011) y la crisis COVID-2019 de 2020 (marzo-abril 2020). En este sentido, los resultados muestran que los gestores de fondos de inversión no reaccionan de la misma manera a los diferentes shocks de mercado. Se concluye que esto puede deberse a diferentes factores como la distinta causa de cada shock o la situación financiera, en cada uno de esos momentos.

En el tercer análisis realizado, los resultados también indican que el nivel de divergencia entre las decisiones de gestión de los distintos fondos de inversión está impulsado por ciertas características a nivel de título. Concretamente, entre parejas de fondos pertenecientes a la misma familia, se encuentra un menor nivel de divergencia en títulos pequeños con un nivel extremo de rentabilidad pasada, bien muy positiva o bien muy negativa y una alta volatilidad. Estos resultados sugieren la existencia de una influencia interna por parte de la alta dirección, dentro de las familias de fondos, en las decisiones de gestión sobre determinadas oportunidades extremas de inversión, así como la existencia de un control interno del riesgo a nivel de organización. Además, en línea con los estudios que documenta una preferencia hacía los títulos más conocidos en el mercado, se encuentra un menor nivel de divergencia en los títulos más populares.

Finalmente, se encuentra que los fondos de inversión que tomas decisiones de compra y venta más diferentes obtienen un rendimiento significativamente mayor. Además, esta evidencia notable se dota de robustez cuando se compara la contribución que las decisiones divergentes tienen a la performance de las carteras con respecto a la contribución que tienen las decisiones convergentes. Los resultados muestran evidencia de que los gestores de fondos de inversión generan valor añadido a través de sus decisiones más divergentes. De esta manera, tanto las familias como los gestores de fondos de inversión pueden verse motivados a buscar nuevas oportunidades de inversión con el objetivo de diferenciarse del resto en la industria, y así también, ofrecer mayor valor a aquellos inversores que les delegan la gestión de sus ahorros.

CONCLUSIONES FINALES

A continuación, se resumen las principales conclusiones y aportaciones de la tesis. En este sentido, las principales razones que me han llevado a investigar las habilidades de los gestores de fondos de inversión han sido, por un lado, la importante cantidad gestionada en la industria de fondos de inversión, y, por tanto, el importante impacto económico y social de la gestión de carteras en los inversores individuales. Por otro lado, ha sido el importante papel que tiene los gestores de fondos en esta industria. La tesis también está motivada por la falta de estudios que analizan el proceso de aprendizaje en la industria de fondos de inversión, y por el objetivo de explorar la influencia del nivel de similitud entre carteras dentro de una familia de fondos en la rentabilidad y diversificación que se ofrece a los inversores, así como la habilidad de los gestores para tomar decisiones diferentes que generen valor añadido en la industria de fondos.

En el primer capítulo, se identifican las decisiones de compra y venta importantes que toman los gestores de los fondos de inversión, basándose en la hipótesis de que no todas las decisiones de gestión tienen la misma importancia en términos de rentabilidad y riesgo, y, por lo tanto, el mismo impacto en el proceso de aprendizaje. En este capítulo, se argumenta que la cuantía de las decisiones importantes representa un porcentaje alto con respecto al tamaño del fondo durante el periodo correspondiente y su importancia relativa es significativamente mayor a la de otras decisiones tomadas por el fondo con otros títulos en el mismo mes, así como, a la importancia de las decisiones del resto de fondo con el mismo título en el mismo mes.

El objetivo del primer capítulo es analizar la evolución del porcentaje de errores importantes como medida del proceso de aprendizaje en la industria de fondos a partir de los errores importantes cometidos en el pasado. En este sentido, los resultados muestran que el porcentaje de errores importantes siguen una tendencia decreciente durante el periodo analizado. Posteriormente, en este capítulo, se examina la capacidad de aprendizaje de cada familia de fondos con respecto al nivel global de aprendizaje en la industria. Los resultados obtenidos provienen evidencia de que un número importante de familias impulsa el proceso de aprendizaje en esta industria. En estas familias de fondos, la disminución del porcentaje de errores es igual o superior a la disminución promedio obtenida en el análisis a nivel de industria.

Finalmente, en este capítulo, se estudia si el tamaño de la familia y su dependencia a grupos bancarios y aseguradoras influyen en la evolución del porcentaje de errores importantes. En términos generales, los resultados no muestran una influencia significativa de estas características en el proceso de aprendizaje.

Los resultados obtenidos en los análisis del primer capítulo tienen implicaciones relevantes para los inversores individuales, gestores de fondos de inversión y supervisores, así como para la eficiencia global de la industria de fondos. La disminución de errores importantes en la gestión de carteras podría incentivar el interés de los partícipes por invertir sus ahorros en esta industria debido a una mayor confianza en la gestión profesional. También, este proceso puede tener una influencia positiva en la compensación económica y reconocimiento del trabajo de los gestores de fondos, y en la eficiencia global de la industria. Finalmente, este estudio es interesante para el órgano supervisor que procura por la protección de los inversores y promueve las buenas prácticas de gestión.

No obstante, dado que los inversores podrían invertir en más de un fondo con el objetivo de reducir el nivel de riesgo idiosincrático de las carteras, otra característica importante es el nivel de similitud entre las carteras de los fondos. En la literatura se ha documentado que los inversores individuales tienden a concentrar todas sus inversiones en la misma familia de fondos debido al coste económico y tiempo invertido que implica un cambio de proveedor. En este sentido, el segundo capítulo de la tesis se centra en el análisis de la parte común de las carteras de los fondos y la autonomía en la selección de títulos dentro de cada industria.

Los resultados obtenidos en el segundo capítulo muestran que la concentración de las inversiones en una misma familia de fondos tiene un impacto negativo y significativo en el nivel de diversificación, especialmente, cuando las familias de fondos son grandes, dependen de un grupo bancario o aseguradora y su experiencia en la industria de fondos es relativamente reducida. También, los resultados ponen de manifiesto que, en las familias con estas características, el nivel autonomía en la selección de títulos es significativamente menor.

Finalmente, en este capítulo, se analizan las implicaciones del nivel de similitud entre las carteras de los fondos y el nivel de autonomía en la rentabilidad que obtienen los inversores, cuando concentrar todas sus inversiones de fondos dentro de la misma familia. Los resultados documentan que una mayor similitud entre los fondos dentro de una familia no solo implica que se esté ofreciendo un menor nivel de diversificación potencial a los inversores individuales, sino que también tiene un efecto negativo y significativo en la rentabilidad obtenida.

Por tanto, los resultados obtenidos en este capítulo son especialmente interesantes en el marcado español de fondos por su alta concentración y dependencia al sector bancario. De acuerdo con los resultados obtenidos, las familias de fondos con una mayor participación en el mercado, muestran un mayor nivel se similitud entre sus carteras.

Los resultados obtenidos en el segundo capítulo conducen a analizar el nivel de divergencia entre las decisiones de compra y venta que toman los fondos de inversión, y su capacidad para generar valor añadido a través de sus decisiones distintivas.

En el tercer capítulo, se propone una medida que capta en qué medida las decisiones de gestión de un fondo se diferencias de las decisiones que se toman en el resto de fondos. En línea con los resultados obtenidos en el segundo capítulo, se encuentra un menor nivel de divergencia en las decisiones de gestión para las parejas de fondos, en las cuales ambos fondos pertenecen a la misma familia. En lo que se refiere a la evolución de este fenómeno, se observa que las decisiones de los fondos son más diferentes entre sí con el paso del tiempo, especialmente, después de la crisis financiera global de 2008, y del inicio del proceso de fusiones de fondos y familias de fondos provocado por la importante restructuración bancaria en el sistema financiero.

En segundo lugar, en el tercer capítulo se analizan los determinantes que impulsan la divergencia en la gestión de carteras. Se proporciona evidencia de que las parejas de fondos con carteras previas más similares son las parejas que muestran un menor nivel de divergencia entre sus decisiones de compra y venta. Este resultado lleva a que, en la medida de divergencia propuesta, se controle el nivel de similitud entre las carteras previas y finales, excluyendo la parte de las decisiones divergentes que llevan a converger en posiciones. Controlando por este aspecto, se observa que la mayor divergencia entre fondos de diferentes familias pierde su significación estadística. Esta pérdida de significación parece lógica ya que las parejas de fondos en la misma familia ya parten de posiciones previas más similares.

No obstante, a pesar de este control, los resultados muestran que el nivel de estrés tiene una influencia negativa y significativa en este fenómeno. Por tanto, la probabilidad de que, en un fondo se toman decisiones más diferentes con respecto al resto de fondo es menor en los periodos de alto estrés en el mercado. Sin embargo, en este capítulo, también se encuentra que los gestores no han reaccionado de la misma manera a los diferentes shocks de mercado, que han tenido lugar durante el periodo analizado, en términos de divergencia en la gestión de sus fondos. El diferente origen de cada uno de los shocks y el proceso de aprendizaje en la industria de fondos podrían tener un papel importante en este resultado.

Este capítulo también se centra en la influencia que tienen las características de los títulos en este fenómeno. Este análisis proporciona resultados interesantes dado que, para las parejas de fondos en la misma familia, se observa una menor divergencia en las compras y ventas de títulos pequeños con un comportamiento extremo en términos de rentabilidad y volatilidad, que podrían considerarse una oportunidad de inversión, pero también implicar un alto nivel de riesgo. Se debe tener en cuenta que las perspectivas sobre oportunidades de inversión pueden ser diferentes entre las distintas familias de fondos debido a sus políticas distintivas de inversión y riesgo.

Finalmente, en línea con los resultados obtenidos en el segundo capítulo, se documenta que los fondos, en los cuales se toman decisiones de gestión más diferentes, muestran una rentabilidad posterior significativamente mayor. La influencia positiva de este fenómeno en la performance de las carteras se confirma cuando se encuentra que la contribución de las decisiones divergentes a la rentabilidad del fondo es significativamente mayor a la contribución de las decisiones convergentes.

El tercer capítulo de la tesis tiene implicaciones relevantes para los gestores de carteras, las familias de fondos y el órgano supervisor. Dado que los gestores de los fondos de inversión parecen tener una cierta capacidad para generar valor añadido con sus decisiones más distintivas, estos agentes financieros podrían aumentar su interés hacía la búsqueda de oportunidades de inversión y tomar decisiones más divergentes.

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