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Article

You Learn When It Hurts: Evidence in the Mutual Fund Industry

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Abstract: This paper aims to contribute to the lack of research on the learning process of mutual fund markets. The empirical design is focused on the ability of the Spanish equity mutual fund industry to learn from its important errors. The choice of this industry is justified by both its relevance in the European mutual fund markets and some specific characteristics, such as the concentration and the banking control of the industry, which may affect the learning process. Our main objectives are to identify important trading errors in mutual fund management by applying three independent filters based on the relative importance of each decision, and then testing the evolution of these errors both at the industry level and at the fund family level. We apply the dynamic model of generalized method of moments (GMM), and we find an overall significant decrease in the percentage of important trading errors over time, thereby providing evidence of the global learning process of the industry. In addition, we find that a large number of fund families drive this evidence. Finally, we obtain that the family size and its dependence on financial groups do not seem to play significant roles in explaining the learning process. Therefore, we conclude that fund managers have incentives to learn from their important trading errors, in order to avoid them in future decisions, due to their serious negative consequences on fund performance, regardless of the characteristics of the families to which they belong.

Keywords: mutual funds; important trading decisions; important errors; learning process

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1. Introduction

The main objective of this study 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 buying or selling decision for a given stock made by a fund in a certain month that simultaneously represents high importance with respect to (1) the fund's total net assets in this month; (2) other trading decisions made by the same fund for other stocks in this month, and (3) other trading decisions for the same stock made by other funds in this month. This important trading decision could be an important trading error if it has a significantly negative effect on the subsequent performance of the fund at 3 months, 6 months and 12 months.

Research into corporate management has analyzed, in some depth, learning from errors (Finkelstein and Sanford 2000; Tjosvold et al. 2004). However, there is little literature regarding errors in mutual fund management. One potential explanation for this gap is the fact that important errors in corporate management often have critical consequences, such as termination of the company (Cardon et al. 2011). However, the consequences of an important error in a portfolio holding management are likely to be less severe due to regulation regarding diversification which is generally required, such as European Union Directive 2009/65/EC of the European Parliament and the Council on the Coordination of Laws (2009).[1] Our interest in shedding light on the learning process in the mutual fund industry is motivated by this lack of research and by the implications—both social and economic—to improve fund management.

In this study, we propose a methodology to capture the important trading errors in fund management at 3 months, 6 months and 12 months. Our hypothesis is that not all trading decisions have the same impact on fund performance, and thus they do not have the same influence on the learning process. Therefore, we focus on important decisions.

First, we analyze the evolution of the important trading errors in fund management. Our null hypothesis is that the percentage of important errors is not significantly different over time. We could expect to reject our null hypothesis and find a decreasing evolution in the percentage of important errors because managers may have relevant incentives to learn from them for reasons of remuneration and reputation. The underlying rationale is that mutual funds are more sensitive to the learning process when the performance consequences of their trading errors are severe. Our hypothesis is in line with previous studies, which note that learning is mainly motivated by past errors (Singh et al. 2007; Zhao 2011). We use the generalized method of moments (GMM) to control for any endogeneity bias, and we find that important trading errors follow a decreasing trend in overall terms; therefore, over time, management makes fewer decisions that have significant negative effects on subsequent performance, which offers evidence of the learning process in the mutual fund industry. This result is robust both 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).

Secondly, we focus on the learning process at the fund family level, comparing the learning level of each fund family with the global learning of the whole mutual fund industry, and we find that this phenomenon is present in most of the fund families.

Finally, we study the influence of the two main dimensions of fund families in the Spanish market, which are, family size and the dependence of the fund family on banking and insurance groups. Our null hypotheses are that there are no significant differences between the largest 10 fund families and the other families and that there are also no significant differences among the dependent and independent fund families in terms of learning. We could expect to reject these null hypotheses and to find the learning level is significantly higher in small or independent families, due to greater incentives to learn in order to attract a greater number of individual investors. However, the results provide evidence that these family characteristics do not play a significant role in explaining the learning process. This finding is consistent with the previous result that shows the learning process is driven by a large number of fund families.

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 from them because their positions, reputations, and salaries may depend on their performance records (Mason et al. 2016). In addition, Agarwal et al. (2009a, 2009b) show that managerial incentives tend to be associated with improved 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 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 (Rousseau and Wachtel 2002) because this industry has experienced significant worldwide growth in recent years and consequently, it manages a significant amount of money. Particularly, this growth is evident in the European market where 15.6 billion EUR of net assets are managed by almost 60,000 mutual funds, making it the second largest mutual fund industry worldwide, according to the European Fund and Asset Management Association, EFAMA (2018).

Our paper is related to the literature that examines the skill of learning in mutual fund management. However, we contribute methodologically to the literature in several aspects. Firstly, this study differs from others as it analyzes the learning process of professional management in contrast to the widely studied behavior of retail investors in the mutual fund industry. Secondly, we focus on important errors by proposing three independent filters to identify the trading decisions that have a higher weight both within a fund and across funds and imply a significantly negative impact on the subsequent fund performance. Thirdly, we measure the learning process through the evolution of the percentage of important errors in important trading decisions over time. Fourthly, we propose a dynamic model that allows comparing the learning level of each fund family and the global learning level of the whole mutual fund industry, and exploring the influence of family characteristics on learning.

The rest of the study is structured as follows: Section 2 presents the literature review 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.

2. Literature Review

One of the most simple cognitive processes is decision making, through which agents make a choice based on the given criteria or strategies (Wang and Ruhe 2007). This process is associated with other mental processes involved in the capturing, synthesizing, and memorizing of information as well as with other factors. Several studies provide evidence of factors that 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), the 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 the 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 (Kacperczyk et al. 2006; Wermers et al. 2012).

In the research about decision-making on portfolios, there are two main trends: rational and behavioral 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; Fama 1968). In addition, previous studies document that the stock market can be characterized as a random walk process in different countries and hence, fund managers cannot generate higher returns than the average return of markets by using past information (Blasco et al. 1997; Durusu-Ciftci et al. 2019; Cisse et al. 2019; Dias et al. 2020; Tegtmeier 2021). On the other hand, behavioral finance considers that agents systematically violate the axioms considered by the rational choice theory (Hirshleifer 2001; Shiller 2003). Koestner et al. (2017) find that numerous empirical studies have shown that these behavioral biases lead to costly errors (Barber and Odean 2013; Cuthbertson et al. 2016). Between both main trends, there are studies that propose a combination of rational and efficient markets with behavioral models (Subrahmanyam 2008; Statman 2014). Similarly, Sargent (1993) defends non-rigid rationality based on the idea that while cognitive biases may lead to making errors, these errors are not persistent over time, which indicates that agents learn from their errors. Additionally, List (2003) finds that market experience plays a significant role in eliminating the behavioral effect on investment decisions. More recently, Shantha (2019) noted that behavioral biases in the context of stock trading follow a dynamic evolution due to market participants being able to learn from their errors and adapt to market conditions. Furthermore, Barras et al. (2020) also provide evidence of better management in the mutual fund industry over time. They examine the management skill and the ability of fund managers to add value and document that skill approaches its optimal level after an adjustment period possibly due to the learning process.

Nichita et al. (2019) emphasize the great importance of the knowledge and skill acquired through formal education and experience because financial and economic decisions are based on these theoretical and practical tools. 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 (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 (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 drive 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 line, 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. In addition, Boh et al. (2020) use an organizational learning perspective that focuses on how knowledge is created, retained and shared within organizations. These studies support the hypothesis that the decision-making and consequently learning abilities of mutual funds are not only specific to individual managers.

Regarding the measure of learning, several papers describe this process as the minimization of cognitive biases identified in the literature on behavioral finance (Nicolosi et al. 2009; Seru et al. 2009; Koestner et al. 2017). These authors describe the experience as the driver of this dynamic process, and they measure it by both the number of years of experience and the number of operations carried out. 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) note that learning from past errors is important for individuals, groups, and organizations as part of the theoretical framework of learning from experience (Argyris 1993; Argote 1999). Errors are costly to organizations, and these costs include economic loss, reputational damage, 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 line, 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. Recent developments in machine learning have provided new methods that simulate human learning to gain knowledge or skills or to reorganize existing knowledge to improve performance. This phenomenon has not left the mutual fund industry unaffected (e.g., Dehghanpour and Esfahanipour 2018; Zhang and Hamori 2020; Park et al. 2020; Haq et al. 2021). According to Chen et al. (2021), as well as the remarkable advantages of machine learning, there are also limitations, such as the lack of inclusion of the prior knowledge and experience that play an important role in the learning process.

3. Data

We explore the learning ability through the evolution of the percentage of important errors in the Spanish equity mutual fund industry from January 2000 to March 2014. Note that the sample period coincides with the maturity of the Spanish fund industry, avoiding effects that could be linked to the increase phase (Autio et al. 2000).

Our data include 292 active equity mutual funds registered in Spain which are managed by 101 fund families. 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. However, our sample includes neither index funds nor dividend funds. Hence, 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.

Portfolio holdings of the mutual funds included in our sample were 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 80% of the monthly portfolio holdings. We analyze 20,572 monthly portfolio holdings: 12,176 portfolio holdings of Euro domestic equity mutual funds and 8296 portfolio holdings of Euro non-domestic equity mutual funds. Monthly holdings capture roundtrip trades that are missing from semi-annual (34.2%) and quarterly data (18.5%), and permit a more accurate estimation of the timing of trades, according to Elton et al. (2010). The comparison between two consecutive monthly portfolio holdings of a mutual fund together with the stock information provided by Datastream[4] gives the number of shares of each stock that are bought or sold by the mutual fund during that period.

Table 1 shows the summary statistics of our fund sample. Both the total number of funds and the total number of fund families are on a downward trend. In the domestic (non-domestic) category, the number of funds and families decreases from 144 (124) to 74 (56), and from 79 (71) to 49 (36), between the pre- and post-crisis periods, respectively. This result can be explained by mergers and acquisitions of funds and families in the Spanish fund industry. Table 1 also shows that the average size of domestic (non-domestic) funds dropped from 69.67 (65.08) to 41.72 (23.95) million EUR during the financial crisis 2008–2011, although it subsequently recovered to 97.50% (66.82%). Furthermore, the average size is larger in Euro domestic than in Euro non-domestic equity mutual funds. This difference may be due to the fact that retail Spanish investors have more confidence in their home market, potentially demonstrating a home bias. Additionally, the average age is approximately double lower in Euro non-domestic equity mutual funds, as this investment category appears later in the Spanish market than the Euro domestic equity category. Additionally, the diversification level of funds is lower at the end of the sample period, which may indicate a preference for greater specialization in fewer stocks by funds over time. In Appendix A, Table A1 indicates the values of the Skewness, Kurtosis and Jarque–Bera test of fund characteristics.

Table 1. Summary Statistics. This table presents the summary statistics of our comprehensive mutual fund sample. Panel A shows the average statistics for Euro domestic equity mutual funds. Panel B shows the same information for Euro non-domestic equity mutual funds. For simplicity, the sample period is split into three sub-periods: pre-crisis (2000–2007), crisis (2008–2011), and post-crisis (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**			
	2000–2007	**2008–2011**	**2012–2014 ***		**2000–2007**	**2008–2011**	**2012–2014 ***
No. of Funds	144	106	74	*No. of Funds*	124	91	56
No. of Families	79	58	49	*No. of 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_No. of stocks				*Fund_No. of 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%

4. Methodology

We analyze 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 in this section. 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.

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 month t, we obtain the difference in the number of shares of each stock s held by fund i from the end of month $t-1$ to the end of month t.

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

$$If\ (N^i_{s,t} - N^i_{s,t-1}) < 0,\ then\ Selling\ decision \tag{2}$$

Once we know the number of shares that each fund has bought and sold, we obtain the euro amount of each trading decision, multiplying this change in the number of shares[5] by the average stock price in month t (Alexander et al. 2007).

$$If\ (N^i_{s,t} - N^i_{s,t-1}) > 0,\ then\ Buy^i_{s,t} = (N^i_{s,t} - N^i_{s,t-1}) \cdot \overline{P_{s,t}} \tag{3}$$

$$If\ (N^i_{s,t} - N^i_{s,t-1}) < 0,\ then\ Sell^i_{s,t} = -(N^i_{s,t-1} - N^i_{s,t}) \cdot \overline{P_{s,t}} \tag{4}$$

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

We calculate the weight of the amount of decision on the fund size measured by the total net assets.

$$Buy\text{-}Weight^i_{s,t} = \frac{Buy^i_{s,t}}{TNA^i_t}\ or\ Sell\text{-}Weight^i_{s,t} = \frac{Sell^i_{s,t}}{TNA^i_t} \tag{5}$$

Once we know the weight of each trading decision, we identify which buying and selling decisions are considered important using 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 high weight on the fund's TNA, (2) a significantly higher weight with respect to other trading decisions made by the fund, and (3) a significantly higher weight with respect to other trading decisions made by the rest of funds in the same stock. In sum, we consider that a trading decision is important when it simultaneously fulfills 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 has a high weight in this month. In this way, we control for the potential influence that the trading decision has in terms of performance, considering that this influence is more significant for decisions that have a higher weight.

We select the 10% of the trading decisions with the higher weight for each fund during its existence in the sample in order to control for the potential time bias of the month analyzed within each fund[6] 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:

$$\begin{aligned} &If\ Buy\text{-}Weight^{i}_{s,t} \ \geq\ 95^{th}\ percentile\ Weight^{i}, \\ &then\ \ Buy^{i}_{s,t}\ \epsilon\ Important\ buying\ decisions^{i}\ \ in\ the\ first\ filter \end{aligned} \tag{6}$$

$$\begin{aligned} &If\ Sell\text{-}Weight^{i}_{s,t} \ \leq\ 5^{th}\ percentile\ Weight^{i}, \\ &then\ \ Sell^{i}_{s,t}\ \epsilon\ Important\ selling\ decisions^{i}\ \ in\ the\ first\ filter \end{aligned} \tag{7}$$

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 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 than the rest of the decisions made by fund i.

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

Secondly, as 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 analyzed. Therefore, according to the second filter, we identify the important trading decisions as follows:

$$\begin{aligned} &If\ \ Buy\text{-}Weight^{i}_{s,t} - \overline{Buy\text{-}Weight^{i}_{p-s,t}} \ \geq\ 95^{th}\ percentile\ Diff\text{-}Weight^{i}, \\ &then\ Buy^{i}_{s,t}\ \epsilon\ Important\ buying\ decisions^{i}\ \ in\ the\ second\ filter \end{aligned} \tag{8}$$

$$\begin{aligned} &If\ Sell\text{-}Weight^{i}_{s,t} + \overline{Sell\text{-}Weight^{i}_{p-s,t}} \ \leq\ 5^{th}\ percentile\ Diff\text{-}Weight^{i}, \\ &then\ Sell^{i}_{s,t}\ \epsilon\ Important\ selling\ decisions^{i}\ in\ the\ second\ filter \end{aligned} \tag{9}$$

where $\overline{Buy\text{-}Weight^{i}_{p-s,t}}$ and $\overline{Sell\text{-}Weight^{i}_{p-s,t}}$ 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. $95^{th}\ percentile\ Diff\text{-}Weight^{i}$ and $5^{th}\ percentile\ Diff\text{-}Weight^{i}$ 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 weight is higher than the weight of the trading decisions taken by the rest of the 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 weight of a trading decision by mutual fund i in stock s in month t with the average weight of the trading decisions of the rest of the funds in this stock s and in month t. Once these excess weights were 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 to the third filter, we identify the important trading decision as follows:

$$\begin{aligned} &If\ \ \ Buy\text{-}Weight^{i}_{s,t} - \overline{Buy\text{-}Weight^{n-i}_{s,t}} \ \geq\ 95^{th}\ percentile\ Diff\text{-}Weight^{i,n-i}, \\ &then\ \ Buy^{i}_{s,t}\ \epsilon\ Important\ buying\ decisions^{i}\ \ in\ the\ third\ filter \end{aligned} \tag{10}$$

$$\begin{aligned} &If\ \ Sell\text{-}Weight^{i}_{s,t} + \overline{Sell\text{-}Weight^{n-i}_{s,t}} \ \leq\ 5^{th}\ percentile\ Diff\text{-}Weight^{i,n-i}, \\ &then\ \ Sell^{i}_{s,t}\ \epsilon\ Important\ selling\ decisions^{i}\ \ \ in\ the\ third\ filter \end{aligned} \tag{11}$$

where $\overline{Buy\text{-}Weight_{s,t}^{n-i}}$ and $\overline{Sell\text{-}Weight_{s,t}^{n-i}}$ 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 that simultaneously fulfills the three filters. First, the amount of the buying decision represents 18.64% of the TNA of fund i in March 2000. This decision fulfills the first filter since this is among the 5% of the buying decisions with the higher weight 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. 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 fulfills the third filter.

Table 2 shows that the average number of buying and selling decisions and the average percentage of important buying and selling decisions decrease over time in Euro domestic and Euro non-domestic equity mutual funds. For domestic (non-domestic) funds, we observe that the average number of buys and sells decreases by 41.37% (44.1%) and 54.21% (60.3%), respectively. This could be related to a decline in the turnover ratio in our sample (see Table 1). Table 2, however, shows that the percentage of important buying and selling decisions that fulfilled our three independent filters remains highly stable, only dipping slightly during the financial crisis.

Table 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	8635
Average no. buys by fund	141	131	137
Average % important buys	7.86%	5.52%	5.72%
Average no. sells	14,106	13,536	6459
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	7877
Average no. buys by fund	198	155	176
Average % important buys	7.26%	4.86%	6.25%
Average no. sells	15,479	14,454	6146
Average no. sells by fund	218	201	132
Average % important sells	5.44%	4.47%	5.05%

4.2. Important Errors in Important Trading Decisions

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

Firstly, we identify trading errors that are, important buying decisions in stock whose performance is negative or important selling decisions in stocks whose performance is positive. Then, we calculate the economic impact of each error by mutual fund i in month t for stock s by multiplying the future performance by 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 in the following three, six and twelve months with the 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]

$$Buy\ economic\ impact^{i}_{s,t+n} = Buy\text{-}Weight^{i}_{s,t} \cdot \alpha_{s,t+n} \tag{12}$$

$$Sell\ economic\ impact^{i}_{s,t+n} = Sell\text{-}Weight^{i}_{s,t} \cdot \alpha_{s,t+n} \tag{13}$$

where $\alpha_{s,t}$ is the Jensen's alpha of the stock s in the month $t + n$ with $n \in \{3,6,12\}$ months.

Third, we consider all funds in the sample period, and we identify the quintiles of important buying and selling decisions with the greatest negative impact on future fund performance. Fourth, for each one of the three time horizons used to calculate the subsequent impact of the errors, we calculate the yearly percentage of important errors for each mutual fund by dividing the number of important errors by the total number of mutual fund trades per year. To avoid potential biases in the number of negative decisions due to a decreasing number of trades per fund over time, we obtain the percentage of important errors (Table 2). Appendix B includes the graphs that show the evolution of the percentage of important errors over time.

4.3. Learning Process in the Mutual Fund Industry

We study the evolution of the percentage of important errors over time in order to measure whether funds are able to learn from their errors.

Therefore, we test the following null hypothesis ($1H_0$):

$1H_0$. *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).

This method is recommended in the literature for a database with a large number of individuals (mutual funds in our study), and a small number of periods (Roodman 2009a). Therefore, we calculated the percentage of important errors by fund and year with monthly data.

Our choice of panel data facilitates the combination of time series, cross-section, and unbalanced data (Wooldridge 2010). Furthermore, the dynamic panel data model makes it easier to include an endogenous structure by including a one-year lagged variable that captures the unobserved time-invariant effects due to individual patterns. Following the econometric research (e.g., Roodman 2009b), we use lags of the dependent variable in our model as an explanatory variable to avoid an endogenous relationship that could lead to model misspecifications.

We apply the dynamic model of generalized method of moments (GMM)[9] of Arellano and Bower (1995) and Blundell and Bond (1998) as follows:[10]

$$\%Important\ errors_{i,t} = \alpha_{i,t} + \gamma_{i,t}\ \%Important\ errors_{i,t-1} + \beta_1 Time_t + \beta_2 Size_{i,t} + \beta_3 Age_{i,t} + \beta_4 No.\ of\ stocks_{i,t} + \beta_5 Turnover_{i,t} + \beta_6 Market\ return_t + \varepsilon_{i,t} \quad (14)$$

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. In Appendix C, Table A2 shows the correlation matrixes between the variables included in Equation (14).

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 (β_1) 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.[11]

The size ($Size_{i,t}$) of each mutual fund is computed from its TNA. We carry out a cross-sectional normalization for better identification of larger funds. This normalization is because the average size of each mutual fund and, thus, the average size of all the mutual funds, can vary over time. Additionally, the probability of detecting important decisions, and consequently important errors, is greater in smaller funds. Hence, fund size may influence the efficiency of the fund families (Pollet and Wilson 2008; Pástor et al. 2015).

After computing the age ($Age_{i,t}$) of each mutual fund based on its inception date, we carry out a cross-sectional normalization to identify younger or older funds based on average age in each year. We divide the age of individual mutual funds by the average age of all the funds in each year in order to avoid the correlation problem with the time variable in Equation (14). Fund age may affect investment style and, therefore, trading decisions made by managers. However, Ferreira et al. (2013) find that the effect of fund age on trading decision efficiency can run in both directions. Younger mutual funds might have more agility and dedication to improving performance to survive, but they may also be at a disadvantage due to lack of experience and due to the increased costs associated with the start-up period.

We define the diversification level ($No.\ of\ stocks_{i,t}$) from the number of stocks held in the portfolio. Our hypothesis is that the level of diversification may have an impact on the efficiency of trading decisions and the likelihood of making important errors. Pollet and Wilson (2008) find a positive relationship between portfolio diversification and efficiency in mutual fund management. However, according to the literature, the effect of diversification on the efficiency of trading decisions can also be the opposite: Droms and Walker (1995), for instance, argue that more diverse portfolio holdings involve lower risk and lower returns.

The variable turnover ratio ($Turnover_{i,t}$) is also included because we consider that it can influence the likelihood of important errors and the ability of mutual fund managers to learn. We also believe that this ratio may have an impact on fund managers' ability to learn from their errors, because of their higher levels of trading activity. Grinblatt and Titman

(1994) argue that managers' ability to earn additional returns is significantly and positively related to turnover. However, Barber and Odean (2000) find that excessive trading leads to poor investment performance, while a low portfolio turnover achieves returns close to the benchmark.

Finally, the probability of an important error may differ in bull and bear markets, hence, we include market return (*Market Return*$_t$) as a control variable in the model. In fact, Kacperczyk et al. (2014) and Alda (2018) argue that managers' ability is influenced by the economic conditions, showing more stock-picking abilities in bull markets.

We also propose an analysis of learning within each fund family, in addition to this learning model for the whole fund industry.

We apply the following dynamic model of generalized method of moments (GMM) of Arellano and Bower (1995) and Blundell and Bond (1998) in which the dummy variable ($Family_{i,t}$) is one when the mutual fund is managed by the analyzed fund family, and zero otherwise, and it interacts with the time variable ($Time_t$). We use this interaction to compare the learning level of each family with respect to the global learning level of the fund industry over time. Thus, we must run Equation (15) for each fund family.

$$\begin{aligned} \%\ Important\ errors_{i,t} &= \alpha_{i,t} + \gamma_{i,t}\ \%\ Important\ errors_{i,t-1} + \beta_1\ Time_t \\ &+ \beta_2\ Size_{i,t} + \beta_3\ Age_{i,t} + \beta_4\ No.\ of\ stocks_{i,t} + \beta_5\ Turnover_{i,t} + \beta_6\ Market\ return_t \\ &+ \beta_7\ (Family_{i,t} \times Time_t) + \varepsilon_{i,t} \end{aligned} \tag{15}$$

where $Family_{i,t}$ has a value equal to one when the mutual fund is managed by the analyzed family in year t, and zero otherwise.

5. Results

5.1. Learning in the Mutual Fund Industry

Tables 3 and 4 show that the coefficient of the time variable ($Time_t$) of Equation (14) is significantly negative for both Euro domestic and non-domestic equity mutual funds. Therefore, the results show a negative and significant relationship between the time variable which captures the trend in our model and the percentage of important trading errors.[12] 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. These important errors are a consequence of the important buying and selling that fulfill the three independent filters explained in the methodology section.[13] 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).[14]

We consider that this decreasing trend in the percentage of important errors is the evidence of learning process and demonstrates the mutual fund industry's overall ability to learn from past errors. The results of our study suggest that behind the errors there is a source of learning that leads mutual funds to make fewer errors over time. 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 study 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 by making errors and the motivation to learn from them.

The lagged dependent variable (% *Important errors*$_{i,t-1}$) allows us to control for endogeneity bias. Tables 3 and 4 show that its coefficient is significantly positive, and its positive and significant influence indicates that each fund presents individual patterns in its trading abilities, which tend to persist over time. 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 ($Time_t$). This result is consistent with Pilbeam and Preston (2019) who show persistence in the relative skill of mutual funds. These authors document that the lowest-performing funds in one period are still the worst-performing funds in the following period.

Table 3. Learning results in Euro domestic equity mutual funds. This table presents the results of Equation (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 normalized 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 ***
$\%\ Important\ errors_{i,t-1}$	0.1060 ***	0.0823 ***	0.0799 ***	0.2591 ***	0.2042 ***	0.1086 ***
$Time_t$	−0.0004 **	−0.0002 ***	−0.0005 ***	−0.0004 *	−0.0006 **	−0.0003 ***
$Size_{i,t}$	−0.0015 *	−0.0012 ***	−0.0013 **	0.0008	0.0013	−0.0006
$Age_{i,t}$	−0.0030	0.0011	0.0027	0.0019	−0.0035	−0.0009
$No.\ stocks_{i,t}$	−0.0003 ***	−0.0002 ***	−0.0003 ***	−0.0005 ***	−0.0005 ***	−0.0002 ***
$Turnover_{i,t}$	0.0197 ***	0.0199 ***	0.0274 ***	0.0214 ***	0.0137 ***	0.0071 ***
$Market\ return_t$	−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 ***
Breusch–Pagan Test	101.59 ***	105.54 ***	87.89 ***	107.10 ***	120.04 ***	103.70 ***
Hausman Test	22.10 ***	29.11 ***	26.33 ***	19.92 ***	21.67 ***	28.80 ***
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	1081	1049	966	1234	1216	1247

Table 4. Learning results in Euro non-domestic equity mutual funds. This table presents the results of Equation (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 normalized 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 ***
% $Important\ errors_{i,t-1}$	0.0500 **	0.1018 ***	0.1076 ***	0.1120 ***	0.1011 *	0.1439 ***
$Time_t$	−0.0002	−0.0008 ***	−0.0007 ***	−0.0013 ***	−0.0013 ***	−0.0012 ***
$Size_{i,t}$	−0.0020	−0.0029 ***	−0.0014 *	−0.0001	−0.0022 **	−0.0012
$Age_{i,t}$	−0.0021	0.0004	0.0067	0.0052	0.0072	0.0067
$No.\ stocks_{i,t}$	−0.0003 ***	−0.0004 ***	−0.0003 ***	−0.0005 ***	−0.0006 ***	−0.0006 ***
$Turnover_{i,t}$	0.0091 ***	0.0059 ***	0.0092 ***	0.0173 ***	0.0177 ***	0.0154 ***
$Market\ return_t$	−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 ***
Breusch–Pagan Test	14.03 ***	15.50 ***	14.42 ***	10.82 ***	21.15 ***	14.78 ***
Hausman Test	20.92 ***	12.97 **	12.07 **	32.90 ***	27.45 ***	86.22 ***
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	1050	1102	1143

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. Tables 3 and 4 show that the coefficients of the variables number of stocks ($No.\ stocks_{i,t}$) and turnover ratio ($Turnover_{i,t}$) are significantly negative and significantly positive, respectively. Thus, 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 Pollet and Wilson (2008) who find a positive relation between portfolio diversification and fund efficiency. In this line, Schoenmaker and Schramade (2019) also show that institutional investors with higher learning capacity form portfolios that are more concentrated.

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, Tables 3 and 4 show that the coefficient of the variable market return ($Market\ return_t$) is significantly negative. Therefore, we find a negative relationship between the percentage of important errors and the market return. Therefore, a lower market return increases the likelihood of an important error, implying that important trading errors are more likely in bearish markets than in bullish markets. This is in line with the findings of Kacperczyk et al. (2014) and Alda (2018), who show that managers' abilities vary according to market conditions, with more evidence of stock-picking ability in bullish markets.

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 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 identify different types of mutual fund families that can coexist depending on their level of learning: (1) fund families with a higher level of learning than the industry, (2) fund families with a similar level of learning to the industry, and (3) fund families with a lower level of learning to the industry.

First, we apply Equation (15) in each mutual fund family. Second, we classify all of the families into the three previously defined groups according to the slope of the interaction between the dummy and time variables in Equation (15). This slope allows us to compare the learning level of each family relative to the global learning level at the industry level over time. Table 5 presents the percentages of each family group based on both the sign and the significance of the interaction slope.

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 ($Family_{i,t}xTime_t$) in Equation (15) is significantly negative or not significant. Table 5 shows that the percentage of fund families for which the coefficient of this interaction is significantly negative or not significant are approximately equal to 70% and above 60% for Euro domestic and non-domestic equity mutual funds, respectively. Therefore, we conclude 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. 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.

5.3. Learning in the Mutual Fund Industry: An Approach Using the Characteristics of Fund Families

In the previous sub-section, we provide evidence that mutual funds in most families learn from their trading errors in the Spanish equity mutual fund industry. Based on this result, our aim is to study whether the families with a higher learning level share any 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.

Table 5. Learning results: a fund family approach. This table presents the percentage of 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 (15) for each fund family. 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 3 and 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.

Panel A: Euro Domestic Equity Mutual Funds						
		Buys			**Sells**	
	Important Errors 3-Month Alpha	**Important Errors 6-Month Alpha**	**Important Errors 12-Month Alpha**	**Important Errors 3-Month Alpha**	**Important Errors 6-Month Alpha**	**Important Errors 3-Month Alpha**
$Family_{i,t}xTime_t$ Negative and Stat. Significant β_7	35.21%	32.00%	33.33%	27.40%	30.67%	32.39%
$Family_{i,t}xTime_t$ Non Significant β_7	35.21%	37.33%	38.67%	35.62%	41.33%	42.25%
$Family_{i,t}xTime_t$ Positive and Stat. Significant β_7	29.58%	30.67%	28.00%	36.99%	28.00%	25.35%
Panel B: Euro Non-Domestic Equity Mutual Funds						
		Buys			**Sells**	
	Important Errors 3-Month Alpha	**Important Errors 6-Month Alpha**	**Important Errors 12-Month Alpha**	**Important Errors 3-Month Alpha**	**Important Errors 6-Month Alpha**	**Important Errors 3-Month Alpha**
$Family_{i,t}xTime_t$ Negative and Stat. Significant β_7	30.65%	37.78%	23.88%	17.91%	35.94%	30.65%
$Family_{i,t}xTime_t$ Non Significant β_7	25.81%	24.44%	17.91%	29.85%	26.56%	27.42%
$Family_{i,t}xTime_t$ Positive and Stat. Significant β_7	43.55%	37.78%	58.21%	52.24%	37.50%	41.94%

5.3.1. Learning Results by Size of Mutual Fund Families

The Spanish mutual fund industry is characterized by important concentration given that the 10 largest fund families manage more than 75% of the fund assets (Inverco 2018). We might identify some unusual issues that characterize the Spanish market when studying learning, due to the highly-concentrated structure, the competition that the top 10 families face is different from the level of competition within the smaller families. Consequently, the learning level may also be different for the top 10 families according to their TNA related to the smaller families. In fact, although there is little research into this aspect of the mutual fund industry, Jashapara (2003) studied the effects of competition on organizational learning at a business level, finding that competitive forces actually encourage learning processes related to efficiency. The underlying concept is based on conclusions shown by Adams and Lamont (2003), and Hatch and Dyer (2004), who consider organizational learning to be a strategic asset to gain a competitive advantage.

Therefore, we aim to determine whether there are significant differences between the level of learning of the largest 10 fund families and the level of learning of smaller fund families. Hence, our null hypothesis is as follows ($2H_0$):

$2H_0$. *There are no significant differences among the largest 10 and the other fund families in terms of learning.*

To test this hypothesis, we use a similar approach to Equation (15) where the dummy 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 largest 10 families and zero otherwise. In this model, a significantly positive (negative) slope of the interaction variable shows that the learning level of the largest 10 families is lower (higher) than that of the smaller families. We could expect the coefficient of this interaction to be positive and significant because the competition level among small companies is higher than among large companies; therefore, the former could have greater incentives to learn from their important past errors in order to attract a greater number of individual investors.

Tables 6 and 7 show that the coefficient of the interaction between the dummy variable TOP-10 and time variable ($TOP\text{-}10_{i,t}xTime_t$) is generally not significant for both Euro domestic and Euro non-domestic equity mutual funds. Hence, we find that family size does not play a significant role in explaining the learning process in the highly concentrated Spanish mutual fund industry with the only exception that for the buy decisions of the Euro domestic equity mutual funds. That is, the different levels of competition between the largest and the smaller families does not generally affect the learning process in this industry.

Table 6. Learning results by fund family size (Euro domestic equity mutual funds). This table presents the results of Equation (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 important error percentage 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 normalized 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. $TOP\text{-}10_{i,t}xTime_t$ is the interaction between the dummy variable TOP-10 and the time variable. *** Significance at 1% level; ** significance at 5% level.

	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 ***
% $Important\ errors_{i,t-1}$	0.1008 ***	0.0730 ***	0.0700 ***	0.0912 ***	0.1850 ***	0.0838 ***
$Time_t$	−0.0005 **	−0.0003 ***	−0.0007 ***	−0.0002 **	−0.0003 **	−0.0003 **
$Size_{i,t}$	−0.0010	−0.0011 **	−0.0010 **	−0.0009 **	0.0009 **	0.0016 **
$Age_{i,t}$	−0.0159 ***	0.0008	−0.0003	−0.0011	0.0029	−0.0066
$No.\ stocks_{i,t}$	−0.0002 ***	−0.0002 ***	−0.0003 ***	−0.0002 ***	−0.0004 ***	−0.0003 ***
$Turnover_{i,t}$	0.0206 ***	0.0202 ***	0.0285 ***	0.0177 ***	0.0158 ***	0.0077 ***
$Market\ return_t$	−0.0051 ***	−0.0072 ***	−0.0069 ***	−0.0041 ***	−0.0040 ***	−0.0015
$TOP\text{-}10_{i,t}xTime_t$	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 ***
Breusch–Pagan Test	103.82 ***	17.21 ***	16.53 ***	39.44 ***	54.49 ***	76.59 ***
Hausman Test	19.03 ***	36.22 ***	33.63 ***	28.48 ***	9.02 **	9.09 **
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	1081	1049	966	1234	1216	1247

Table 7. Learning results by size of fund family (Euro non-domestic equity mutual funds). This table presents the results of the Equation (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 important error percentage 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 normalized 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.

	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*$_{i,t-1}$	0.0418 ***	0.0502 ***	0.1907 ***	0.1125 ***	0.1475 ***	0.1907 ***
Time$_t$	−0.0001	−0.0005 **	−0.0010 **	−0.0012 ***	−0.0011 ***	−0.0010 **
Size$_{i,t}$	−0.0016	−0.0024	0.0002	−0.0001	−0.0006	0.0002
Age$_{i,t}$	−0.0041	−0.0087 **	0.0037	0.0049	0.0093	0.0037
No. stocks$_{i,t}$	−0.0003 ***	−0.0003 ***	−0.0007 ***	−0.0005 ***	−0.0007 ***	−0.0007 ***
Turnover$_{i,t}$	0.0096 ***	0.0087 **	0.0173 ***	0.0173 ***	0.0189 ***	0.0173 ***
Market return$_t$	−0.0065 ***	−0.0122 ***	−0.0079 ***	−0.0069 ***	−0.0075 ***	−0.0079 ***
TOP-10$_{i,t}$*xTime*$_t$	−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 ***
Breusch–Pagan Test	14.54 ***	25.08 ***	14.75 ***	65.05 ***	48.54 ***	60.98 ***
Hausman Test	81.85 ***	20.22 ***	19.90 ***	19.55 ***	23.71 ***	22.90 ***
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	1050	1102	1143

5.3.2. Learning Process by Independence of Fund Families from Financial Service Groups

We discussed in the previous subsection that one of the key characteristics of the Spanish mutual fund industry is its high concentration. The relatively high importance of fund families controlled by banks and insurance groups is another defining feature of the Spanish market. Cambon and Losada (2014) study the structure of the mutual fund industry in Spain and demonstrate that most fund assets are managed by families belonging to credit institutions, emphasizing the universal banking model as a distinguishing characteristic of this market. In fact, in Spain, approximately 90% of families belong to a banking or insurance group, a figure that is significantly higher than in other European markets such as Germany, Portugal, Italy, France, and the United Kingdom (EFAMA 2018). 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 insurance group.

In this section, we test the following null hypothesis ($3H_0$):

$3H_0$. *There are no significant differences among the dependent and independent fund families in terms of learning.*

Similar to our analysis of fund company size, we use Equation (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 ($Independent_{i,t}xTime_t$) is the same as in the previous subsection. We could expect the coefficient of this interaction to be negative and significant because the independent fund families could have greater incentives to learn from their important past errors in order to attract a greater number of investors and thus, increase their market shares.

Table 8. Learning results by independence of fund family from financial service groups (Euro domestic equity mutual funds). This table presents the results of Equation (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 normalized 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 **
% $Important\ errors_{i,t-1}$	0.0984 ***	0.0835 ***	0.0753 ***	0.2653 ***	0.2114 ***	0.1593 ***
$Time_t$	−0.0003 ***	−0.0002 **	0.0005 ***	−0.0005 **	−0.0007 ***	−0.0006 ***
$Size_{i,t}$	−0.0008 *	−0.0012 **	−0.0012 **	0.0009	0.0013	0.0008
$Age_{i,t}$	−0.0016	0.0007	0.0021	0.0015	−0.0049	−0.0004
$No.\ stocks_{i,t}$	−0.0002 ***	−0.0002 ***	−0.0007 ***	−0.0005 ***	−0.0005 ***	−0.0002 ***
$Turnover_{i,t}$	0.0183 ***	0.0199 ***	0.0279 ***	0.0222 ***	0.0153 ***	0.0075 **
$Market\ return_t$	−0.0036 ***	−0.0074 ***	−0.0054 ***	−0.0090 ***	−0.0038 **	−0.0014 *
$Independent_{i,t}xTime_t$	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 ***
Breusch–Pagan Test	93.48 ***	39.59 ***	39.72 ***	63.68 ***	63.55 ***	62.54 ***
Hausman Test	23.79 ***	41.63 ***	32.22 ***	23.05 ***	23.28 ***	23.75 ***
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	1081	1049	966	1234	1216	1247

Table 9. Learning results by independence of fund family from financial service groups (Euro non-domestic equity mutual funds). This table presents the results of Equation (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 normalized 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*$_{i,t}$x*Time*$_t$ 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*$_{i,t-1}$	0.0209 *	0.0563 **	0.0978 **	0.1125 ***	0.1504 ***	0.1920 ***
Time$_t$	−0.0004	−0.0006 **	−0.0006 **	−0.0013 ***	−0.0011 ***	−0.0008 **
Size$_{i,t}$	−0.0028 ***	−0.0026	−0.0013	−0.0001	−0.0006	0.0001
Age$_{i,t}$	−0.0007	−0.0056	0.0061	0.0058	0.0089	0.0037
No. stocks$_{i,t}$	−0.0005 ***	−0.0003 ***	−0.0002 ***	−0.0005 ***	−0.0007 ***	−0.0007 ***
Turnover$_{i,t}$	0.0079 ***	0.0071 *	0.0090 ***	0.0174 ***	0.0190 ***	0.0174 ***
Market return$_t$	−0.0074 ***	−0.0127 ***	0.0013	−0.0069 ***	−0.0075 ***	−0.0081 ***
Independent$_{i,t}$x*Time*$_t$	−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 ***
Breusch–Pagan Test	60.96 ***	28.91 ***	39.35 ***	48.54 ***	58.33 ***	52.95 ***
Hausman Test	25.98 ***	25.70 ***	27.75 ***	26.78 ***	31.89 ***	25.22 ***
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

As we can observe in Table 8, the coefficient of the interaction between the independent dummy variable and the time variable (*Independent*$_{i,t}$x*Time*$_t$) is significantly positive for Euro domestic equity mutual funds, with the exception of buying decision at 12 months. Therefore, we generally find that the learning level in the dependent families of domestic funds is higher than for the independent families. However, in Table 9 we can observe that this interaction is not significant for Euro non-domestic funds, that is, there are no significant differences between the learning level of dependent and independent families. Hence, in general terms, families' dependence on financial groups is not important in explaining the learning process in the Spanish equity mutual fund industry.

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 high weight and this weight 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, demonstrating significant learning by managers. Despite the inclusion of the dependent variable lagged as an instrument to control for endogeneity bias and several control variables on fund characteristics and market conditions 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 a large number of the fund families in Spain drive its learning process. In addition, we examine the learning process considering two important characteristics of these fund families: size and 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.

Despite the fact that the previous literature has documented that the market stock is actually a random walk, we conclude that the trading errors are a source of learning for the fund management, especially the important errors that have a significant cognitive impact. Furthermore, we conclude that mutual funds have incentives to learn from their important past errors in order to avoid them in future decisions, regardless of the fund family characteristics in which they belong. These results are very interesting particularly for the Spanish fund market because of the high concentration of the total net assets in a few fund families and the high dependence on the banking sector.

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, and to explore the determinants of the important trading errors, such as the mutual fund fee structure. Further studies could explore the influence of fund fees on the learning process in other fund markets in which performance-based fees predominate, and in which the differences in terms of the fee structure between funds are significant. According to previous research, mutual funds with higher fees that depend on their performance may have more incentives to learn from important errors. In addition, we can expect that funds with redemption may have greater incentives to seek new investment opportunities, even though this increases the risk of making an important error.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The Skewness, Kurtosis and Jarque–Bera values. This table shows the values of the Skewness, Kurtosis and Jarque–Bera of fund characteristics. Panel A presents the results for Euro domestic equity mutual funds. Panel B presents the same information for Euro non-domestic equity mutual funds. *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 first column shows the Skewness values. The second column shows the Kurtosis values. The third column shows the Jarque–Bera values. The last column shows the result of the normality test. The results on the absence of normality are common in the financial variables. This issue was controlled by applying the robust standard errors in the dynamic and fixed-effect models.

Panel A: Euro Domestic Equity Mutual Funds				
	Skewness	**Kurtosis**	**Jarque–Bera Probability**	**p-Valor**
Fund_Size	0.8171	3.2202	5.9193%	0.0000
Fund_age	3.7782	5.3240	1.2964%	0.0000
Fund_No. of stocks	2.8967	6.0312	6.0634%	0.0000
Fund_turnover	1.2523	2.4632	4.9906%	0.0000
Panel B: Euro Non-Domestic Equity Mutual Funds				
	Skewness	**Kurtosis**	**Jarque–Bera Probability**	**p-Valor**
Fund_Size	0.9403	5.3184	6.1410%	0.0000
Fund_age	1.3917	4.4947	5.0643%	0.0000
Fund_No. of stocks	4.3365	1.5865	2.0415%	0.0000
Fund_turnover	3.1473	3.0231	4.4207%	0.0000

Appendix B

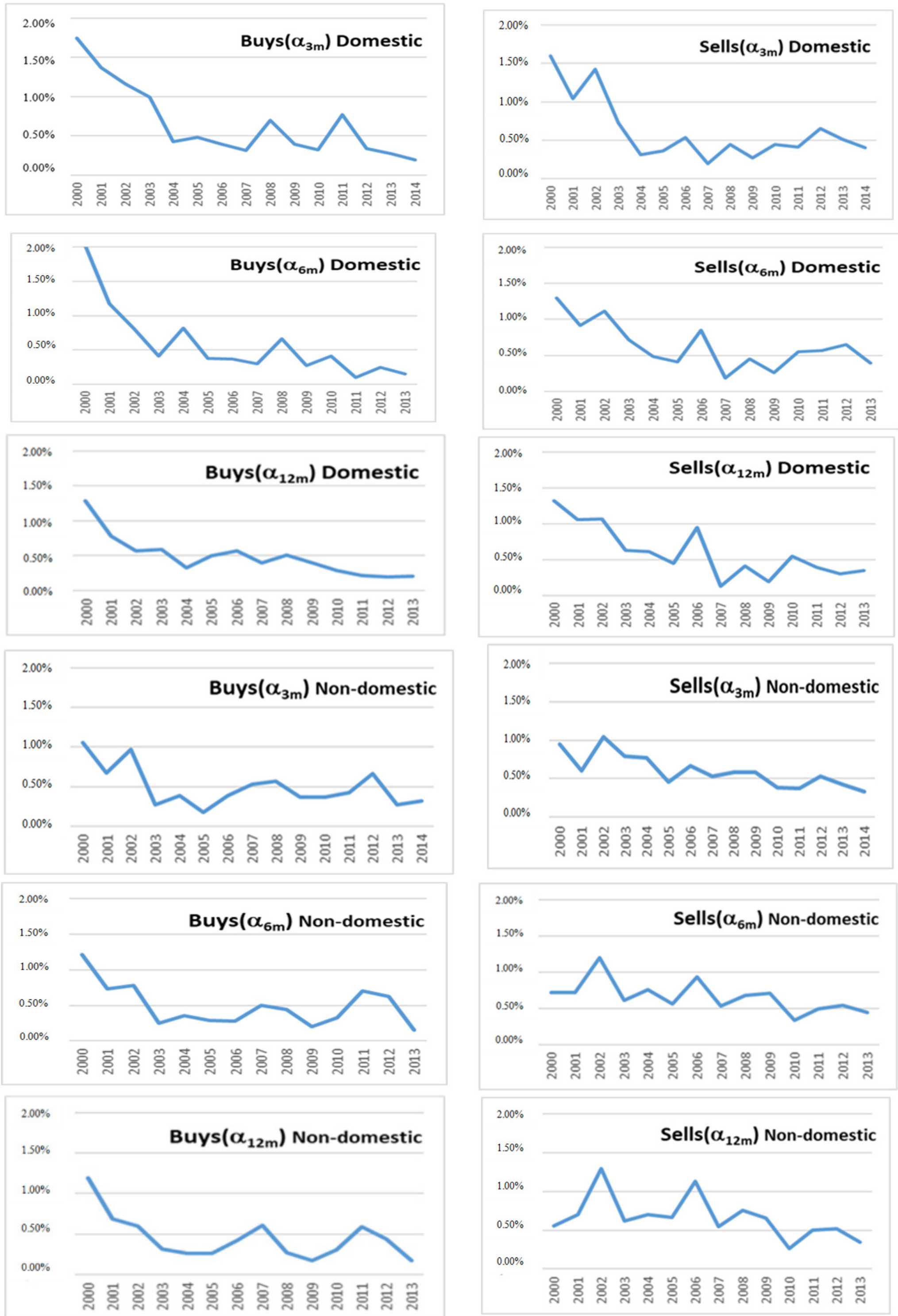

Figure A1. The evolution of important errors. These graphs show the evolution of the percentage of important trading errors in buys and sells for Euro domestic equity mutual funds (Domestic) and Euro non-domestic equity mutual funds (Non-domestic) from January 2000 to March 2014. The results are divided 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.

Appendix C

Table A2. Correlation matrixes. This table shows the results of the correlation matrixes between the dependent and independent variables included in Equations (14) and (15). Panels A and B present the correlation matrixes for Euro domestic equity mutual funds with important errors in buying and selling decisions, respectively. Panels C and D present the same information for Euro non-domestic equity mutual funds.

Panel A: Euro Domestic Equity Mutual funds_Important Errors in Buying Decisions							
	% Important Errors	**Time**	**Age**	**Size**	**No. of Stocks**	**Turnover**	**Market Return**
% Important errors	1.0000						
Time	−0.2784	1.0000					
Age	−0.1529	0.0178	1.0000				
Size	−0.1401	−0.0662	0.0245	1.0000			
No. Of stocks	−0.0810	0.0305	0.0218	0.0789	1.0000		
Turnover	0.0350	−0.0040	−0.0732	−0.0874	0.0512	1.0000	
Market return	−0.0423	0.0583	0.0098	0.0015	0.0055	0.0166	1.0000
Panel B: Euro Domestic Equity Mutual Funds_Important Errors in Selling Decisions							
	% Important Errors	**Time**	**Age**	**Size**	**No. of Stocks**	**Turnover**	**Market Return**
% Important errors	1.0000						
Time	−0.3571	1.0000					
Age	0.0419	−0.0526	1.0000				
Size	−0.0198	0.0275	0.0924	1.0000			
No. Of stocks	−0.1005	0.0410	0.0912	0.0494	1.0000		
Turnover	0.0970	−0.0249	−0.0784	−0.0461	0.0570	1.0000	
Market return	−0.0207	0.0560	0.0020	0.0059	0.0060	0.0170	1.0000
Panel C: Euro Non-Domestic Equity Mutual Funds_Important Errors in Buying Decisions							
	% Important Errors	**Time**	**Age**	**Size**	**No. of Stocks**	**Turnover**	**Market Return**
% Important errors	1.0000						
Time	−0.3125	1.0000					
Age	−0.0082	0.0380	1.0000				
Size	−0.0359	0.0249	0.0761	1.0000			
No. Of stocks	−0.1153	0.0340	0.0214	0.0158	1.0000		
Turnover	0.1555	−0.0047	−0.1344	−0.0316	0.1243	1.0000	
Market return	−0.0324	0.0925	0.0134	0.0034	−0.0005	0.0477	1.0000
Panel D: Euro Non-Domestic Equity Mutual Funds_Important Errors in Selling Decisions							
	% Important Errors	**Time**	**Age**	**Size**	**No. of Stocks**	**Turnover**	**Market Return**
% Important errors	1.0000						
Time	−0.2914	1.0000					
Age	−0.0238	0.0357	1.0000				
Size	−0.0276	0.0103	0.0847	1.0000			
No. Of stocks	−0.1421	0.0312	0.0278	0.0693	1.0000		
Turnover	0.1405	−0.0197	−0.1309	−0.0403	0.1199	1.0000	
Market return	−0.0431	0.0875	0.0155	0.0021	−0.0033	0.0498	1.0000

Notes

1. European Union Directive 2009/65/EC of the European Parliament and the Council on the Coordination of Laws 2009 (2009) on the coordination of laws, regulations, and administrative provisions relating to the Undertakings for Collective Investment in Transferable Securities (UCITS). This Directive was implemented in all member countries of the European Union.
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 investment objective. We label Euro domestic equity funds a sub-sample of funds that self-report their investment objective in the Spanish market and the rest of the funds in the Euro equity category are labeled 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.

4 Datastream provides stock information about the main capital operations, such as splits and the payment of dividends.

5 To obtain the number of shares, we consider the main capital operations, such as splits and the payment of dividends.

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

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.

8 To obtain Jensen's (1968) alpha, 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.

9 Following Mileva (2007) and Roodman (2009a), 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 (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. Details are available on request.

11 In spite of the fund fee being a usual control variable in this kind of study, we do not consider it in our model because all funds included in the sample apply asset-based fees being these percentages similar among them. Other kinds of fee structures such as performance-based fees or redemption fees may affect the learning process. On the one hand, Lhabitant (2007) compared asset-based and performance-based fees, concluding that the latter could be used as a control of the portfolio risk. In addition, Agarwal et al. (2009a, 2009b) argue that performance-based fees provide better incentives to obtain superior performance. On the other hand, Cumming et al. (2019) also documents that fee structures that penalize investment withdrawal lead managers to feel less pressure from investor sentiment.

12 We apply alternative specifications of our model to confirm that our results are robust. First, we perform Equation (14) on a quarterly basis and we use also the fixed effects (FE) model on monthly, quarterly and annual frequency, and we obtain a significant negative relationship between the percentage of important errors and time. Second, we add a quadratic term of the time variable to Equation (14), and the main results remain similar to our original model specification. Third, we add the market volatility as an additional control variable to Equation (14) and obtain consistent results. The details are available on request.

13 We also apply Equation (14) to errors from non-important decisions. The results are different from the conclusions drawn from Tables 3 and 4. That is, time does not influence the percentage of trading errors, thereby rejecting the evidence of significant learning from non-important decisions. Details are available on request.

14 The results shown in Tables 3 and 4 consider the quintiles of important buys and sells with the most negative influence on the performance for all the funds across our sample period. We also obtained similar findings for quartiles and deciles, thereby providing even more robustness to this empirical evidence.

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