# Does mutual fund industry learn from its past errors?

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**Abstract**

This paper aims to contribute to the lack of research in the learning process of mutual fund markets. The empirical design is focused on the ability of the Spanish mutual fund industry to learn from its past errors in relevant trading decisions. We use dynamic panel data to find an overall significant decrease in the percentage of relevant trading errors over time, thereby stating the global learning process of the industry. The consideration of some control variables in our dynamic model shows that relevant trading errors are positively related to the fund portfolio turnover and negatively related to both the number of stocks held in the portfolio and the market return. Finally, we find that learning evidence is driven by a large group of mutual fund companies which learn even more than the whole industry.

**Keywords:** mutual fund industry; relevant trading decisions; important errors; learning.

## 1. Introduction

This paper is focused on the ability of the mutual fund industry to learn from its past trading errors. While the consequences of management errors have been widely analysed in corporate finance (e.g., Finkelstein and Sanford, 2000; Benson-Rea and Wilson, 2003; Tjosvold *et al.*, 2004; Fuller-Love, 2006) there is a lack of research regarding to portfolio management. This difference may be explained because an important error in corporate management may have critical consequences such as the termination of the company (Cardon *et al.*, 2011). In contrast, the consequences of a relevant trading error in mutual funds may be less severe due to the diversification rules which are generally required, such as the current European Union Directive 2009/65/CE[1] in the euro area. However, this lack of research and the important social and economic implications of a better mutual fund management justify the outstanding interest of shedding light on the learning process of the mutual fund industry from its past trading errors.

The findings of the study may have several implications for the relevant agents involved in the mutual fund industry. The underlying assumption is that mutual fund managers could have incentives to avoid errors or learn from them because their positions, reputations and salaries may depend on their performance records (e.g., Agarwal *et al.*, 2009; Kempf *et al*., 2009). This study is also of interest to management companies due to the relation between fund flows and performance (e.g., Sirri and Tufano, 1998; Jain and Wu, 2000). Berk and Green (2004) find a consistent flow-performance relationship with high average levels of manager skills. Thus, the learning process should improve both the performance records and the potential flows into

[1] Directive 2009/65/EC of the European Parliament and of the Council of 13 July 2009 on the coordination of laws, regulations and administrative provisions relating to Undertakings for Collective Investment in Transferable Securities (UCITS). This current directive has been implemented in all member countries of the European Union, including the market sample in our paper, i.e., Spain.

mutual funds. Additionally, mutual funds have experienced a relevant growth worldwide during the last years. This growth is particularly evident in Europe where €15,6 billion of net assets are managed by almost 60,000 mutual funds, thereby strengthening as the second most relevant mutual fund industry in the world (European Fund and Asset Management Association, EFAMA, 2018). Furthermore, more efficient mutual funds may imply superior levels of financial efficiency and an improvement of the socio-economic aspects of the country (e.g., King and Levine, 1993a; Levine *et al.*, 2000; Rousseau and Wachtel, 2002). In this way, Wang (2011) argues that the mutual fund industry has experienced an important growth during the last decades, which has been encouraged by the increase of retail investors' confidence in professional investment management. However, professional management is not perfect and these sophisticated managers must make decisions continuously, thus, they may make wrong decisions (Frydman and Camerer, 2016).

Decision-making is one of the basic cognitive processes of human behaviour through which the agent should choose a preferred alternative based on given criteria or strategies (Wilson and Keil, 2001; Wang and Ruhe, 2007). In this line and following the seminal ideas of Lipschutz (1967), Wang and Ruhe (2007) propose an axiom of choice which considers three basic elements: 1) the decision goals, 2) a set of alternatives and, 3) a set of selection criteria or strategies. Within the area of psychology and behavioural sciences, the study of decision-making involves the analysis of conditions and cognitive-behavioural processes. The objective is to explain how and why an alternative is chosen in a given situation and to determine the factors that influence on this decision-making (e.g., Ranyard *et al.*, 1997; Payne *et al.*, 1993). Several studies provide evidence of some of these factors such as knowledge and experience (Calvet *et al.*, 2009), uncertainty environment and context (McDevitt *et al.*, 2007), ability to predict future (Kahneman, 1994), decision difficulty (Tversky and Shafir, 1992), time in decision making (Ariely and Zakay, 2001), temporal separation on future decisions (Loewenstein and Elster, 1992) and feelings, moods and emotions (George, 2000). The influence of these factors may depend on both the kind of decision and the context in the decision-making process. Additionally, it is important to bear in mind that each decision has a different impact level on the final result, depending on its relative importance in this process and the difference with respect to other decisions.

Focusing on mutual funds, the manager selects the assets included in the mutual fund portfolio and the time period that these assets are held. According to Campbell (2006), Fisher and Gerhardt (2007) distinguish six different decisions: evaluation of initial situation; selection of risk level and time horizon; asset allocation; stock selection; open/close positions and track positions. The relative importance of each decision may determine its economic influence on the fund performance. Therefore, portfolio holdings, which are disclosed by mutual funds, provide useful information to measure fund managers' skills in these decisions (e.g., Daniel *et al.*, 1997; Wermers, 2000; Kacperczyk *et al.*, 2006; Wermers *et al.*, 2012).

In research about mutual fund decision-making process, there are two different trends: rational and behavioural models. On the one hand, most of the classical models and theories are based mainly on the seminal assumptions that the agents are rational and the markets are efficient (e.g., Markowitz, 1952; Sharpe, 1964; Lintner, 1965; Fama, 1968). On the other hand, behavioural finance questions this rational approach in the decision-making process. Some authors consider that the standard models of expected utility are not always acceptable, because agents systematically violate the axioms considered by rational choice theory (e.g., De Bondt and Thaler, 1985; Tversky and Kahneman, 1986; Hirshleifer, 2001; Shiller, 2003). Koestner *et al.*, (2017) also note that numerous empirical studies have documented that these behavioural biases suppose costly errors (e.g., Weber and Camerer, 1998; Goetzmann and Kumar, 2005; Calvet *et al.*, 2009; Bailey *et al.*, 2011; Barber and Odean, 2013).

Between both trends, there are authors who suggest combining rational and efficient markets with behavioural models (e.g., Tseng, 2006; Subrahmanyam, 2008; Statman, 2014). Sargent (1993) defends a non-rigid rationality which is based on the idea that agents can make errors affected by cognitive biases but these wrong decisions are not persistent over time, thereby suggesting the notion that investors learn from their past errors. Additionally, List (2003) finds that market experience plays a significant role in eliminating the behavioural effect on investment decisions.

According to the previous authors, learning is the process by which the information becomes knowledge. Stanovich and West (2000) establish that repetition allows the incorporation of techniques that help to improve efficiency. This statement is consistent with the learning by learning concept which was initially studied by Arrow (1962). In this way, Argyris and Schön (1996) consider learning as a cyclical process because it allows the progressive constitution of a judgment capacity for future decisions, being a result of experiences. Crossan *et al.* (1999) consider a multilevel learning perspective: individual, group and organizational levels. The process of organizational learning has generated interest by practitioners and academics in the economic environment because it is considered a strategic asset on which sustainable competitive advantages are based over time (e.g., Dierickx and Cool, 1989; March, 1991; Adams and Lamont, 2003; Hatch and Dyer, 2004). According to Levitt and March (1988), organizational learning is viewed as routine-based and history-dependent. In this way, Marsick and Watkins (2015) note that past errors are a key tool for organizational learning. Albernathy and Wayne (1974) and Argote *et al.* (1990)

consider the accumulated experience and the level of knowledge transferred among institutional members. Additionally, Crossan and Bapuji (2003) defend that the traditional measurement of learning is related with the so-called curves of learning and experience, where the ability of institutions to learn is a function of time that is considered as internal learning.

In addition to this institutional approach, academics have recently shown interest in the learning process in the research field of household finance. There are several authors who have studied whether individual investors learn, considering this process as the reduction of cognitive biases identified by the behavioural finance (e.g., Dhar and Zhu, 2006; Campbell, 2006; Nicolosi *et al.,* 2009; Seru *et al.,* 2009; Koestner *et al.,* 2017). Additionally, these authors identify the experience as the source of this dynamic process, measuring it with both the number of experienced years and the number of accumulated operations.

Therefore, the review of the existing literature reveals both the relevance of the learning process in the economic field and the lack of results in mutual funds, which could further extend the previous learning evidence in one of the most relevant financial industries in the world. According to this, the main objective of this paper is to check for the ability of the mutual fund industry to learn from its past trading errors. Our contribution to literature is as follows. First, we analyse the learning process at the level of professional management in contrast to the widely studied behaviour of retail investors. Therefore, we assume that these decision makers have sophisticated knowledge about portfolio management. Second, we extend the potential individual learning ability from mutual fund managers to the organizational level, that is, to the mutual fund management companies competing in the mutual fund industry. Third, we suggest that all trading decisions do not have the same importance and as consequence, the same influence on the fund performance. Therefore, we measure learning process from past trading errors in the relevant decisions, based on the idea that managers are much more sensitive to the learning experience when the consequences of their errors are very negative (Singh *et al.*, 2007).

Our empirical results support learning evidence from past relevant errors in the Spanish mutual fund industry and this evidence is driven by most of the mutual fund management companies.

The remainder of the paper proceeds as follows. Section 2 introduces our mutual fund database. Section 3 describes the methodology. Section 4 includes the results of the empirical analysis. Finally, Section 5 concludes.

## 2. Data

The study examines whether Spanish mutual fund industry learns from its past trading errors from January 2000 to March 2014. Mutual funds have experienced a growth and consolidation process into the collective investment industry of Europe over the last twenty years. However, we focus on the Spanish fund industry because it represents a unique setting for our research objectives. First, Spain is one of the most relevant Euro mutual fund industries. In fact, the Spanish mutual fund industry is ranked 5$^{th}$ in the euro area in terms of number of registered mutual funds (EFAMA, 2018), thus, the economic implications of our research are important. Second, the relevant concentration in the Spanish mutual fund market, where the top 10 fund companies manage more than 75% of the total fund assets (Inverco, 2018), allows for an appropriate identification of the role in the learning process of the assorted characteristics of the competitors in this industry. Third, the Spanish mutual fund industry is a more recent industry than the U.S. industry or other relevant European markets, such as France, Germany and the U.K. The great boom of Spanish mutual funds occurred during the 1990`s. Therefore, our sample period coincides with the maturity stage of the Spanish mutual fund industry, avoiding possible effects of expansion and growth stages that may affect the learning process (e.g., Penrose, 1959; Autio *et al.*, 2000).

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

Portfolio holdings of the mutual funds included in our sample have been obtained from the Spanish Securities and Exchange Commission (CNMV) and Morningstar. We analyse 20,572 portfolio holdings: 12,176 portfolio holdings of domestic equity mutual funds and 8,296 portfolio holdings of Euro equity mutual funds. We control all quarterly portfolio holdings and more than the 80% of the monthly portfolio holdings of our fund sample from the matching of the information of CNMV and Morningstar[3].

The comparison between two consecutive portfolio holdings of a mutual fund together with the stock information provided by Datastream[4] allows us to obtain the number of stocks which are both bought and sold by the mutual fund during that period and therefore, the trading decisions taken by mutual fund managers.

[2] CNMV establishes a classification of mutual funds according to the types of assets included in the portfolios. Thus, Euro equity 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 of the euro area. Hence, we construct a subsample of funds which self-report their objective of investing in the Spanish market and we label this subsample as domestic equity funds.

[3] The mutual fund holdings used in this study rely on the monthly portfolio holdings information provided by the CNMV for each fund from December 1999 to December 2006. This information was provided for research purposes. However, from March 2007 the CNMV provides us only 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 prices considering the main capital operations.

CNMV also provides the additional information required by the control variables included in the empirical analysis. Finally, we compute the turnover ratio for each mutual fund following Elton *et al.,* (2010).

Table 1 shows the summary statistics of our fund sample. We observe that both the total number of funds and the total number of management companies have a downward trend. Mergers and acquisitions of funds and management companies in the maturity stage of the Spanish fund industry mainly explain this result. Additionally, Table 1 shows that the average fund size decreased during the crisis period 2008-2011 but this figure recovered intensely in the later years. We also appreciate that average size is bigger in domestic than in Euro equity mutual funds. This finding may be explained because retail Spanish investors may feel more confident investing their money in their home market, thereby highlighting a potential home bias. Finally, the average age is lower in Euro equity mutual funds because this investment category appears later in the Spanish market than the domestic equity category.

Regarding to the number of stocks and annual turnover, both average values decrease slightly over the years, being higher in Euro equity mutual funds. On the one hand, the slight decrease in the level of diversification could lead to a more negative influence of trading errors on the mutual fund performance. On the other hand, the greater diversification level in Euro equity mutual funds could be explained by the higher number of investment alternatives in the euro area than in the Spanish stock market. Finally, the decreasing trend of the turnover ratio provides evidence that managers of Spanish equity funds make a lower number of trading decisions over time.

## Table 1: Summary Statistics

This table shows summary statistics of our mutual fund sample. Panel A reports average statistics about domestic equity mutual funds included in our sample, such as number of funds and management companies, fund size, fund age, the number of stocks held by the portfolios and turnover ratio. Quintiles 1 and 5 are additionally provided. Panel B reports the same information of Euro equity mutual funds included in our sample. For simplicity, we split our sample period into three sub-periods: pre-crisis period (2000-2007); crisis period (2008-2011); post-crisis period (2012-2014).

[*] The study period ends in March 2014.

**Panel A: Domestic equity mutual funds**

| | **2000-2007** | **2008-2011** | **2012-2014**[*] |
|---|---|---|---|
| **No. funds** | 144 | 106 | 74 |
| **No. management companies** | 79 | 58 | 49 |
| **Fund_Size** (Total net asset in thousand €) | | | |
| Mean | 69,670 | 41,718 | 67,930 |
| Q1 | 7,461 | 6,379 | 7,923 |
| Q5 | 100,319 | 45,031 | 70,156 |
| **Fund_Age** (Years) | | | |
| Mean | 8 | 12 | 16 |
| Q1 | 3 | 7 | 12 |
| Q5 | 11 | 17 | 20 |
| **No. of stocks** | | | |
| Mean | 43 | 40 | 38 |
| Q1 | 33 | 31 | 29 |
| Q5 | 52 | 45 | 43 |
| **Fund_AnnualTurnover** | | | |
| Mean | 41% | 40% | 41% |
| Q1 | 19% | 17% | 17% |
| Q5 | 61% | 60% | 58% |

**Panel B: Euro equity mutual funds**

| | **2000-2007** | **2008-2011** | **2011-2014**[*] |
|---|---|---|---|
| **No. funds** | 124 | 91 | 56 |
| **No. management companies** | 71 | 51 | 36 |
| **Fund_Size** (Total net asset in thousand €) | | | |
| Mean | 65,081 | 23,952 | 43,495 |
| Q1 | 5,082 | 3,474 | 5,375 |
| Q5 | 75,485 | 24,151 | 52,121 |
| **Fund_Age** (Years) | | | |
| Mean | 6 | 10 | 12 |
| Q1 | 2 | 5 | 8 |
| Q5 | 9 | 13 | 16 |
| **No. of stocks** | | | |
| Mean | 60 | 50 | 50 |
| Q1 | 48 | 39 | 40 |
| Q5 | 71 | 60 | 62 |
| **Fund_AnnualTurnover** | | | |
| Mean | 55% | 50% | 43% |
| Q1 | 28% | 18% | 11% |
| Q5 | 80% | 85% | 71% |

## 3. Methodology

### 3.1. Relevant buys and sells.

In order to analyse the learning process of the mutual fund industry from its past trading errors, we first determine the trading in each period, that is, month (or quarter when monthly information is not available). After that, we only select relevant buys and relevant sells by applying three different filters, as we will describe below.

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

For each stock *j* and each period *t*, we measure the change in the number of shares held in this stock by mutual fund *i* from the end of period *t-1* to the end of period *t.* Once we know the number of stocks that have been bought and sold, we calculate the amount of each trade multiplying the change in the number of shares by the average market price of the stock in that period (Alexander *et al.,* 2007).

Table 2 shows a consistent decrease over time of the number of buys and sells in both domestic equity and Euro equity mutual funds. This evidence may be related to the decline of the diversification level and the turnover ratio in our sample (Table 1).

For our study of the learning process, we only select relevant buys and relevant sells of all the trading decisions previously identified. Singh *et al.* (2007) identify four aspects affected by errors which are defined as economic, social, psychologist and physiological. According to these authors, our underlying assumption is that mutual fund managers learn when the economic influence of their errors on the performance are important because their positions, reputations and salaries may depend on their performance records (Agarwal *et al.*, 2009; Kempf *et al.*, 2009). The economic impact of a trading decision depends on both its relative importance and its subsequent return.

### Table 2: Stock trades

This table shows the yearly average figures of the stock trading of our mutual fund sample. Panel A reports trading data about domestic equity mutual funds included in our sample. Panel B reports the same information of Euro equity mutual funds included in our sample. For simplicity, we split our sample period into three sub-periods: pre-crisis period (2000-2007); crisis period (2008-2011); post-crisis period (2012-2014).
[*] The study period ends in March 2014.

**Panel A: Domestic equity mutual funds**

| | **2000-2007** | **2008-2011** | **2012-2014[*]** |
|---|---|---|---|
| Average of no. buys | 14,728 | 11,896 | 8,635 |
| Average of no. buys by fund | 141 | 131 | 137 |
| Average of % relevant buys | 7.86% | 5.52% | 5.72% |
| Average of no. sells | 14,106 | 13,536 | 6,459 |
| Average of no. sells by fund | 135 | 147 | 100 |
| Average of % relevant sells | 7.32% | 6.69% | 7.20% |

**Panel B: Euro equity mutual funds**

| | **2000-2007** | **2008-2011** | **2012-2014[*]** |
|---|---|---|---|
| Average of no. buys | 14,086 | 11,006 | 7,877 |
| Average of no. buys by fund | 198 | 155 | 176 |
| Average of % relevant buys | 7.26% | 4.86% | 6.25% |
| Average of no. sells | 15,479 | 14,454 | 6,146 |
| Average of no. sells by fund | 218 | 201 | 132 |
| Average of % relevant buys | 5.44% | 4.47% | 5.05% |

We consider that a trading decision for stock $j$ by mutual fund $i$ in period $t$ is relevant when it fulfils three filters simultaneously. Each filter coincides with a condition that we impose to identify that the decision is having a high relative importance to the fund TNA and that this relative importance is significantly different to other trading decisions by the same mutual fund as well as all the competitor funds. Therefore, we identify the relevance of the mutual fund trading decisions based on 1) their relative importance to the fund TNA and 2) their relative difference with respect to other trading decisions, both 2.a) at the fund level and 2.b) at the industry level.

According to the first filter, we assume that a trading decision is relevant when it represents a high percentage to the fund TNA. Hence, we compute this relative importance as the trade in euros divided by the fund assets in the same period.

After that, we orthogonalise these relative percentages by selecting 5 percent tails of the trading distributions in each mutual fund for all our sample period. In this way, we identify the trading decisions of greatest relative importance by fund *i* during its existence, after controlling the potential bias of the analysed year. Distinguishing between buys and sells and, thus, keeping the sign of the trading decision, the top (bottom) 5 percent tail is referring to the most relevant buys (sells) along the sample period that fulfil the first filter.

In the second filter, we assume that a trading decision is relevant when its relative importance is significantly different to the relative importance of other trading decisions by the same mutual fund with other stocks in the same period. We compare the relative importance of a trading decision for stock *j* by mutual fund *i* in the period *t* and the relative average importance for the rest of stocks (excluding *j*) held by the same mutual fund *i* in period *t*, distinguishing between buys and sells.

Once the differences of this relative importance have been obtained, we orthogonalise these relative differences for each mutual fund similarly to the first filter. That is, we select the top (bottom) 5 percent tail of these difference distributions which include the most different buys (sells) by fund *i* along its existence after controlling the potential bias of the analysed year.

Finally, in the third filter, we assume that a trading decision is relevant when it has a relative importance significantly different to the relative importance of other trading decisions by other mutual funds in the same stock and period. Thus, we compute the difference between the relative importance of a trading decision for stock *j* by mutual fund *i* in the period *t* and the average relative importance[5] of the trading decisions for the same stock *j* and period *t* by the remaining mutual funds in our sample, excluding fund *i*.

Once these differences have been obtained, we orthogonalise across each period considering the whole fund sample. That is, we select the top (bottom) 5 percent tail of these difference distributions which are referring to the most different buys (sells) by the fund sample across the whole period, controlling the potential bias of the analysed year[6]. Table 2 shows that the percentage of relevant buys and relevant sells that have fulfilled our three filters remain highly stable.

### 3.2. Relevant errors

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

Therefore, first, we identify as trading errors those relevant buys (sells) for stocks whose performance is negative (positive) in future. Second, we obtain the economic impact of each relevant trading decision for stock *j* by mutual fund *i* in the month *t* by multiplying its performance by its relative importance to the fund TNA.

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[5] In buys, we obtain the average after considering all the funds which are included in our sample in each period *t*, but in sells, we only consider those funds which hold the stock in the month previous t-1 due to the fact that all funds can buy a stock but only the funds that hold the stock can sell it.

[6] For illustrative purposes, we identify a relevant buy for stock *j* by the fund *i* in March 2000 that fulfils the three filters. First, the amount of this buy represents the 18.64% of the TNA of fund *i* in March 2000. This great relative importance fulfils the first filter after the orthogonalisation process. Second, the average of the remaining buys in other stocks of fund *i* in March 2000 represents the 0.60% of its TNA. Thus, the difference with stock *j* is significant and it fulfils the second filter after the orthogonalisation process. Finally, the average of the buys in stock *j* by the rest of mutual funds in March 2000 represents the 0.11% of their TNA. Thus, the difference with mutual fund *i* is also significant and it fulfils the third filter after the orthogonalisation process.

Finally, we identify both the quintiles of relevant buys and sells with the most negative influence on the fund performance, considering all funds across the sample period.

We evaluate the performance of each stock *j* across the entire time period of the sample, through the Jensen's alpha (1968) at different time horizons: 3-month alpha, 6-month alpha and 12-month-alpha which have been estimated using rolling windows of 60, 120 and 240 daily data, respectively. The objective is to observe the effect of the error in the very short term (3-month period) and in longer terms (6-month and 12-month periods)[7].

### 3.3. Learning process in the mutual fund industry

To measure the ability of the mutual fund industry to learn from its past trading errors, we test our null hypothesis that the percentage of relevant errors is not significantly different over time. Hence, if we will reject this null hypothesis it would suggest a trend pattern of the percentage of relevant errors over time. Additionally, if this pattern is negative it would suggest a learning process in the current maturity stage of the Spanish mutual fund industry. To obtain the percentage of relevant errors, we divide the number of relevant errors obtained in the previous subsection by the total number of mutual fund trades, distinguishing between buys and sells, because we observe a decreasing trend in the number of trades per fund over time. From this approach we avoid potential biases in the number of wrong decisions due to a lower level of trading.

We use a dynamic panel data model to contrast the relationship between the percentage of important errors and the time variable in the mutual fund industry. The literature recommends this methodology for a database with a large number of individuals, i.e., mutual funds in our study, and a small period of time (Roodman,

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

2006). Therefore, we compute the percentage of important errors by fund and year from the monthly data (or quarter when monthly information is not available).

Our choice of panel data methodology allows the combination of time series, cross-section and unbalanced data (Wooldridge, 2010). In addition, dynamic panel data model allows the incorporation of an endogenous structure in the model through instrumental variables with a delay in the endogenous variable, thereby integrating the past effects and the unobserved time invariant individual effect (e.g., the innate individual abilities or historical and structural factors). Thus, this dynamic model allows us to analyse the relationship between dependent variable and independent variables from an evolutionary perspective of dependence on the past or the accumulative process (Dosi, 1988).

We apply the Generalized Method of Moments (GMM) dynamic model[8] of Arellano-Bower (1995) and Blundell-Bond (1998) as follows:

$$\begin{aligned} \%\ \mathit{Important\ errors}_{i,t} = {} & \alpha_{i,t} + \gamma_{i,t}\ \%\ \mathit{Important\ errors}_{i,t-1} + \beta_1\,\mathit{Time}_t + \beta_2\,\mathit{Size}_{i,t} + \beta_3\,\mathit{Age}_{i,t} + \\ & \beta_4\,\mathit{No.\ of\ stocks}_{i,t} + \beta_5\,\mathit{Turnover}_{i,t} + \beta_6\,\mathit{Market\ return}_t + \varepsilon_{i,t} \\ & \textit{for } t = 1, ..., 15 \textit{ years} \\ & \textit{for } i = 1, ..., 145 \textit{ domestic equity mutual funds} \\ & \textit{for } i = 1, ..., 147 \textit{ Euro equity mutual funds} \end{aligned} \tag{1}$$

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*$_{i,t-1}$ (percentage of 1-year delayed important errors for fund *i*).
$\beta_1$ is the coefficient of the variable $Time_t$.
$\beta_2$ is the coefficient of the control variable $Size_{i,t}$ of fund *i* and year *t*.
$\beta_3$ is the coefficient of the control variable $Age_{i,t}$ of fund *i* and year *t*.
$\beta_4$ is the coefficient of the control variable *No. of stocks* $_{i,t}$ held by fund *i* and year *t*.
$\beta_5$ is the coefficient of the control variable $Turnover_{i,t}$ of fund *i* and year *t*.
$\beta_6$ is the coefficient of the control variable *Market return*$_t$ in year *t*.
$\varepsilon_{i,t}$ is the residual term of the model.

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

To contrast the relationship between the percentage of important errors and the time, we introduce in our dynamic model the time variable. Our sample period covers 15 years, from January 2000 to March 2014.

Additionally, to verify the robustness of our results, we include five control variables about fund characteristics and the market environment which may influence on the percentage of important errors: fund size, fund age, the number of stocks held in the portfolio, the turnover ratio and the market return.

We first compute the size (*Size*) for each mutual fund from its TNA. Then, we carry out a cross-section normalisation for a better discrimination of larger funds in each period. This normalisation is justified because we obtain the relative importance of each trading decision by dividing the traded amount by the fund TNA, which is logically smaller in the small funds. Thereby, we suggest that the probability that we would detect relevant decisions and as a consequence, important errors, might be greater in smaller funds. Additionally, fund size may have a relevant influence on the fund efficiency (e.g., Pollet and Wilson, 2008; Pástor *et al.*, 2015). Finally, even though there is a lack of research regarding to the next, we advocate that the fund size may influence on the learning process of mutual funds at organizational level.

We compute the age (*Age*) for each mutual fund from its inception date. Then, we carry out a cross-section normalisation for a better discrimination of younger/older funds in each period. We suggest that the fund age may influence on the investment style and thus, on the trading decisions by mutual fund managers. According to the previous literature, the effect of fund age on the efficiency of a trading decision can run in both directions (e.g., Cremers and Petajisto, 2009; Cuthbertson *et al.*, 2016).

We compute the diversification level (*No. of stocks*) from the number of stocks held in portfolio. Our intuition is based on the idea that the diversification level may have an influence on the efficiency of trading decisions and the probability of making important errors. On the one hand, we consider that the higher the level of diversification of the fund, the greater the number of trading decisions made by the mutual fund manager has to carry out and thus, the greater the probability of important errors. On the other hand, we also consider that the higher the level of diversification of the fund, the lower the relative importance of each trading decision and thus, the lower probability of important errors. In this way, the previous literature finds that the effect of diversification on efficiency of trading decisions may also run in both directions. Droms and Walker (1995) suggest that more diversified portfolios are related with lower risk and lower returns. However, Pollet and Wilson (2008) show a positive relation between portfolio diversification and fund efficiency.

We include the variable turnover ratio (*Turnover*) because we consider that this ratio can influence on the probability of making important trading errors and the ability of mutual fund managers to learn. On the one hand, the underlying assumption is based on that the higher the turnover ratio is, the greater the probability that managers make errors. On the other hand, we also advocate that this ratio may influence on the ability of fund managers to learn due to higher levels of trading experience as a consequence of higher turnover ratios. Grinblatt and Titman (1994) suggest that turnover is significant and positively related to the manager skills to earn extra returns.

Finally, we include in the model the market return (*Market Return*) as a control variable since we can suggest that the probability of an important error may not be the same in bull markets as in bear markets (Chauvet and Potter, 2000).

In addition to this learning model of the mutual fund industry as a whole, we also propose the analysis of the learning process for each mutual fund management company. However, we cannot apply individually our previous model to a relevant number of companies due to the low proportion between the number of observations and the number of parameters to estimate in the model. Alternatively, to shed additional light in our objective of analysing the potential learning process within each management company, we include a set of dummy variables for each company. This dummy variable (*Management*) is 1 when the mutual fund is managed by the analysed fund company or 0 otherwise, and it interacts with the time variable (*Time)*. This interaction (*Management x Time)* allows us to compare the learning level of each mutual fund management company regarding to the global learning level of the mutual fund industry over time. Thus, we must run the following model (2) for each different management company which is being considered by this dummy variable.

We apply the Generalized Method of Moments (GMM) dynamic model[9] of Arellano-Bower (1995) and Blundell-Bond (1998) as follows:

$$\begin{aligned}\%\ Important\ errors_{i,t} = {} & \alpha_{i,t} + \gamma_{i,t}\,\%\ Important\ errors_{i,t-1} + \beta_1 Time_t + \beta_2 Size_{i,t} + \beta_3 Age_{i,t} + \\ & \beta_4 No.\ of\ stocks_{i,t} + \beta_5 Turnover_{i,t} + \beta_6 Market\ return_t + \\ & \beta_7 (Management\ x\ Time_t) + \varepsilon_{i,t}\end{aligned} \quad (2)$$

*for t = 1, ..., 15 years*
*for i = 1, ..., 145 domestic equity mutual funds*
*for i = 1, ..., 147 Euro equity mutual funds*

Where:

$\%\ Important\ errors_{i,t}$ is the percentage of important errors for fund *i* and year *t.*
$\alpha_{i,t}$ is the constant variable.
$\gamma_{i,t}$ is the coefficient of the variable $\%\ Important\ errors_{i,t-1}$ (percentage of 1-year delayed important errors for fund *i*).
$\beta_1$ is the coefficient of the variable $Time_t$.
$\beta_2$ is the coefficient of the control variable $Size_{i,t}$ of fund *i* and year *t*.
$\beta_3$ is the coefficient of the control variable $Age_{i,t}$ of fund *i* and year *t*.
$\beta_4$ is the coefficient of the control variable $No.\ of\ stocks_{i,t}$ held by fund *i* and year *t*.
$\beta_5$ is the coefficient of the control variable $Turnover_{i,t}$ of fund *i* and year *t*.
$\beta_6$ is the coefficient of the control variable $Market\ return_t$ in year *t*.
$\beta_7$ is the coefficient of the interaction between the dummy variable $Management_{i,t}$ (1 if the mutual fund *i* is managed by the analysed fund company in year *t*, or 0 otherwise) and the variable $Time_t$.
$\varepsilon_{i,t}$ is the residual term of the model.

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

## 4. RESULTS

### 4.1 Learning in the mutual fund industry

We use the GMM dynamic model of Arellano-Bower (1995) and Blundell-Bond (1998) to study the learning process in the mutual fund industry. Table 3 and Table 4 show that time has a significant negative influence on the percentage of important trading error distribution. This finding is consistent in both domestic and Euro equity mutual fund categories. That is, the percentage of important trading errors of the mutual fund industry decreases significantly over time. These important errors are a consequence of the relevant buys and sells that fulfil the three filters explained in the methodology section and these important errors have a significant negative influence on the fund performance. Hence, we reject the null hypothesis that the percentage of important errors is not significantly different over time. This evidence is significant in both relevant buys and sells and it is also consistent with the percentage of important errors which have been obtained from different time horizons; i.e., 3-month alpha, 6-month alpha and 12-month-alpha, thereby shedding robustness in these empirical results[10].

The identification of this decreasing trend of relevant errors as a learning process shows the ability of the mutual fund industry to learn from their past trading errors. Our result is consistent with the findings of several studies in household finance field which find that individual investors learn from their management experience (e.g., Dhar and Zhu, 2006; Nicolosi *et al.*, 2009 and Koestner *et al.*, 2017).

[10] The results shown in Table 3 and 4 have been obtained considering the quintiles of relevant buys and sells with the most negative influence on the fund performance for all funds across our sample period. Additionally, we have obtained similar findings for quartiles and deciles, thereby providing robustness to this empirical evidence. Details are available upon request.

## Table 3: Learning results in domestic equity mutual funds.

This table reports the results of the dynamic panel data model (1) for domestic equity mutual funds from January 2000 to March 2014. The learning results are split into buys and sells after considering different time horizons to compute these errors: 3-month alpha, 6-month alpha and 12-month-alpha.

| | BUYS | | | SELLS | | |
|---|---|---|---|---|---|---|
| | **Errors at 3-month alpha** | **Errors at 6-month alpha** | **Errors at 12-month alpha** | **Errors at 3-month alpha** | **Errors at 6-month alpha** | **Errors at 12-month alpha** |
| ***Constant*** | 0.0175*** | 0.0081*** | 0.0094*** | 0.0209*** | 0.0256*** | 0.0103*** |
| ***% Important errors*** $_{i,t-1}$ | 0.1060*** | 0.0082*** | 0.0799*** | 0.2591*** | 0.2042*** | 0.1086*** |
| ***Time*** $_t$ | -0.0005** | -0.0002*** | -0.0005*** | -0.0004* | -0.0005** | -0.0003*** |
| ***Size*** $_{i,t}$ | -0.0015* | -0.00120** | -0.0013** | 0.0008 | 0.0013 | -0.0006 |
| ***Age*** $_{i,t}$ | -0.0030 | 0.0011 | 0.0027 | 0.0019 | -0.0035 | -0.0009 |
| ***No. of stocks*** $_{i,t}$ | -0.0003*** | -0.0002*** | -0.0003*** | -0.0005*** | -0.0004*** | -0.0001*** |
| ***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*** |
| **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 |

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

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 delay 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 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 Ibex-35 total return in year *t*. We use Ibex-35 as the benchmark for domestic equity mutual funds.

## Table 4: Learning results in Euro equity mutual funds

This table reports the results of the dynamic panel data model (1) for domestic equity mutual funds from January 2000 to March 2014. The learning results are split into buys and sells after considering different time horizons to compute these errors: 3-month alpha, 6-month alpha and 12-month-alpha.

| | BUYS | | | SELLS | | |
|---|---|---|---|---|---|---|
| | **Errors at 3-month alpha** | **Errors at 6-month alpha** | **Errors at 12-month alpha** | **Errors at 3-month alpha** | **Errors at 6-month alpha** | **Errors at 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. of stocks*** $_{i,t}$ | -0.0003*** | -0.0004*** | -0.0004*** | -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** | 666.50*** | 139.77*** | 504.70*** | 102.74*** | 889.30*** | 868.4 |
| **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 |

*** Significance at 1% level; ** significance at 5% level; * significance at 10% level.
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 delay 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 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 EuroStoxx-50 total return in year *t*. We use EuroStoxx-50 as the benchmark for Euro equity mutual funds.

We also find that the 1-year delay of the endogenous variable is significant and positive in our model. This finding suggests that the relevant errors in each mutual fund depend on its past relevant errors, thereby supporting persistent evidence from the better and worse managers within a global learning trend in the mutual fund industry.

According to the control variables included in our model, on the one hand, size and age do not show a clear influence on the decreasing pattern of errors. On the other hand, we find significant interactions between the relevant trading errors and the remaining control variables. Regarding the number of stocks held by the mutual fund portfolio and its turnover ratio, we find that more diversified funds with lower turnover ratios make fewer important trading errors.

The previous result about the diversification could be explained because trading decisions may have a smaller relative importance to the TNA in more diversified fund portfolios than in more concentrated fund portfolios. Therefore, the probability of making relevant trading decisions and as a consequence, the probability of making trading important errors could be higher in less diversified funds. According to Koestner *et al.* (2017), a higher level of financial sophistication can help to reduce the number of errors in portfolio management. Indeed, sophistication has been related to higher levels of portfolio diversification (Goetzmann and Kumar, 2008; Calvet *et al.*, 2007).

The previous evidence about the portfolio turnover is consistent with our rationale that when the turnover ratio is lower, the probability of making an error is also lower due to fewer trading decisions than in mutual funds with higher turnover ratios.

Finally, we find a negative relationship between the percentage of important errors and the market return. Therefore, the probability of an important error is higher with lower market returns. That is, it is more likely to make relevant trading errors in bearish than in bullish markets.

**4.2. Learning in the mutual fund industry: a management company approach.**

In the previous sub-section, we provide evidence of learning from past relevant errors in the maturity stage of the Spanish mutual fund industry. The next step in our empirical analysis is to study how this learning process is driven by the mutual fund management companies of this industry. That is, we test whether the learning evidence previously detected is consistently driven by most of the management companies registered in the Spanish market. In order to do that, we compare the learning level of the whole industry previously found with the learning level of each individual management company.

We suggest that different groups of mutual fund management companies may coexist, depending on the level of its learning process: (1) management companies whose level of learning is higher than the industry level; (2) management companies whose level of learning is similar to the industry level; (3) management companies whose level of learning is lower than the industry level.

First, we have run the dynamic panel data model (2) for each management company. Second, we have classified all the management companies into the three previously defined groups according to the results of the interaction slope ($\beta_7$) of model (2). This slope allows us to compare the learning level of each mutual fund management company regarding to the global learning level of whole the mutual fund industry over time. Table 5 shows the classification of each management company group based on both the sign and the significance of the interaction slope.

On the one hand, the learning in the mutual fund companies is higher or not significantly different than the learning evidence of the mutual fund industry in those cases of significant negative or not significant slope coefficients of the interaction between the dummy variable $Management_{i,t}$ and the variable $Time_t$ of model (2). Table 5 shows that the learning evidence provided by approximately 60% of management companies is higher or the same than the learning for the whole mutual fund industry.

### Table 5: Learning results: a management company approach

This table reports the percentage of mutual fund management companies based on both the sign and the significance of the slope of the interaction between the dummy variable $Management_{i,t}$ and $Time_t$ in our dynamic model (2). We have computed this model (2) to each management company included in our sample. Panel A reports the results for those companies which manage domestic equity funds and Panel B reports the results for those companies which manage Euro equity mutual funds. Similarly to Table 3 and Table 4, the learning results are split into buys and sells after considering different time horizons to compute these errors: 3-month alpha, 6-month alpha and 12-month-alpha.

PANEL A: Domestic Equity Mutual Funds

| | Buys | | | Sells | | |
|---|---|---|---|---|---|---|
| | Errors at 3-month alpha | Errors at 6-month alpha | Errors at 12-month alpha | Errors at 3-month alpha | Errors at 6-month alpha | Errors at 12-month alpha |
| Management x Time negative and significant slope | 35.21% | 32.00% | 33.33% | 27.40% | 30.67% | 32.39% |
| Management x Time not significant slope | 35.21% | 37.33% | 38.67% | 35.62% | 41.33% | 42.25% |
| Management x Time positive and significant slope | 29.58% | 30.67% | 28.00% | 36.99% | 28.00% | 25.35% |

PANEL B: Euro Equity Mutual Funds

| | Buys | | | Sells | | |
|---|---|---|---|---|---|---|
| | Errors at 3-month alpha | Errors at 6-month alpha | Errors at 12-month alpha | Errors at 3-month alpha | Errors at 6-month alpha | Errors at 12-month alpha |
| Management x Time negative and significant slope | 30.65% | 37.78% | 23.88% | 17.91% | 35.94% | 30.65% |
| Management x Time not significant slope | 25.81% | 24.44% | 17.91% | 29.85% | 26.56% | 27.42% |
| Management x Time positive and significant slope | 43.55% | 37.78% | 58.21% | 52.24% | 37.50% | 41.94% |

On the other hand, the learning evidence in the mutual fund companies is lower than in the mutual fund industry in those cases of significant positive slope coefficients of the interaction between the dummy variable $Management_{i,t}$ and the variable $Time_t$ of model (2). Table 5 shows that approximately 40% of management companies learn less than the mutual fund industry or even they do not learn. Nonetheless, our approach cannot split up the percentage of management companies into each group.

Our findings support that learning from past relevant trading errors in the Spanish mutual fund industry is driven by a large group of mutual fund companies. These findings are generally consistent for buys and sells and for trading errors obtained from different time horizons: 3-month alpha, 6-month alpha and 12-month-alpha.

## 5. CONCLUSIONS

Our study is the first to examine the ability of mutual fund industry to learn from its past trading relevant errors. This research is motivated by the lack of learning evidence regarding to portfolio management and the important implications for the main agents involved in the mutual fund industry. Our identification of relevant trading decisions is based on the hypothesis that mutual fund managers may have incentives to avoid important errors or learn from these errors because their positions, reputations and salaries may depend on their performance records. In our study, a relevant trading decision must have a high relative importance respect to the fund TNA and this relative importance must be significantly different from other trading decisions by the same fund and by other funds in our sample.

Our empirical analysis is focused on the learning process in the maturity stage of the Spanish mutual fund industry for the period 2000-2014. In the first part of our analysis, we find that the percentage of important trading errors decreases significantly over time. Therefore, we find a significant learning evidence from past management errors in the Spanish mutual fund industry. This decreasing pattern keeps being significant despite the inclusion of five control variables that may influence on the percentage of important errors in relevant trading decisions. These findings are consistent in both buys and sells and for different time horizons used to compute the Jensen's alpha-based errors: 3-month alpha, 6-month alpha and 12-month-alpha.

In the second part of our empirical analysis, we find that this learning evidence is driven by a large group of the management companies registered in Spain. However, further research is forthcoming in our paper about the fund company characteristics which drive this learning evidence.

## REFERENCES


Abernathy, J. M., & Wayne, K, 1974. Limits of the learning curve. *Harvard Business Beview*. 52(5), 109-119

Adams, G. L., & Lamont, B. T., 2003. Knowledge management systems and developing sustainable competitive advantage. *Journal of knowledge management*, 7(2), 142-154.

Agarwal, V., Daniel, N. D., & Naik, N. Y., 2009. Role of managerial incentives and discretion in hedge fund performance. *The Journal of Finance*, 64(5), 2221-2256.

Alexander, G. J., Cici, G., & Gibson, S., 2007. Does motivation matter when assessing trade performance? An analysis of mutual funds. *The Review of Financial Studies*, *20*(1), 125-150.

Arellano, M., & Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2), 277-297.

Arellano, M., & Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, 68(1), 29-51.

Argote, L., Beckman, S. L., & Epple, D., 1990. The persistence and transfer of learning in industrial settings. *Management science*, 36(2), 140-154.

Argyris, C., & Schon, D. A., 1996. *Organiational learning II*. Addison Wesley

Ariely, D., & Zakay, D., 2001. A timely account of the role of duration in decision making. *Actapsychologica*, 108(2), 187-207.

Arrow, K. J., 1962. The economic implications of learning by doing. *The review of economic studies*, *29*(3), 155-173.

Autio, E., Sapienza, H. J., & Almeida, J. G., 2000. Effects of age at entry, knowledge intensity, and imitability on international growth. *Academy of management journal*, 43(5), 909-924.

Bailey, W., Kumar, A., & Ng, D., 2011. Behavioral biases of mutual fund investors. *Journal of Financial Economics*, *102*(1), 1-27.

Barber, B. M., & Odean, T., 2013. The behavior of individual investors. *Handbook of the Economics of Finance*, 2, 1533-1570.

Benson-Rea, M., & Wilson, H., 2003. Networks, learning and the lifecycle. *European Management Journal*, 21(5), 588-597.

Berk, J. B., & Green, R. C., 2004. Mutual fund flows and performance in rational markets. *Journal of political economy*, 112(6), 1269-1295.

Blundell, R., & Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1), 115-143.

Calvet, L. E., Campbell, J. Y., & Sodini, P., 2009. Measuring the financial sophistication of households. *American Economic Review*, 99(2), 393-98.

Calvet, L. E., Campbell, J. Y., & Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy*, 115(5), 707-747.

Campbell, J. Y., 2006. Household finance. *The journal of finance*, *61*(4), 1553-1604.

Cardon, M.S., Stevens, C.E., & Potter, D.R., 2011. Misfortunes or mistakes? Cultural sense making of entrepreneurial failure. *Journal of Business Venturing*, *26*(1), 79-92.

Chauvet, M., & Potter, S., 2000. Coincident and leading indicators of the stock market. *Journal of Empirical Finance*, *7*(1), 87-111.

Cremers, K. M., & Petajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. *The Review of Financial Studies*, 22(9), 3329-3365.

Crossan, M. M., Lane, H. W., & White, R. E., 1999. An organizational learning framework: From intuition to institution. *Academy of management review*, *24*(3), 522-537.

Crossan, M. M., & Bapuji, H. B., 2003. Examining the link between knowledge management, organizational learning and performance. In *Proceedings of the 5th International Conference on Organizational Learning and Knowledge, Lancaster University, Lancaster*, 30.

Cuthbertson, K., Nitzsche, D., & O'Sullivan, N., 2016. A review of behavioural and management effects in mutual fund performance. *International Review of Financial Analysis*, 44, 162–176.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of finance,* 52(3), 1035-1058.

De Bondt, W. F., & Thaler, R., 1985. Does the stock market overreact? *The Journal of finance*, 40(3), 793-805.

Dhar, R., & Zhu, N., 2006. Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5), 726-740.

Dierickx, I., & Cool, K., 1989. Asset stock accumulation and sustainability of competitive advantage. *Management science*, 35(12), 1504-1511.

Directive 2009/65/EC of the European Parliament and the Council on the coordination of laws, regulations and administrative provisions relating to undertakings for collective investment in transferable securities (UCITS)(recast), 2008/0153(COD),19 June 2009.

Dosi, G., 1988, Sources, procedures, and microeconomic effects of innovation, *Journal of Economic Literature XXVI*, 1120- 1171.

Droms, W. G., & Walker, D. A., 1995. Determinants of variation in mutual fund returns. *Applied Financial Economics*, 5(6), 383-389.

European Fund and Asset Management Association (EFAMA), 2018. *International Statistical Release* (Third Quarter of 2018).

Elton, E.J., Gruber, M.J., Blake, C.R., Krasny, Y., and. Ozelge, S.O., 2010. The effect of holdings data frequency on conclusions about mutual fund behavior. *Journal of Banking & Finance*, 34(5), 912-922.

Fama, E. F., 1968. Risk, return and equilibrium: some clarifying comments. *The Journal of Finance, 23*(1), 29-40.

Finkelstein, S., & Sanford, S.H., 2000. Learning from corporate mistakes: The rise and fall of Iridium. *Organizational Dynamics, 29*(2), 138-148.

Fischer R. & Gerhardt, R., 2007. Investment Mistakes of Individual Investors and the Impact of Financial Advice, *Working paper, European Business School*.

Frydman, C., & Camerer, C.F., 2016. The psychology and neuroscience of financial decision making. *Trends in cognitive sciences,* 20(9), 661-675.

Fuller-Love, N., 2006. Management development in small firms. *International Journal of Management Reviews,* 8(3), 175-190.

George, J. M., 2000. Emotions and leadership: The role of emotional intelligence. *Human relations,* 53(8), 1027-1055.

Goetzmann, W. N., & Kumar, A., 2005. *Why do individual investors hold under-diversified portfolios?* (No. ysm454). Yale School of Management.

Grinblatt, M., & Titman, S., 1993. Performance measurement without benchmarks: An examination of mutual fund returns. *Journal of business*, 47-68.

Grinblatt, M., & Titman, S., 1994. A study of monthly mutual fund returns and performance evaluation techniques. *Journal of financial and quantitative analysis*, 29(3), 419-444.

Hatch, N. W., & Dyer, J. H., 2004. Human capital and learning as a source of sustainable competitive advantage. *Strategic management journal*, 25(12), 1155-1178.

Hirshleifer, J., 2001. *The dark side of the force: Economic foundations of conflict theory*. Cambridge University Press.

Inverco, 2018. *Statistical of mutual funds* (November 2018).

Jain, P. C., & Wu, J. S., 2000. Truth in mutual fund advertising: Evidence on future performance and fund flows. *The journal of finance,* 55(2), 937-958.

Jensen, M. C., 1968. The performance of mutual funds in the period 1945–1964. *The Journal of finance*, *23*(2), 389-416.

Jiang, G. J., Yao, T., & Yu, T., 2007. Do mutual funds time the market? Evidence from portfolio holdings. *Journal of Financial Economics*, *86*(3), 724-758.

Kacperczyk, M., Sialm, C., & Zheng, L., 2006. Unobserved actions of mutual funds. *The Review of Financial Studies*, *21*(6), 2379-2416.

Kahneman, D., 1994. New challenges to the rationality assumption. *Journal of Institutional and Theoretical Economics*, *150(1)*, 18-36.

Kempf, A., Ruenzi, S., & Thiele, T., 2009. Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry. *Journal of Financial Economics*, *92*(1), 92-108.

King, R.G., & Levine, R., 1993a. Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics*, 108(3), 717-738.

Koestner, M., Loos, B., Meyer, S., & Hackethal, A., 2017. Do individual investors learn from their mistakes? *Journal of Business Economics*, *87*(5), 669-703.

Levine, R., Loayza, N., & Beck, T., 2000. Financial intermediation and growth: Causality and causes. *Journal of monetary Economics*, 46(1), 31-77.

Levitt, B., & March, J. G., 1988. Organizational learning. *Annual review of sociology*, *14*(1), 319-338.

Lintner, J., 1965. Security prices, risk, and maximal gains from diversification. *The journal of finance*, *20*(4), 587-615.

Lipschutz, S., 1967. *Schaum's outline of set theory and related topics*. McGraw-Hill Inc

List, J. A., 2003. Does market experience eliminate market anomalies? *The Quarterly Journal of Economics*, *118*(1), 41-71.

Loewenstein, G., & Elster, J., 1992. *Choice over time.* Russell Sage Foundation.

March, J. G., 1991. Exploration and exploitation in organizational learning. *Organization science*, 2(1), 71-87.

Markowitz, H., 1952. Portfolio selection. *The journal of finance*, 7(1), 77-91.

Marsick, V., & Watkins, K., 2015. *Informal and Incidental Learning in the Workplace (Routledge Revivals).* Routledge.

McDevitt, R., Giapponi, C., & Tromley, C., 2007. A Model Ethical Decision Making: The Integration of Process and Content. *Journal of Business Ethics*, 73(3), 219-229.

Mileva, E., 2007. Using Arellano-Bond dynamic panel GMM estimators in Stata. *Economics Department, Fordham University*, 1-10.

Nicolosi, G., Peng, L., & Zhu, N., 2009. Do individual investors learn from their trading experience?. *Journal of Financial Markets*, *12*(2), 317-336.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A., 2015. Scale and skill in active management. *Journal of Financial Economics*, 116(1), 23-45.

Payne, J.W., Bettman, J.R., & Johnson, E.J., 1993. *The adaptive decision maker*.Cambridge University Press.

Penrose, E. T., 1959. *The Theory of the Growth of the Firm*, New York: John Wiley

Pollet, J. M., & Wilson, M., 2008. How does size affect mutual fund behavior? *The Journal of Finance*, 63(6), 2941-2969.

Ranyard, R., Crozier, W. R., & Svenson, O. (Eds.), 1997. *Decision making: Cognitive models and explanations* (Vol. 1). Psychology Press.

Roodman, D., 2009. A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1), pp. 135-158.

Roodman, D., 2006. How to do xtabond2: An introduction and “difference” and “system” GMM in Stata *(Working Paper No. 103).* Washington, DC: Center for Global Development.

Rousseau, P. L., & Wachtel, P., 2002. Inflation thresholds and the finance–growth nexus. *Journal of international money and finance*, *21*(6), 777-793.

Sargan, J.D., 1958. The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, pp. 393-415.

Sargent, T.J., 1993. Bounded rationality in macroeconomics: The Arne Ryde memorial lectures. *OUP Catalogue*.

Seru, A., Shumway, T., & Stoffman, N., 2009. Learning by trading. *The Review of Financial Studies*, 23(2), 705-739.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425-442.

Shiller, R. J., 2003. From efficient markets theory to behavioral finance. *Journal of economic perspectives*, 17(1), 83-104

Singh, S., Corner, P., & Pavlovich, K., 2007. Coping with entrepreneurial failure. *Journal of Management & Organization*, 13(4), 331-344.

Sirri, E.R., & Tufano, P., 1998. Costly search and mutual fund flows. *The Journal of Finance*, 53(5), 1589-1622.

Stanovich, K. E., & West, R. F., 2000. Individual differences in reasoning: Implications for the rationality debate? *Behavioral and brain sciences*, *23*(5), 645-665

Statman, M., 2014. Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65-73.

Subrahmanyam, A., 2008. Behavioural finance: A review and synthesis. *European Financial Management*, *14*(1), 12-29.

Tjosvold, D., Yu, Z.Y., & Hui, C., 2004. Team learning from mistakes: the contribution of cooperative goals and problem-solving. *Journal of Management Studies*, *41*(7), 1223-1245.

Tseng, K. C., 2006. Behavioral finance, bounded rationality, neuro-finance, and traditional finance. *Investment Management and Financial Innovations*, *3*(4), 7-18.

Tversky, A., & Kahneman, D., 1986. Rational choice and the framing of decisions. *Journal of business*, S251-S278.

Tversky, A., & Shafir, E., 1992. Choice under conflict: The dynamics of deferred decision. *Psychological Science*, 3(6), 358-361.

Wang, Y., & Ruhe, G., 2007. The cognitive process of decision making. *International Journal of Cognitive Informatics and Natural Intelligence*, 1(2), 73-85.

Wang, Y., 2011. *Information Content of Mutual Fund Portfolio Disclosure* (No. EPS-2011-242-F&A).

Weber, M., & Camerer, C. F., 1998. The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior & Organization, 33*(2), 167-184.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance,* 55(4), 1655-1695.

Wermers, R., T. Yao, and J. Zhao, 2012. Forecasting stock returns through an efficient aggregation of mutual fund holdings. *The Review of Financial Studies*, 25(12), 3490-3529.

Wilson, R.A., & Keil, F.C., 2001. *The MIT encyclopedia of the cognitive sciences*. MIT press.

Wooldridge, J. M., 2010. *Econometric analysis of cross section and panel data*. MIT press.