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THREE ESSAYS ON BEHAVIOURAL BIASES OF MUTUAL FUND MANAGERS: OVERCONFIDENCE, DISPOSITION EFFECT AND TOURNAMENTS

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Three essays on behavioural biases of mutual fund managers: overconfidence, disposition effect and tournaments

PhD Programme in Accounting and Finance

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To Victor, thanks for everything, Amor.

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General introduction

"A full understanding of human limitations will ultimately benefit the decision-maker more than will naïve faith in the infallibility of his intellect."

– Paul Slovic

The central axioms of classical finance models present rational agents interacting in efficient markets. Though desirable, these premises hardly ever hold in practice. In fact, investors evolve in an environment where there are numerous pieces of information to process, combined with diverging opinions, differing interpretations, and information asymmetry. Yet, environment is only one part of the equation as investors also have to deal with their own biases and heuristics, and they are subject to flaws of reasoning, to mistakes and to their own emotions.

Not only does behavioural finance incorporate utility maximization and risk aversion in the design of its models, but it also takes into account heuristics, biases, cognitive shortcuts, and emotions, to which all humans are subject. The aim of behavioural finance is to bridge the gap between theory and practice. Behavioural finance is the sub-field of behavioural economics that investigates how psychological factors and biases affect the behaviour of retail investors, financial practitioners, and the market as a whole. As such, behavioural finance strives to provide insights not only to individual investors, but also to professional investors. Indeed, evidence has shown that biases are not only limited to individual investors, but that they are inherent to human behaviour.

By correcting their biases, professional mutual fund managers can become more efficient and given the size of the portfolios they manage, their biases could have a great impact on financial markets. Cognitive errors, biases and fallacies are part of human behaviour and the first step to avoid falling prey to them is to become aware of their existence.

Because of the considerable share of the financial market that professional fund managers oversee, the findings provided in this thesis are of importance both to academic research and to the financial industry.

This thesis also responds to the considerable and long-lasting interest of investors in mutual funds as a saving instrument. Indeed, there is a strong demand for mutual funds and flows into these funds have grown exponentially in the last decade. The total net assets (TNA) under management in regulated funds grew sevenfold in two decades and only in the period year-end 2020 to year-end 2021, the TNA of mutual funds grew from USD 63.0 trillion to USD 71.1 trillion worldwide (Investment Company Institute, 2022).[1]

Alongside the rapid growth in demand for mutual funds, there has been an increase in the demand for specific types such as Socially Responsible Investment (SRI) funds. In just a four years' period, the Global Sustainable Investment Alliance (2020) reported a 55% increase in the total assets under management of global sustainable investments professionally managed, reaching USD 35.3 trillion at the start of 2020.[2]

Behavioural finance is a well-established field of study. Still, there are several questions related to behavioural finance that remain unexplored. In this work, three issues worthy of attention were identified and will be addressed in separate chapters:

1. Because evidence has shown that the overconfidence bias has a potentially negative impact on performance, how can we detect overconfident fund managers? What are the characteristics of fund managers that are more prone to this bias?
2. Based on prior literature, we know that investors in socially responsible investments (SRI) have a dual motivation, both financial and social. So, do SRI

[1] Investment Company Institute (2022). *2022 Investment Company Fact Book*. Available at https://www.ici.org/system/files/2022-05/2022_factbook.pdf. Last accessed in January 2023.
[2] Global Sustainable Investment Alliance. (2020). *Global Sustainable Investment Review 2020.* Available at http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf. Last accessed in January 2023.

fund managers trade differently compared with non-SRI fund managers? Do both groups present differences when it comes to a bias such as the disposition effect?

3. Because it has been empirically tested that the winner takes it all in terms of inflows from investors, how efficient are fund managers reacting to their mid-year performance rankings? How efficient are fund managers in the tournament as a whole?

As such, the aim of Chapter 1 is to design a measure that can single out overconfident fund managers with greater accuracy than proxies used in isolation in literature. The main contribution of this work is the Overconfidence Composite Score and the recommendations on the choice and on the calibration of proxies used in this score.

Simply put, in Chapter 2, the aim is to find evidence of disposition effect in a pool of SRI funds and a matching pool of non-SRI funds. This study complements other studies that compare the behaviour of SRI fund managers with the behaviour of non-SRI managers. Additionally, it fills the void in literature by investigating the disposition effect in SRI funds.

Finally, Chapter 3 aims to elucidate the dynamics of the tournament in the mutual fund industry. We propose a three-stage model and employ a Network Data Envelopment Analysis (DEA) to evaluate the efficiency of mutual fund managers in the tournament. To our knowledge, our study is the first to employ Network DEA to evaluate behaviour in the mutual fund industry.

Chapter 1: Know thyself: A novel scoring system for assessing mutual fund managers' overconfidence*

"What would I eliminate if I had a magic wand? Overconfidence."

– **Daniel Kahneman**

The main aim of this chapter is to build a scoring system that tests for the overconfidence bias in equity fund managers. Based on the commonalities of three proxies (turnover ratio, active share, and equity exposure), we first assess the relationship between confidence level and past performance by using the first principal component of these proxies. From this primary analysis, we use relative ranks to build an overconfidence composite scoring system that is derived from the independent calibration of managers: Equity fund managers who simultaneously trade the most, deviate the furthest from their benchmark, and hold the greatest percentage of their assets in equity are deemed overconfident. Our analysis reveals that our score permits the selection of overconfident managers with a greater accuracy than the solitary measures traditionally used in literature. We also find that female mutual fund managers or managers who hold a master's degree or a Chartered Financial Analyst (CFA) designation are more prone to overconfidence, meanwhile industry experience does not seem to impact overconfidence. On the consequences of overconfidence, we reach the conclusion that top performers who display high levels of confidence subsequently obtain significantly lower relative performance, while low performers who display high levels of confidence obtain significantly better results in the following quarters.

* An early draft of this chapter was presented at the 11th Portuguese Finance Network Conference, at the A&F Research Seminar of Newcastle University Business School (United Kingdom), at the III Brown Bag Seminars of the University of Zaragoza and at the XI Workshop for Young Researchers of the University of Zaragoza.

1.1 Introduction

The early interest of economists in overconfidence can be traced back to Adam Smith, who is widely considered as the father of modern economics. In one of his most famous writings known as *The Wealth of Nations*, he asserted that “the over-weening conceit which the greater part of men have of their own abilities, is an ancient evil remarked by the philosophers and moralists of all ages” (Adam Smith, 1776, Book I, Chapter X). Much more recently, the psychologist and Nobel laureate in Economics Daniel Kahneman in an interview for The Guardian confessed that if he had a magic wand, he would get rid of overconfidence (Shariatmadari, 2015).

Overconfidence is a robust and well-documented behavioural bias. Generally, overconfidence is said to occur when people’s perception of their abilities is greater than their objective performance. Originally from the field of psychology, the concept has grown even more influential in other fields of study over the past decade. Due to its prevalence, overconfidence is often presented as the root cause behind many events, from wars (Johnson, 2004) to strikes (Neale and Bazerman, 1985), from high rates of new start-ups despite notable entrepreneurial failure (Van Zant and Moore, 2013) to financial crashes and bubbles (Michailova and Schmidt, 2016). Moore and Healy (2008) presented an exhaustive review of papers in this line. In the words of Griffin and Tversky (1992, p. 432): “The significance of overconfidence to the conduct of human affairs can hardly be overstated”.

Several empirical studies conducted on the general population reveal the predominance of this bias. A popular example is the analysis performed by Svenson (1981). Based on a sample of US students, he provides a clear illustration: More than 80% of the students surveyed believed to be among the top 30% in terms of driving safety. In the field of finance and investment, a similar study was carried by James Montier (2006) on a pool of 300 professional fund managers. The results of the study revealed that 74% of fund managers believed their job performance to be above average and 26% judged their performance to be average, leaving 0% viewing themselves below average. These studies clearly illustrate what has been coined as the better-than-average effect.

While the pre-eminence and the ubiquity of overconfidence are well-established, there is a gap in literature on the empirical identification of overconfidence. Some studies resort to the use of laboratory type experiments to gauge overconfidence because the validity of proxies is still to be established (for instance, Duxbury, 2015), other studies resort to the use of overconfidence proxies to overcome the potential lack of a real-world component in laboratory-type experiments (for example, Puetz & Ruenzi, 2011). The main proxies used in literature to detect overconfidence are trading activity (Barber & Odean, 2000; Barber & Odean, 2001; Glaser & Weber, 2007; Odean, 1999; Puetz & Ruenzi, 2011), active management (Choi & Lou, 2010), and risk exposure (O'Connell & Teo, 2009), with trading activity being one of the most used proxies.

However, the use of a single proxy could lead to biased estimations because one could be capturing other phenomena, e.g., flow-induced trading and tournament behaviours (Coval & Stafford, 2007; Kempf et al., 2009). In addition, in some markets the proxies generally used in literature might not be very effective because of their relatively low levels of variation between mutual funds. For instance, Beckmann et al. (2008) have shown that asset managers in countries with a culture of uncertainty avoidance tend to deviate less from their benchmark. In such markets, active share could be relatively low and may not present much variation between funds.

Properly detecting overconfidence is of prime importance because of its potential consequences on the financial market. Daniel Kahneman perceives overconfidence as "the most damaging" of behavioural biases (Shariatmadari, 2015, para. 4). Indeed, several empirical investigations are consistent with the idea that overconfidence can be detrimental to mutual funds' performance (Choi & Lou, 2010; Cuthbertson et al., 2016; Puetz & Ruenzi, 2011). In this regard, the self-serving attribution bias hypothesis suggests that overconfident managers will only pay attention to confirming signals and ignore disconfirming signals, leading to poor portfolio allocation and consequently poorer results (Choi & Lou, 2010).

The aim of this study is to design an Overconfidence Composite Score (OCS) that could help identify overconfidence in mutual fund managers. In this study, we combine turnover ratio, active share and equity exposure to build a score that gauges the confidence level of mutual fund managers. It is our contention that mutual fund managers who simultaneously trade the most, deviate the most from their benchmark and hold the highest percentage of their total net assets in equity can be deemed overconfident with more certainty.

There are several advantages to combining various proxies. First, it is not exactly clear that what single proxies capture is overconfidence and not another event or phenomenon. For example, turnover ratio has also been employed to search for window dressing (Elton et al., 2010; Ortiz et al., 2015). By combining proxies, we provide an improved method of detection of overconfidence in mutual fund managers. Finally, because it allows for the assignation of different weights to each proxy, our OCS could be much more flexible and adaptable to each market than the use of a single proxy.

This study uses the Principal Component Analysis (PCA) to assess the influence of past performance on the confidence level (CL) of fund managers. The role of the PCA is to establish the commonalities between the three most used proxies: turnover ratio, active share and equity exposure. In the second phase, our study validates this novel composite score which simultaneously includes the three proxies and its relationship with prior outstanding performance.

An additional contribution of our study is the use of relative confidence levels instead of absolute values of confidence. Absolute levels of overconfidence might not be very informative for industries where participants already have a higher confidence level or are required to have some confidence in their abilities in order to do their job. Schulz and Thöni (2016), when analysing the link between overconfidence and career choice, found significant differences across fields of study and reach the conclusion that students in business-related fields displayed the highest levels of confidence. For this reason, using a relative measure of overconfidence that compares mutual fund managers to their peers is more appropriate. In addition, the use of relative measures would allow for calibration depending on the market.

Simply put, our approach aims to gauge the confidence level of fund managers in relation to their peers and then to provide an overconfidence score that can be calibrated for and adapted to different contexts and fund markets. Our primary analysis is oriented at detecting overconfident mutual fund managers. Later, we use this initial analysis to identify the characteristics of overconfident fund managers, namely, gender, education, and experience. Afterwards, we test the robustness and the consistency of our measure. And finally, we investigate the impact of overconfidence on subsequent performance.

Section 1.2 of this work provides a background study of overconfidence. Section 1.3 describes the data and variables used. Section 1.4 presents the empirical analysis performed. Finally, Section 1.5 concludes.

1.2 Overconfidence bias

The current financial literature on overconfidence has mainly focused on retail investors rather than on professional investors. A possible justification for this trend is that professional investors could generally be expected to possess more experience and have more financial knowledge than a lay person. However, empirical studies have shown that overconfidence is not solely limited to amateurs. For instance, Lambert et al. (2012) compared a group of 20 bankers and a group of 64 students. They found no differences between both groups in the degree of confidence, suggesting that both groups were equally prone to overconfidence.

Indeed, overconfidence is not solely restricted to inexperienced individuals, especially when predictability is low, as is the case in financial markets (Griffin & Tversky, 1992). This behavioural bias is also displayed by professional investors including and not limited to advisors, analysts and fund managers (Kyle & Wang, 1997; Menkhoff et al., 2006; Mishra & Metilda, 2015). Furthermore, analysing the behaviour of fund managers is of prime importance. Given that they generally manage larger portfolios than individual investors, behavioural biases of fund managers could have a great impact on the financial market.

Prior literature has identified the self-serving attribution bias as the cause of overconfidence (Doukas & Petmezas, 2007; Puetz & Ruenzi, 2011). The self-serving attribution bias leads investors to attribute their successes to their own dispositions and skills, while they tend to attribute poor performance to chance or external forces. In this line, Choi and Lou (2010) state that investors receive noisy feedback from the market and tend to dismiss disconfirming signals, meanwhile confirming signals lead them to overestimate their abilities.

Relatedly, Bekiros et al. (2017) claim that high positive returns prompt overconfidence and change individuals' perception of reality, increasing the propensity of these individuals to rely more on their private information and to underrate public information. As a result, it is expected that after a good performance, investors become more overconfident, but following a poor performance, they do not become less confident. For this reason, we do not expect a linear relationship between past performance and the confidence level of managers. As suggested by Bai et al. (2019), we follow the assumption that confidence occurs on a spectrum, with overconfidence on one end and underconfidence on the other end of the spectrum. In the current study, overconfident managers are identified for each quarter based on the general confidence level of contemporary mutual funds managers. In this regard, it is a relative measure rather than an absolute one.

There are distinct types of overconfidence in literature. As pointed out by Moore and Healy (2008), researchers often implicitly or explicitly assume the distinct types of overconfidence to be interchangeable, despite the fact that confounding the varieties of overconfidence might result in empirical inconsistencies and methodological problems. Three types of overconfidence are commonly found in literature: Overprecision in the accuracy of one's belief or miscalibration, overestimation of one's abilities or illusion of control, and overplacement of one's performance in relation to others' or better-than-average effect (Glaser et al., 2013; Glaser & Weber, 2007; Moore & Healy, 2008).

Glaser and Weber (2007) highlighted the importance of distinguishing between the types of overconfidence as they have disparate consequences: miscalibration, for instance, is not related to high trading volumes, while better-than-average effect is. Consequently, they should be measured through different experiments and with distinct proxies. The current study is geared towards the better-than-average effect which has been associated with high trading volumes (Glaser and Weber, 2007) and with deviations from the benchmark indices (Jin et al., 2015).

The proper selection of proxies for overconfidence remains challenging in financial literature and their effectiveness needs to be established (Duxbury, 2015). The current study uses PCA initially to create a single variable to gauge the confidence level of each manager for each quarter. Through the PCA, all three proxies, turnover ratio, active share and equity exposure are merged into one single measure. It is our contention that employing the three measures simultaneously reduces noise and permits the detection of overconfidence with greater accuracy.

After that, we use PCA as a preliminary test to figure out whether there is an influence of past performance on the confidence level of fund managers. Subsequently, we build our composite score. Based on the eigenvalues of the proxies in the PCA, we determine the weight of each proxy in our composite score. Fund managers who simultaneously trade the most, deviate the most from their benchmark and hold the highest percentage of their assets in equity are considered overconfident.

Both analyses are thus interconnected: we first use PCA to identify the commonalities between the three proxies and determine the relationship between past performance and the confidence level. In the second phase, we use the OCS to single out overconfident managers, to analyse how prior performance influences the confidence level of fund managers and to determine the characteristics of overconfident managers.

An earlier study by Adebambo and Yan (2016) used PCA to measure overconfidence and they also created a composite score based on the results of the PCA. Our study adds to the work of Adebambo and Yan (2016) in two main aspects. First, unlike Adebambo and Yan (2016) who used managers' characteristics such as being a male manager or the length of managers' tenure as proxies for overconfidence, we choose proxies that result directly from managers' investment decisions.

The main issue with using managers' characteristics such as gender as proxies for overconfidence is that they are time-invariant for the same subject or do not present much variation between subjects. For this reason, they cannot be a proper reflection of managers' dynamic investment decisions. Furthermore, when employing characteristics as proxies, it then becomes harder to analyse the characteristics of overconfident managers. This renders the analysis more rigid, less informative, and less effective. Therefore, we believe that it is preferable to choose variable that are time-variant and dependent on managers' investment decisions as proxies for overconfidence.

Secondly, Adebambo and Yan (2016) automatically assigned equal weights to all proxies in the scoring system, even though they had returned different eigenvalues in the PCA. We would rather recommend that the weight of each proxy in the scoring system respond to their eigenvalues in the PCA and proxies must not automatically be assigned equal weights within the score. Each eigenvalue provides information about the relative proportion of the dataset variance explained by a given proxy. As a result, the derived scoring system becomes more accurate and more adaptable to the context of each mutual fund industry or market.

We close this literature review section, by contributing to the ongoing debate over the use of the term *conviction* rather than *overconfidence*. Jin et al. (2020), for instance, advocated for the use of the term conviction rather than the terms confidence or overconfidence in contexts where the optimum decision can only be known ex-post and where the outcome cannot be controlled, as is the case in the mutual fund industry.

From the analysis of Jin et al. (2020), several differences between overconfidence and conviction can be highlighted. First, a careful analysis of the work of Jin et al. (2020) reveals that conviction could occur on a spectrum, with high conviction (overconviction) on one end of the spectrum. Bai et al. (2019) proposed a similar spectrum for confidence. If anything, overconfidence should then bear comparison with overconviction and not with conviction.

Secondly, while in the current context they both refer to self-persuasion, conviction is directed towards external beliefs, ideas or opinions (Jin et al., 2020; Cremers, 2017) such as the belief that one is making the right investment decision. Confidence, however, is more internal, i.e., directed at one's abilities and skills. Tjan (2017) provided a similar distinction between overconfidence and conviction.

To conclude, while conviction seems to be a positive trait, overconfidence appears not to be. Jin et al. (2020) affirmed that developing a certain level of conviction is vital for fund managers. Otherwise, reaching a decision would be a difficult feat due to the uncertainty of the environment in which fund managers work. Overconfidence, on the other hand, has been widely viewed as a behavioural bias (see Moore and Healy, 2008). Barber and Odean (2002) and Griffin & Tversky (1992) considered stock selection to be the epitome of the task in which people display overconfidence because of its low level of predictability and its noisy feedback.

1.3 Data and variables

1.3.1 Data

The initial dataset consists of quarterly data of portfolio holdings, Net Asset Value and total net assets (TNA) of all equity funds registered in Spain. This information, publicly available for investors and for the general public, was provided by the Spanish Securities and Exchange Commission (CNMV). The use of publicly available information is especially appropriate in this study because we are measuring the better-than-average effect: Fund managers might become overconfident if, based on the information available to everyone, they are ranked better than their peers.

The study period covers December 1999 to December 2016. We narrow our analysis to the two most relevant equity investment categories in Spain in terms of TNA: domestic equity funds and Euro equity funds, that represents 32% of the TNA managed in the equity fund industry in the year 2016. At the end of the entire screening process, we obtain a total of 279 equity funds and 9,831 quarterly portfolios. The sample is free of both the survivorship bias and the look-ahead bias. Indeed, all funds that enter the database are taken into account in the analysis, even if at some point within the time period under study they ceased to exist.

We exclude the portfolios of index funds from the final sample, given that they are not a result of active management. Consequently, they cannot properly reflect fund managers' confidence level. Only active management would be valid to gauge overconfidence. We also control for mergers and acquisitions within the sample of funds to ensure that variations in TNA reflect the non-exceptional fund activity. Finally, we exclude 16 funds for not providing information for at least 5 consecutive quarters. This minimum period is required in order to compute the yearly performance data.

From our initial sample, with the objective of properly determining overconfident managers characteristics, we construct two subsamples. First, we obtain a smaller subsample comprising only solo-managed funds. Under this set, we group funds for which we have information about the personal characteristics of managers, namely gender, education, and length of industry experience. The information about industry experience, about the full names of fund managers and about management structure of mutual funds is obtained from Morningstar and the information about managers' level of education is hand-collected from official websites and professional social networks. Gender is manually assigned based on the first names of the fund managers.

Then, we design a second and wider subsample consisting of all funds for which we have information about management structure. We include both solo-managed and team-managed funds. In total, the subsample of solo-managed funds, the smaller sample, comprises 114 equity funds and 2,717 quarterly portfolios; the second subsample comprises 173 equity funds and 4,650 portfolios.

To compare domestic funds and Eurozone funds against their benchmark, we use the quarterly weightings of the constituents of the Spanish benchmark Ibex35 and Eurozone benchmark EuroStoxx50 respectively. Both sets of data are provided by Datastream.

1.3.2 Overconfidence proxies

1.3.2.1 Turnover ratio

The main proxy used in financial literature to gauge overconfidence is trading activity. Various models (Gervais & Odean, 2001; Moore & Healy, 2008; Odean, 1998) and empirical analyses (Barber & Odean, 2000; Barber & Odean, 2001; Glaser & Weber, 2007; Odean, 1999) support the hypothesis that the higher the level of overconfidence of an investor, the greater their trading activity. Consistent with these theories, Statman et al. (2006) and Puetz and Ruenzi (2011) used high trading volumes after good performance as a significant indicator of overconfidence. It should be noted that not all types of overconfidence are captured with the use of trading activity. Indeed, Glaser and Weber (2007) specifically identified better-than-average effect as the type of overconfidence linked with high trading volumes. They conclude that investors who think they are better than the average investor tend to trade more, while miscalibration does not appear to be related to high trading volumes. Because in this study, we are focused on the better-than-average effect, using turnover ratio as one of the proxies is appropriate.

We compute the turnover ratio of a portfolio as a proxy for trading activity in line with the approach of Elton et al. (2010). Turnover ratio is defined as the lesser of purchases or sales divided by the average net asset value of portfolio *p* in the period *t.* Stock mergers and acquisitions were not computed as turnover because only voluntary trading would qualify as a sound proxy for overconfidence. Similarly, because exclusions of stocks from the market do not stem from active management, they were not considered when computing sales.

$$Turnover\ Ratio_{p,t} = \min\left(C_{p,t}^{+}, C_{p,t}^{-}\right) / \overline{TNA}_{p,t} \quad [1]$$

where:

$$C_{p,t}^{+} = \sum_i \left(N_{p,i,t} - N_{p,i,t-1}\right)\bar{P}_{i,t} \text{ for all } i\text{, where } \left(N_{p,i,t} - N_{p,i,t-1}\right) \geq 0 \quad [2]$$

$$C_{p,t}^{-} = \sum_i \left(N_{p,i,t} - N_{p,i,t-1}\right)\bar{P}_{i,t} \text{ for all } i\text{, where } \left(N_{p,i,t} - N_{p,i,t-1}\right) < 0 \quad [3]$$

$C_{p,t}^{+}$ represents the total purchases of portfolio *p* in period *t*

$C_{p,t}^{-}$ represents the total sales of portfolio *p* in period *t*

$N_{p,i,t}$ is the total number of shares of stock *i* in portfolio *p* at the end of the period *t*

$N_{p,i,t-1}$ is the total number of shares of stock *i* in portfolio *p* at the end of the period $t-1$

$\bar{P}_{i,t}$ is the average price of stock *i* over period *t*

$\overline{TNA}_{p,t}$ is the average of the TNA of portfolio *p* in period *t*

1.3.2.2 Active share

Active share refers to the percentage of stock holdings in a portfolio that differs from its benchmark. Cremers and Petajisto (2009) introduced active share to assess how active a portfolio manager is and to predict performance. To compute active share, we use the following formula they proposed:

$$Active\ Share_{p,t} = \frac{1}{2}\sum_{i=1}^{T}\left|w_{p,i,t} - w_{index,i,t}\right| \qquad [4]$$

where:

$w_{p,i,t}$ is the weight of stock *i* in portfolio p at the end of period *t*

$w_{index,i,t}$ is the weight of stock *i* in the benchmark index at the end of period *t*

T is the universe of all stocks

The use of active share as a proxy for overconfidence is recent in the literature. The hypothesis is that overconfident managers will try to beat their benchmark and to do so, they need to deviate from it: the more confident the manager, the greater the active share of the portfolio. Choi and Lou (2010) concluded that managers increase their active share after a good performance, but do not decrease it after a poor performance. They also find this result to be more pronounced in novice managers than in more experienced managers.

1.3.2.3 Equity exposure

Equity exposure represents the percentage of a portfolio allocated to equities, in other words, it is measured by the total sum of the weights of all the stock holdings in any given portfolio. It is worth to mentioning that equity funds are constrained by CNMV's definition to hold at least 75% of the TNA in equity. Our hypothesis is that a high portfolio exposure to equity could indicate overconfidence (Barber & Odean, 2001; O'Connell & Teo, 2009; Broihanne et al., 2014). We compute equity exposure as follows:

$$Equity\ Exposure_{p,t} = \sum_{i=1}^{t} w_{p,i,t} \qquad [5]$$

where:

$w_{p,i,t}$ is the weight of stock *i* in portfolio *p* at the end of period *t*

t is the number of stock holdings of portfolio *p*

1.3.2.4 Proxy combination approach

Meanwhile turnover ratio, active share and equity exposure used in isolation could characterize other different managerial and behavioural patterns, their combined use could provide a more accurate measure for overconfidence.

Indeed, most of the aforementioned studies have resorted to employing a single proxy. When using a single proxy, one might capture other management and behavioural patterns different from overconfidence. For instance, turnover ratio has also been employed to test window dressing (Elton et al., 2010; Ortiz et al., 2015); active share has mostly been used to predict performance (Cremers & Petajisto, 2009); and equity exposure has been used to assess risk shifting (Huang et al., 2011). It is our contention that using the cumulative contribution of the three proxies permits us to single out overconfident managers with a high level of certainty. Fund managers who simultaneously trade the most, deviate the most from their benchmark, and hold the highest portfolio percentage in equities compared with their peers can be said to display a better-than-average behaviour with a high level of certainty. However, we also need to recognize that a potential downfall of using three proxies simultaneously is the restrictiveness of this method, and consequently, we might leave out some managers who are overconfident but do not simultaneously make it to the top of the three measures.

Initially, following the method used by Adebambo and Yan (2016), our first methodology is to use the Principal Component Analysis (PCA). The PCA is used to identify commonalities across the three proxies. Based on the hypothesis explained previously, this might be argued to be the confidence level of managers. The PCA is used to determine the relationship between prior performance and the subsequent confidence level obtained by mutual fund managers.

Based on the results of the PCA, we build an overconfidence composite score in which all proxies are weighted according to their eigenvalues. The composite score serves as a tool to classify fund managers in each quarter as either overconfident or not overconfident, according to a specific threshold.

Table 1.1 presents the descriptive statistics of our sample for the three proxies employed in our analysis. We have split our time frame into three periods: the pre-crisis (2000-2007), the financial crisis and its aftermath (2008-2012) and the post-crisis (2013-2016).[1] We observe that there are only slight variations in the mean and dispersion of the three proxies for these sub-periods. Overall, the mean turnover ratio is around 10%. Compared with the US mutual fund industry where Puetz and Ruenzi (2011) found a mean turnover ratio of slightly over 90%, the turnover ratio of the Spanish equity fund sample is considerably lower, maybe due to institutional and/or cultural factors.

[1] The Euro sovereign debt crisis was a prominent consequence of the global financial downturn that affected Eurozone members in 2008-2009, especially in Greece, Italy, Ireland, Portugal and Spain. The proposed periods are based on the lower levels of market stress indicators until this downturn (Galliani et al., 2014) and the positive reaction of these indicators to the European Central Bank's announcement in mid 2012 of unlimited support to save the Euro (also known as the Draghi effect).

Table 1.1 Descriptive Statistics of the proxies combined to measure overconfidence.

Proxies		2000-2007	2008-2012	2013-2016	2000-2016
Turnover ratio	*Mean*	10.50%	9.59%	9.46%	10.07%
	Std. Dev.	9.33%	9.02%	8.94%	9.19%
Active share	*Mean*	45.77%	44.49%	50.77%	45.07%
	Std. Dev.	24.14%	25.95%	25.75%	25.02%
Equity exposure	*Mean*	84.90%	84.14%	87.99%	85.19%
	Std. Dev.	13.81%	14.27%	10.03%	13.49%

This table presents the mean and standard deviation for the three proxies used to measure overconfidence: turnover ratio, active share, and equity exposure. We divide our time frame into three periods: pre-crisis, crisis, and post-crisis. The last column provides information about the entire time frame of our study. Given that we need at least two consecutive quarterly values to compute quarterly turnover ratio, the table starts in the first quarter of the year 2000.

1.3.3 Variables

The aim of our study is to investigate whether equity fund managers display overconfidence subsequent to outstanding results. For this reason, for each fund and each quarter, we compute excess returns (Exc_Ret$_{p,t-1}$) to assess performance. Alongside the definition of excess returns, Appendix 1.1 presents a detailed definition of all the variables included in the models.

Polkovnichenko (2005) showed that investors appear to under-diversify their portfolios when they are strongly certain of the positive outcome of their strategy. Fuertes et al. (2014) reached the conclusion that finance professionals show poorer diversification levels, possibly explained by overconfidence. Goetzmann and Kumar (2008) consistent with Odean (1999) also provided evidence for a strong correlation between under-diversification, overconfidence, and local stocks, i.e., familiarity with local stocks suggested that overconfident investors tend to hold concentrated portfolios of domestic stocks. Thus, our models control for portfolio concentration using the Herfindahl-Hirschman Index ($Herf\_Index_{p,t}$) of fund p in quarter t (Rhoades, 1993). It is worth mentioning that the percentage of its assets that a mutual fund can invest in certain financial assets is regulated by the European Union. This is however not a concern as this limitation applies equally to all funds.[2]

The strong preference for local stocks has been extensively documented around the world both among individual investors and professional investors. According to Broer (2017), notwithstanding the financial globalization that started in the 1980s, it appears that investors around the globe still hold excessively larger amounts of local shares in their portfolios, in comparison with the amounts of foreign equities they hold. Chan et al. (2005) observed the presence of home bias in 26 countries, though at varying degrees. Nevertheless, even when trading at an international level, investors show a strong preference for firms with local presence (Ke et al., 2010). A common justification for the existence of home bias is the absence of comprehensive information on foreign markets. Indeed, asymmetry of information between local and nonlocal investors instigates professional investors to display more optimism when dealing with their domestic equities than when dealing with international equities (Tesar & Werner, 1995) and thus "familiarity with local stocks could exacerbate the illusion of control" (Goetzmann & Kumar, 2008, p.17). To cater for the effect of home bias in the current study, our models include a dummy variable ($Fund\_Obj_{p,t}$) that distinguishes between the primary investment objective in domestic equities or in Eurozone equities of fund p in quarter t.

The noteworthy effect of the management company in attracting money inflows into mutual funds (Sánchez-González et al., 2017) might cause managers to wrongly attribute these inflows to their own performance, when in reality these flows are a consequence of the marketing and selling force of the company. This issue might be particularly relevant in the Spanish fund industry where large bank-owned companies play a more prominent role as

[2] For more information on the portfolio concentration limits: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32009L0065&from=EN

providers of mutual fund investments than in other European markets (European Fund and Asset Management Association, 2018). Our models control for these effects using three variables. First, our models include both the dummy bank-ownership ($Bank_{p,t}$) and the size ($TNA_{p,t}$) of the management company of fund p in quarter t. Finally, our models control for the flow-related trading of fund p in quarter t. To cater for this effect, the models also include the dummy variable $Flow_{p,t}$.

Our models also control for the management structure and managerial characteristics, namely gender, education and experience. Management structure might play a vital role when it comes to overconfidence. Overconfidence is expected to be more pronounced among individual managers than when fund managers work as a team. The reasoning behind this is that individual managers are more prone to the self-serving attribution bias (Adebambo and Yan, 2018). That is, compared with team managers, individual managers display a higher tendency to attribute successful outcomes to their own abilities and failures to external events. Bär et al. (2011) discussed two conflicting views in literature about the effect of management structure on investment style. On the one hand, the group shift hypothesis suggests that teams are inclined to support the decision of the leader who tends to have a high confidence level, thus making teams more inclined to overconfidence than individual managers. On the other hand, it is also suggested that team members could converge to a more rational decision and discard extreme options because of the diversity of opinions. Based on the results of their study, Bär et al. (2011) concluded that, compared with single managers, management team pursued less extreme investment styles and held more industry-diversified portfolios. However, Puetz and Ruenzi (2011) did not find any significant difference in their sample between team-managed and solo-managed funds in terms of overconfidence.

Based on previous literature, it appears that overconfidence is not solely related to a particular gender. Barber and Odean (2001) investigated the behaviour of retail investors and stated that, whilst both men and women do display signs of overconfidence, the bias is more pronounced in men than in women and this disparity is exacerbated when dealing with masculine tasks. Ludwig et al. (2017) found similar gender disparities which they ascribe to social expectations and women's general shame aversion. However, Bliss and Potter (2002), grounding their study on existing literature that suggested that women are more risk-averse and less overconfident than men, hypothesized that female fund managers would hold portfolios with less risk than did their male counterparts. Contrary to their initial hypotheses, they found that women held riskier portfolios. Furthermore, they found no significant difference in overconfidence between male and female managers, using turnover ratio as a proxy. A possible explanation for these findings is the recruitment of women with so-called masculine traits and their coping mechanisms in male-dominated industries (Gardiner & Tiggemann, 1999). To control for this gender effect, the model includes a dummy variable $Gender_{p,t}$ for fund p in quarter t.

In addition to gender, the model also controls for two managerial characteristics: education and industry experience. Several studies have investigated the relationship between the level of education and the behaviour of mutual fund managers or their performance (Andreu & Puetz, 2017; Golec, 1996; Mishra & Metilda, 2015). Andreu and Puetz (2017) concluded that managers holding simultaneously a Chartered Financial Analyst designation and a Master's in Business Administration display significantly lower risk levels in their portfolios than managers holding only one of both qualifications and that the former also tend to invest more conservatively. Mishra and Metilda (2015), by distinguishing between high school educated investors, graduates, and postgraduates, reached the conclusion that overconfidence increases with the level of education. In the current study, to create the dummy variable $Education_{p,t}$, we differentiate between fund managers who hold either a Chartered Financial Analyst designation or at least a master's degree and fund managers who do not.

When looking at the simultaneous effect of education and experience, Golec (1996) concludes that we could expect better risk-adjusted portfolios from fund managers who simultaneously held a master's in business administration and with longer tenure at their funds. With respect to experience alone, Gaba et al. (2022) supported the idea that experience made managers overconfident. They reached the conclusion that experienced mutual fund managers are less susceptible to obtain poor performance and are less likely to change their investment decisions as a result of negative performance. Gervais and Odean (2001) found that the overconfidence of traders increased in the early years of their career, but later decreased the more traders gained experience. It is important to note that because overconfidence is a phenomenon in which managers compare themselves to their peers, relative experience could be more informative than absolute experience in this case. For this reason, to appraise the effect of experience, we design the dummy variable $Ind\_Exp_{p,t}$ which takes the value 1 for the top quartile of most-experienced managers based on their cumulative years of experience in the mutual fund industry and 0 for the rest.

Finally, it should be noted that though the information about fund managers' age was available, this variable was left out due to its high correlation with industry experience and we estimated that, in this context, industry experience was more relevant and more informative.

1.4 Empirical analysis

The objective of our empirical analysis is to construct a suitable composite score for identifying overconfident mutual fund managers through the combination of measures previously used in isolation in literature to detect overconfidence. For this purpose, we assume the empirically validated hypothesis that overconfidence is enhanced in investors who experience good return records (Gervais & Odean, 2001; Puetz & Ruenzi, 2011; Statman et al., 2006).

1.4.1 Principal component Analysis (PCA)

The PCA will permit us merge all three proxies into one single measure and later determine whether there is a positive relationship between confidence level and past returns by relating the confidence level of managers of fund *p* in quarter *t* to the return of their respective portfolios in quarter *t-1*. Our general assumption is that outstanding past returns will lead managers to have relatively high levels of confidence compared with their peers. It is the contention of this study that fund managers who, when compared with others in the industry, simultaneously traded the most, deviate the most from their benchmark, and hold the highest percentage of their asset in equity are displaying overconfidence.

As shown in Table 1.2, the first principal component of the three proxies explains close to 52% of the entire sample variance, thus capturing a great proportion of the common variation. We employ the first principal component to collapse the three measures, namely, turnover ratio, active share and equity exposure, into one single measure: the confidence level (CL). In the next section, we will employ this first principal component as a single measure to determine the general relationship between the confidence level of managers in each quarter and their past performance. Subsequently it will also help us to establish the contribution of each of the three proxies in total variance based on the results of the first principal component.

In this regard, the results of the PCA indicate that all three proxies return the same sign and quite similar eigenvectors in PC_1, leading to the conclusion that the first principal component is capturing the commonalities as expected and that the three proxies have quite similar explanatory power into the total variance of the full sample.

Table 1.2 Analysis of the Principal components.

	Eigenvectors		
Proxies	PC_1	PC_2	PC_3
Turnover ratio	0.61	-0.33	-0.72
Active share	0.60	0.85	0.05
Equity exposure	0.52	-0.41	0.69
Eigenvalue %	155.41	79.14	65.45
Proportion %	51.80	26.38	21.82
Cumulative %	51.80	78.18	100.00

This table presents the principal components of the three proxies: turnover ratio, active share, and equity exposure and their respective eigenvectors. In total, we have three principal components. The last three rows provide information about the eigenvalues of the principal components, the proportion of variance they explain, and the cumulative variance explained by the proxies.

1.4.2 Past performance and Confidence Level

In this subsection, we perform an analysis of the correlation between past performance and the confidence level (CL) measured by first principal component. The aim is to explore whether there is a preliminary relationship between past performance and a single measure grouping turnover ratio, active share and equity exposure. In order words, before exploring the behaviour of managers that trade the most, deviate the most from their benchmark and hold the highest percentage of portfolio in equity, we respond to the question the possibility of a direct and simultaneous relationship between past performance and turnover ratio, active share and equity exposure.

For this purpose, we employ the first principal component as the confidence level ($CL_{p,t}$) and we measure past performance on a quarterly basis by using the average excess returns of fund p in the previous 12-month period ($\beta_E Exc\_Ret_{p,t-1}$). To compute the excess returns, depending on whether the primary investment objective of a fund p was Eurozone or domestic equities, we use EuroStoxx50 or Ibex35 as a benchmark, respectively. Given that the PCA can be extremely sensitive to outliers, we perform our analysis with and without outliers and obtained consistent results.[3]

Our first panel data regression model is restricted to solo managers for whom we include information about personal characteristics, namely gender, educational background, and industry experience:

$$CL_{p,t} = \alpha_{p,0} + \beta_E Exc\_Ret_{p,t-1} + \beta_H Herf\_Index_{p,t} + \beta_V Fund\_Obj_{p,t} + \beta_B Bank_{p,t} \\ + \beta_{FT} TNA_{p,t} + \beta_{FL} Flow_{p,t} + \beta_G Gender_{p,t} + \beta_E Education_{p,t} + \beta_{IE} Ind\_Exp_{p,t} + \varepsilon_{p,t} \quad [6]$$

To extend the scope of our analysis, we apply our model to all types of management structures, in other words both solo fund managers and teams.

$$CL_{p,t} = \alpha_{p,0} + \beta_E Exc\_Ret_{p,t-1} + \beta_H Herf\_Index_{p,t} + \beta_V Fund\_Obj_{p,t} + \beta_B Bank_{p,t} \\ + \beta_{FT} TNA_{p,t} + \beta_{FL} Flow_{p,t} + \beta_{TM} Team_{p,t} + \varepsilon_{p,t} \quad [7]$$

We then extend our analysis to our entire sample of mutual fund managers, regardless of whether we have information about the management structure of fund managers or not:

$$CL_{p,t} = \alpha_{p,0} + \beta_E Exc\_Ret_{p,t-1} + \beta_H Herf\_Index_{p,t} + \beta_V Fund\_Obj_{p,t} + \beta_B Bank_{p,t} \\ + \beta_{FT} TNA_{p,t} + \beta_{FL} Flow_{p,t} + \varepsilon_{p,t} \quad [8]$$

The results of Equations [6], [7] and [8] are presented in Table 1.3. Broadly speaking, when analysing the reduced sample that includes managers' characteristics (Equation [6]) and the entire sample (Equation [8]), our results are consistent with Puetz and Ruenzi (2011). By measuring the confidence level (CL) using the first principal component of the three most-used proxies, we find a positive relationship between confidence level and past performance. This result has an even stronger significance when extending the analysis to the entire sample of fund managers. The results of Equation [7] suggest that there is not a significant relationship between past performance and confidence level for the sample of funds for

[3] We define as outlier any absolute value greater than 1.5 times the interquartile values that we further examine within the context of the dataset.

which we have information about management structure. In subsequent sections, we will further investigate to see if this relationship is significant for high confidence level managers.

In line with Odean (1999) and Goetzmann and Kumar (2008), we reach the conclusion that there is also a positive relationship between the confidence level and the Herfindahl-Hirschman Index, meaning that funds with concentrated portfolios tend to be associated with higher levels of confidence. We also find that the management company might influence the confidence level of fund managers. It appears that solo-managers who belong to non-bank institutions are more prone to obtain higher confidence level. However, both relationships are not significant when extending the analysis to a wider sample. However, our results indicate that the bigger the management company in terms of TNA, the higher the confidence level of the fund managers. These results are strongly significant for Equations [6], [7] and [8].

Both the inflows into the funds and their dedication to either domestic or Eurozone equities seem to impact the level of overconfidence of fund managers. In line with Goetzmann and Kumar (2008), it appears that investing in domestic equities might aggravate the illusion of control. Nonetheless, our results lead to the conclusion that inflows do not positively influence overconfidence. This could be explained by the fact that the Spanish mutual fund industry is bank-dominated, and flows seem to be more a function of the marketing efforts of the bank than a result of the management of the fund (Sánchez-González et al., 2017). These results are only significant when applied to mutual funds for which we have information about management structure, which represent half of the entire sample.

When looking at the characteristics of solo managers, our results reveal that female fund managers or managers who hold either a master's degree or a Chartered Financial Analyst designation display higher levels of confidence. Industry experience, on the contrary does not appear to influence the confidence level of fund managers. As asserted by Gardiner and Tiggemann (1999), women in male dominated industries might be more inclined to exaggerate their masculine traits as a coping mechanism. Furthermore, holding either a master's degree or a Chartered Financial Analyst designation might provide fund managers with a false sense of security and lead them to rely too much on their own biased judgement, consistent with the results of Mishra and Metilda (2015).

Finally, we observe from the results of Equation [7] that the team variable is positively and significantly correlated with the confidence level of managers. These results are consistent with the group shift hypothesis mentioned in Bär et al. (2011), suggesting that fund managers in teams might be subject to groupthink.

Table 1.3 Regression analysis of confidence level based on the PCA.

	CL	CL	CL
Constant	-1.006	-1.182	-0.848
Exc_Ret	0.340	0.095	0.552
	(0.083)	(0.569)	(0.000)
Herf_Index	0.024	0.004	-0.005
	(0.020)	(0.626)	(0.481)
Fund_Obj	-0.962	-0.350	0.023
	(0.179)	(0.024)	(0.802)
Bank	-0.402	0.068	0.127
	(0.006)	(0.741)	(0.258)
TNA	0.136	0.099	0.053
	(0.000)	(0.000)	(0.000)
Flow	-0.038	-0.041	-0.026
	(0.182)	(0.084)	(0.164)
Gender	-1.041		
	(0.000)		
Education	0.871		
	(0.000)		
Ind_Exp	-0.052		
	(0.256)		
Team		0.182	
		(0.000)	
Fund Fixed Effects	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000
N	2,525	4,329	8,408

This table presents the results of the panel data regression model for solo managers, for equity funds for which we have information about management structure and for the whole sample (Equations [6], [7] and [8] in columns 2, 3 and 4, respectively). The dependent variable is the confidence level (CL) measured with the first principal component of the three proxies: turnover ratio, active share, and equity exposure. The independent variable is Excess Return (*Exc_Ret*) and the control variables in the first column are defined in detail in Appendix 1.1. Estimated coefficients are given, with p-values in parentheses underneath.

1.4.3 Overconfidence Composite Score (OCS)

We construct an overconfidence composite score in order to subsequently assess the relationship between prior performance and overconfidence through a logistic regression. To construct the OCS, first for each proxy, we rank the portfolios and generate a dummy score: 1 for portfolios that are in the top quartile at any given period and 0 for the others. The proxies receive equal weight in the OCS because in the PCA, they obtained similar eigenvalues. For this reason, to obtain the final score, we sum all three dummy scores for each portfolio and for each period. Portfolios that score 3 are classified as overconfident, corresponding to managers who concurrently trade the most, deviate the furthest from their benchmark, and hold the greatest percentage of their assets in equities.

In Table 1.4, we compare the statistics of two fund groups: Top OCS funds (belonging to managers who score 3 on the OCS) and Low OCS funds (belonging to managers who score 0 on the OCS). Because our aim is to select only the most overconfident funds, our OCS is quite restrictive and generates a skewness: Funds have a higher probability of scoring 0 than of scoring 3. As a matter of fact, the mean total percentage of funds that score 3/3 is 4.39% for the entire study period.

By and large, it can be observed that the three overconfidence proxies present clear differences between Top OCS funds and Low OCS funds, especially for the variable active share and based on the table, we can appreciate the magnitude of the difference between both groups. Another striking finding is the generally low turnover ratio, even for Top OCS funds, consistent with the statistics previously reported by Table 1.1. Because OCS is conceptually designed to identify funds that simultaneously trade the most, deviate the most from their benchmark and hold the greatest proportion of their assets in equity, it can be more accurate in distinguishing overconfidence from other potential managerial biases.

Table 1.4 Descriptive Statistics of Top OCS Funds and Low OCS Funds.

Year (Fund quarters)	OCS Group	Frequency	Turnover Ratio	Active Share	Equity Exposure
2000	TOP	4.13%	26.97%	74.50%	99.24%
(646)	LOW	49.13%	7.99%	32.60%	79.09%
2001	TOP	4.90%	25.83%	74.36%	98.91%
(668)	LOW	50.38%	6.43%	32.48%	76.77%
2002	TOP	5.19%	26.47%	79.14%	99.83%
(648)	LOW	48.74%	5.56%	31.41%	77.13%
2003	TOP	5.63%	18.73%	80.70%	98.71%
(639)	LOW	51.45%	4.95%	27.98%	75.42%
2004	TOP	4.27%	21.14%	85.22%	98.08%
(643)	LOW	50.16%	4.93%	28.12%	75.10%
2005	TOP	3.70%	21.12%	76.43%	97.92%
(664)	LOW	47.69%	5.43%	30.29%	77.74%
2006	TOP	2.64%	24.04%	78.79%	99.25%
(696)	LOW	47.44%	6.05%	29.44%	80.28%
2007	TOP	4.82%	27.37%	79.61%	99.20%
(714)	LOW	48.51%	6.42%	30.78%	81.56%
2008	TOP	5.23%	21.79%	78.97%	98.55%
(692)	LOW	49.42%	4.60%	28.19%	76.88%
2009	TOP	4.83%	26.27%	83.68%	98.71%
(627)	LOW	51.45%	5.65%	30.30%	73.69%
2010	TOP	5.40%	25.86%	82.80%	98.15%
(579)	LOW	50.17%	5.07%	31.33%	77.64%
2011	TOP	4.92%	24.59%	82.92%	96.70%
(530)	LOW	49.43%	5.16%	30.23%	76.72%
2012	TOP	3.90%	27.02%	84.99%	98.09%
(466)	LOW	45.99%	5.09%	30.81%	80.87%
2013	TOP	4.15%	22.42%	83.24%	97.65%
(411)	LOW	46.59%	5.12%	34.17%	81.24%
2014	TOP	3.26%	23.02%	80.89%	96.57%
(371)	LOW	44.57%	4.40%	36.40%	81.18%
2015	TOP	2.52%	18.80%	84.94%	96.21%
(357)	LOW	47.06%	5.10%	34.89%	84.93%
2016	TOP	3.33%	19.51%	88.92%	97.47%
(330)	LOW	43.94%	5.42%	36.23%	87.57%
2000-2016	TOP	4.39%	23.95%	80.54%	98.42%
(9,831)	LOW	48.71%	5.56%	31.00%	78.40%

This table presents a comparison of funds that score 3 on the OCS (funds which belong to the top quartile in all three overconfidence proxies) and funds that score 0 on OCS (funds which do not belong to the top quartile in none of the three overconfidence proxies). In the first column we have the year, and the total number of fund quarters analysed that year in parentheses below. For each year, we provide two rows of information: one for Top OCS funds and the other for Low OCS funds. The second column gives information about the OCS Group. The third column presents the frequency of Top OCS funds and beneath that of Low OCS funds as a percentage of the total number of quarterly portfolios. Finally, the three last columns present the average of the three overconfidence proxies included in the OCS.

1.4.4 Past performance and overconfidence

To investigate how prior performance affects overconfidence, we run a panel data logit model. A logistic regression is well fitted for this case, as our main objective here is to analyse the binary classification that, based on the OCS, could differentiate between managers who are overconfident against managers who are not. Given that the three proxies (turnover ratio, active share and equity exposure) yielded approximately equal eigenvalues, they were assigned equal weights in the OCS. Unlike Adebambo and Yan (2016), our choice of equal weights is motivated by the scoring coefficients of the proxies within the first principal component. In other words, the weight of proxies in the scoring system is determined by the result of the PCA.

Our main aim is to estimate the probability of displaying overconfidence after superior performance records. Complementary to the first principal component that provides us with a value of the confidence level of managers, the OCS will permit us create a binary classification of fund managers for each quarter (funds score 1 if OCS=3 and 0 otherwise). To estimate the past performance, at the end of each quarter we calculate the average excess returns of fund *p* in the previous 12-month period. Following Puetz and Ruenzi (2011), we use quintile ranks instead of absolute returns as professional managers pay more attention to their relative position compared with other professional managers than to their absolute performance. We classify the lagged ordinal variable $Exc\_RetRanked_{p,t-1}$ into three categories: LOW for the bottom performance quintile, MID for the three middle performance quintiles and TOP for the uppermost performance quintile.

Thus, the logistic probability function of a fund *p* being overconfident in quarter *t* after good excess returns in quarter *t-1* is:

$$Pr(Overconfidence)_p = exp(\beta' x_p)/(1 + exp(\beta' x_p)) \quad [9]$$

Where:

$$\beta'^{x_p} = \alpha_{p,0} + \beta_E Exc_{RetRanked_{p,t-1}} + \beta_H Herf_{Index_{p,t}} + \beta_V Fund_{Obj_{p,t}} + \beta_B Bank_{p,t} + \beta_{FT} TNA_{p,t} + \beta_{FL} Flow_{p,t} + \beta_G Gender_{p,t} + \beta_E Education_{p,t} + \beta_{IE} Ind\_Exp_{p,t} + \varepsilon_{p,t}$$

To extend the scope of our analysis, we apply our model to funds for which we have information about management structure, meaning both team- and solo-managed funds:

$$Pr(Overconfidence)_p = exp(\beta' x_p)/(1 + exp(\beta' x_p)) \quad [10]$$

Where:

$$\beta'^{x_p} = \alpha_{p,0} + \beta_E Exc\_RetRanked_{p,t-1} + \beta_H Herf_{Index_{p,t}} + \beta_V Fund\_Obj_{p,t} + \beta_B Bank_{p,t} + \beta_{FT} TNA_{p,t} + \beta_{FL} Flow_{p,t} + \beta_{TM} Team_{p,t} + \varepsilon_{p,t}$$

We extend our analysis to the entire sample of fund managers, regardless of the availability of the information about their personal characteristics:

$$Pr(Overconfidence)_p = exp(\beta' x_p)/(1 + exp(\beta' x_p)) \quad [11]$$

Where:

$$\beta'^{x_p} = \alpha_{p,0} + \beta_E Exc\_RetRanked_{p,t-1} + \beta_H Herf_{Index_{p,t}} + \beta_V Fund\_Obj_{p,t} + \beta_B Bank_{p,t} + \beta_{FT} TNA_{p,t} + \beta_{FL} Flow_{p,t} + \varepsilon_{p,t}$$

The previous results of the Principal Component Analysis suggested that the confidence level of managers is positively correlated with their excess returns of the previous quarter, except for the subsample for which we had information about management structure. The differentiation of LOW, MID and TOP managers in terms of past performance enables us to evaluate prior performance and overconfidence in terms of categories of prior performance through a simplified binary classification to possibly observe common patterns within each group. Thus, the results of the logistic regression models in Equations [9], [10] and [11] provide a factual analysis of overconfidence. These results are presented in Table 1.5.

Table 1.5 Logit results for managers who score 3 on the OCS.

	OCS_3	OCS_3	OCS_3
Constant	-2.373	-1.849	-0.882
Exc_RetRanked: MID	0.043	-0.191	-0.116
	(0.877)	(0.343)	(0.423)
Exc_RetRanked: TOP	1.124	0.685	0.935
	(0.000)	(0.003)	(0.000)
Herf_Index	-0.066	-0.084	-0.111
	(0.270)	(0.044)	(0.000)
Fund_Obj	2.268	1.511	1.437
	(0.000)	(0.000)	(0.000)
Bank	-0.492	-0.213	-0.209
	(0.108)	(0.335)	(0.173)
TNA	-0.093	-0.118	-0.181
	(0.123)	(0.011)	(0.000)
Flow	-0.080	0.062	-0.001
	(0.719)	(0.705)	(0.993)
Gender	-0.890		
	(0.002)		
Education	0.826		
	(0.001)		
Ind_Exp	-1.546		
	(0.011)		
Team		0.021	
		(0.899)	
Fund Fixed Effects	Yes	Yes	Yes
LR χ^2	138.86	115.57	259.88
χ^2 p-value	0.000	0.000	0.000
Pseudo R^2	0.166	0.080	0.090
N	2525	4329	8408

This table presents the results of the logit panel data model, first for solo managers, then for the equity funds for which we have information about management structure and finally for the whole sample (results of Equations [9], [10] and [11] presented in columns 2, 3 and 4, respectively). The dependent variable is the dummy variable OCS_3 which takes the value of 1 for managers who are in the top quartile of the three proxies simultaneously. The independent variable is Excess Return (*Exc_RetRanked*) divided into top, mid and low performers, with low being the base. The control variables in the first column are defined in detail in Appendix 1.1. Estimated coefficients are given, with p-values in parentheses underneath.

As hypothesized, we find compelling evidence across all samples that managers whose portfolios are in the top quintile in terms of excess returns have a significantly higher probability of scoring 3 on the OCS in the next quarter than managers with low excess return portfolios. The coefficient for mid performers with respect to low performers is not significant. We can now conclude that the impact of past performance on overconfidence is clearly driven by top performers because TOP is significantly different from LOW, whereas MID is not significantly different from LOW. Therefore, we find that the combination of turnover ratio, active share and equity exposure is significantly consistent with the evidence of overconfidence subsequent to an outstanding performance. For further robustness check, we repeat our analysis calibrating OCS to identify top overconfident mutual fund managers as the ones above the median in each proxy, instead of the top quartile and obtain consistent results.[4]

When analysing the sample construction with managers' characteristics, we also find that female managers, managers who hold either a master's degree or a Chartered Financial Analyst designation or managers in charge of funds that invest primarily in the Eurozone are more prone to overconfidence. On the contrary, industry experience appears to have a negative relationship with overconfidence: the more experienced the managers, the less likely they are to be classified as overconfidence by the OCS.

For the full sample construction and management structure construction, we find that the Herfindahl-Hirschman Index and the TNA under management by the fund company are statistically significant and negative. We also conclude that the less concentrated the portfolio or the smaller the TNA under the management of the fund company, the more likely the manager is to be overconfident. The positive coefficient of investment in Eurozone stocks and the relationship between diversification and overconfident might support the idea that Spanish managers consider the Eurozone as a wider local investment area.

1.4.5 Robustness and consistency check

To test the robustness of our OCS compared with the use of a single proxy, we repeat Equations [9], [10] and [11] by using turnover ratio, active share and equity exposure as single dependent variables. We also test the consistency of our analysis by looking into the influence of past performance on low confidence scores.

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[4] Results are available in Appendix 1.2.

Table 1.6 reports in Panels A, B and C, the results of the logit models of turnover ratio, active share and equity exposure, respectively. Panel A rejects a significant impact of good past performance on the confidence level of managers. This finding is not consistent with the overconfidence hypothesis. Similarly, Panel B reports the results of active share as a measure of overconfidence. Although active share apparently correlates well with overconfidence, we find that mid performers have a significantly lower probability than low performers of having subsequent high active share and turnover ratio. There are alternative explanations, apart from overconfidence, that could lead to significant high levels of active share for poor performers compared with mid performers, such as tournament incentives. Li et al. (2022) found that fund managers with poor performance, not having much to lose, increase the active share of their portfolio in an attempt to catch up with the others. This further confirms the utility of a composite index.

Finally, Panel C shows that the influence of past performance on equity exposure is more consistent with the overconfidence hypothesis than the other single measures, but in a smaller magnitude than the OCS. This smaller magnitude could be explained by the fact that Spanish equity funds must hold more than 75% of their portfolio holdings in equity to fulfil the rules required by CNMV. Given that managers have to meet a minimum percentage of assets in equity as a requirement, the effect of performance on subsequent equity exposure is somehow curbed just as managers use of this tool is limited.

There are atleast two advantages to the use of our OCS compared with the use of single proxies to assess overconfidence. Because these proxies have also been used to identify other behavioural biases or as measures of other phenomena, their use as measures of overconfidence is weakened and can be questioned. By combining turnover ratio, active share, and equity exposure, we are more likely to identify the most overconfident funds with a greater degree of accuracy. Secondly, our OCS provides some degree of flexibility. By matching the proportion of each proxy in the OCS, this scoring system can be adapted to fit the idiosyncrasies of each market or industry.

Finally, Panel D tests the robustness of our OCS by investigating how well it captures the behaviour of managers that are at the bottom of the confidence spectrum. Included in this panel are portfolios that are simultaneously in the bottom quartile of each proxy included in the OCS ($OCS\_0_{p,t}$)..

As supported by Bai et al. (2019), based on the assumption that confidence lies on spectrum, the presence of overconfidence implies that of underconfidence. As a whole the model fits adequately and is consistent with our previous findings. The results confirm the overconfidence theory: top performers are less likely than low performers to be classified in the bottom 25% of all three proxies of the OCS which can be equated to underconfidence. Further confirming that the effectiveness of our measure.

Mid performers, on the other hand, are more likely than low performers to be in this OCS group. These findings confirm that mid performers, followed by low performers, then by top performers are more likely to trade the least, deviate the least from their benchmarks and hold the smallest percentage of the TNA in equity. The results of top performers reinforce the evidence on generally high confidence levels subsequent to outstanding performance. Furthermore, the results of low performers are consistent with the idea that poor performers change their strategy to improve their performance records (Coval & Stafford, 2007; Ippolito, 1992; Khorana, 1996). Consequently, these results suggest that the desperate search for better return records of poor performers drives similar management patterns than overconfidence. In the next part of this analysis section, we test whether this assumption holds based on the comparison between the results in subsequent periods of low performers with high OCS and the results of high performers with high OCS.

Table 1.6 Comparative analysis of logit results.

	Panel A			Panel B			Panel C			Panel D		
	TR25	TR25	TR25	AS25	AS25	AS25	EE25	EE25	EE25	OCS_0	OCS_0	OCS_0
Constant	0.165	-0.268	0.514	0.773	0.435	1.464	0.213	-0.434	-0.480	-2.911	-2.176	-2.394
Exc_RetRanked: MID	-0.662	-0.573	-0.403	-0.338	-0.378	-0.345	0.018	-0.060	-0.052	0.529	0.455	0.355
	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.895)	(0.544)	(0.441)	(0.000)	(0.000)	(0.000)
Exc_RetRanked: TOP	-0.105	-0.075	0.045	0.952	0.957	1.142	0.422	0.343	0.380	-0.442	-0.554	-0.649
	(0.490)	(0.517)	(0.577)	(0.000)	(0.000)	(0.000)	(0.006)	(0.005)	(0.000)	(0.004)	(0.000)	(0.000)
Herf_Index	-0.120	-0.044	-0.063	0.018	-0.053	-0.089	0.012	0.003	0.013	0.033	0.014	0.030
	(0.000)	(0.013)	(0.000)	(0.460)	(0.007)	(0.000)	(0.608)	(0.869)	(0.301)	(0.107)	(0.387)	(0.009)
Fund_Obj	0.372	0.548	0.742	1.005	0.959	1.063	1.207	1.222	1.346	-0.805	-1.059	-1.338
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank	-0.055	0.271	-0.042	-1.650	-2.044	-1.590	-0.142	-0.440	-0.202	1.113	1.495	1.160
	(0.724)	(0.022)	(0.602)	(0.000)	(0.000)	(0.000)	(0.334)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)
TNA	-0.004	-0.049	-0.093	-0.047	0.001	-0.107	-0.143	-0.063	-0.086	0.106	0.064	0.116
	(0.885)	(0.019)	(0.000)	(0.106)	(0.980)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)
Flow	-0.134	-0.081	-0.099	0.258	0.239	0.154	0.048	0.008	-0.082	-0.106	-0.088	0.021
	(0.185)	(0.286)	(0.069)	(0.011)	(0.003)	(0.009)	(0.634)	(0.922)	(0.143)	(0.282)	(0.209)	(0.675)
Gender	-0.279			-0.494			-0.197	-0.178		0.339		
	(0.038)			(0.000)			(0.166)	(0.021)		(0.007)		
Education	0.239			-0.024			0.611			-0.337		
	(0.044)			(0.848)			(0.000)			(0.002)		
Ind_Exp	-0.918			-0.127			-0.232			0.521		
	(0.000)			(0.343)			(0.086)			(0.000)		
Team		0.042			-0.184						0.153	
		(0.565)			(0.024)						(0.025)	
Fund Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LR χ^2	171.37	150.79	394.98	481.35	883.56	1574.8	230.29	330.61	742.27	402.84	716.57	1536.80
χ^2 p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.061	0.031	0.042	0.162	0.179	0.171	0.082	0.070	0.079	0.115	0.120	0.132
N	2525	4329	8408	2525	4329	8408	2525	4329	8408	2525	4329	8408

This table presents the results of the logit panel data (Equations [9], [10] and [11]) when each proxy is used as a single measure. TR25, AS25 and EE25 are dummy variables that take the value 1 for funds in the top quartile of turnover ratio, active share and equity exposure respectively. OCS_0 is a dummy variable that takes the value 1 for fund that score 0 in the OCS score. Panel A, the dependent variable is TR25, meanwhile AS25, EE25 and OCS_0 are the dependent variables used in Panel B, C and D, respectively. The independent variable is Excess Return (*Exc_RetRanked*) divided into top, mid and low performers, with low being the base. The dependent variables in the first column are defined in detail in Appendix 1. Estimated coefficients are given, with p-values in parentheses underneath.

1.4.6 Consequences of overconfidence on subsequent performance

Because overconfidence serves as a motivation to trade more aggressively (Barber & Odean, 2001); a few authors have suggested that it may result in higher expected profits (Kyle & Wang, 1997). Indeed, there are some studies in previous literature that suggest that overconfidence could have a positive effect on performance. These studies are mainly theoretical models such as the work of Zhou (2015).

Contrary to what these theoretical models predict, the self-attribution hypothesis suggests that overconfident managers will rely too much on their abilities and ignore disconfirming signals, this will then lead to poorer portfolio allocation and poorer performance (Choi & Lou, 2010). Moreover, Cuthbertson et al. (2016) concluded that behavioural biases are prevalent in the mutual fund industry, and they usually lessen returns. In addition, Puetz and Ruenzi (2011) provided evidence for the fact that increased turnover linked to overconfidence affects subsequent performance negatively. Choi and Lou (2010) found evidence of worsened performance as a consequence of the self-serving attribution bias. Based on the self-serving attribution bias, our hypothesis is that subsequent to obtaining a high score on our OCS, the performance of top performing funds will be significantly deteriorated.

Following Jin et al. (2020), we employ the relative position of funds to evaluate performance. Indeed, because they belong to a highly competitive industry, fund managers might be more concerned about their relative position than about their raw returns. For this reason, using the relative position of funds in each quarter will provide us with a more accurate picture. For each quarter, we perform a normalized ranking of funds. This distribution allows us to compare the relative position of funds from one quarter to another, regardless of the change in the total number of funds over time. To normalize the distribution, we rank funds from 0 to 1 according to their excess returns above the benchmark: The fund with the highest excess returns is assigned a value of 1 and the fund with the lowest excess returns receives a value of 0.

Table 1.7 presents a comparative analysis of the difference in performance rankings of funds that score 3 on the OCS in any given quarter. We perform a Wilcoxon sign rank test to compare the performance of groups of funds in *t-1* with their performance in subsequent quarters (*t-1* minus each subsequent quarter). To better analyse the impact of overconfidence on subsequent performance, we first divide funds into three groups based on their relative ranks: TOP for the top quintile, MID for the three mid and LOW for the low quintile funds. This division will permit us to better analyse the extreme subsequent performance groups.

Consistent with empirical investigations of Puetz and Ruenzi (2011) our results reveal that overconfidence leads to poorer subsequent results for top performers. Generally, we find that the group of top performers in any given quarter *t-1* who scored 3 on the OCS in quarter *t* obtain a poorer relative performance in *t*, *t+1*, *t+2* and *t+3*: Two thirds of funds (70/107) fall in rank in the next quarter and close to 80% (84/107) obtain a lower relative position a year later. It also appears that while the mean percentile rank of top performers is 91,36% in *t-1*, it falls to 78,26% and 60,13% in *t* and in *t+3*, respectively.

In the previous section, we did not find any significant relationship between belonging to one of the three middle quintiles and scoring 3 on the OCS. Similarly, the results of the Wilcoxon sign rank test suggest that there is no significant difference in the mean percentile rank of mid quintile funds with high OCS, when comparing their performance in *t-1* with their performance in *t*, *t+1*, *t+2* or *t+3*. In other words, these results indicate that there is no significant difference in relative performance for mid performers who score 3 on the OCS.

The last panel of Table 1.7 reports the results of the Wilcoxon sign rank test for performers in the lowest quintile of performance who scored 3 in the OCS in a subsequent quarter. Generally, our results reveal that having a relatively high score in the OCS is beneficial to low performers. By and large, low performers with high OCS scores obtain a significantly higher relative performance in each of the following four quarters. More than 68% (53/77) and close to 85% (65/77) of low performers with high active share, high turnover ratio and high equity exposure in relation to their peers obtain a higher relative performance in *t* and in *t+3*, respectively.

As a whole, Table 1.7 suggests that for managers with high OCS that perform low in previous quarters subsequently perform better, while top performers with high OCS tend to fall in rank and mid performers tend to maintain their level. As suggested in the previous sections of this study and consistent with Puetz and Ruenzi (2011), scoring high on the OCS for low and mid performers does not appear to be driven by overconfidence. Based on their positive subsequent results, low performers, with the highest turnover ratio, the highest active share and the highest equity exposure might respond to a rational Bayesian learning process, meaning that they update their decision-making process after learning from their previous errors, as suggested by Puetz and Ruenzi (2011).

Table 1.7 Changes in rankings for high OCS managers using Wilcoxon sign rank test.

Panel A: High OCS TOP performers

	t-1Vs t			*t-1 Vs t+1*			*t-1 Vs t+2*			*t-1 Vs t+3*		
Sign	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected
Positive	70	4,471	2,881.5	77	4,839.5	2,884	78	4,915	2,887.5	84	5,139	2,889
Negative	32	1,292	2,881.5	26	928.5	2,884	27	860	2,887.5	23	639	2,889
Zero	5	15	15	4	10	10	2	3	3	0	0	0
All	107	5,778	5,778	107	5,778	5,778	107	5,778	5,778	107	5,778	5,778
z		4.941			6.078			6.302			6.993	
Prob > |z|		0.0000			0.0000			0.0000			0.0000	
Mean percentile rank	91.36% (78.26%)			91.36% (68.97%)			91.36% (67.97%)			91.36% (60.13%)		

Panel B: High OCS MID performers

	t-1 Vs t			*t-1 Vs t+1*			*t-1 Vs t+2*			*t-1 Vs t+3*		
Sign	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected
Positive	57	3,590.5	3,570	54	3,323.5	3,570	61	3,623	3,570	61	3,589	3,570
Negative	62	3,549.5	3,570	65	3,816.5	3,570	58	3,517	3,570	58	3,551	3,570
Zero	0	0	0	0	0	0	0	0	0	0	0	0
All	119	7,140	7,140	119	7,140	7,140	119	7,140	7,140	119	7,140	7,140
z		0.054			-0.654			0.141			0.050	
Prob > |z|		0.9566			0.5133			0.8882			0.9598	
Mean percentile rank	50.61% (49.92%)			50.61% (51.89%)			50.61% (49.84%)			50.61% (50.21%)		

Panel C: High OCS LOW performers

	t-1 Vs t			*t-1 Vs t+1*			*t-1 Vs t+2*			*t-1 Vs t+3*		
Sign	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected	Obs	Sum Ranks	Expected
Positive	21	534	1,498.5	19	470	1,496.5	17	255	1,501	11	147	1,501
Negative	53	2,463	1,498.5	54	2,523	1,496.5	59	2,747	1,501	65	2,855	1,501
Zero	3	6	6	4	10	10	1	1	1	1		1
All	77	3,003	3,003	77	3,003	3,003	77	3,003	3,003	77	3,003	3,003
z		-4.897			-5,213			-6.327			-6.875	
Prob > |z|		0.0000			0.0000			0.0000			0.0000	
Mean percentile Rank	7.87% (22.59%)			7.87% (26.58%)			7.87% (37.10%)			7.87% (47.18%)		

This table presents a comparative analysis between prior and subsequent percentile ranks of fund quarters with high OCS scores. Each panel tracks the performance of a group of funds, ranked based on their performance in *t-1*. The results of a Wilcoxon sign rank test of the difference between the performance of the group of funds in *t-1* and the performance in subsequent quarters for TOP, MID and LOW quintiles in term of performance are presented in Panels A, B and C, respectively. Finally, each panel provides information about the mean percentile rank of each group of funds, first for period *t-1* then for each of the subsequent periods in parenthesis.

1.5 Conclusions

This work constructs a score to assess the overconfidence of professional investors based on the Principal Component Analysis (PCA). This overconfidence score is based on the independent calibration of three proxies according to the relative ranks of fund managers. Fund managers who simultaneously trade the most, deviate the furthest from their benchmark, and hold the greatest percentage of their assets in equity are considered overconfident. Our overconfidence score can be adapted to other mutual fund industries or other equity fund markets by recalibrating the variables depending on the results of the PCA.

This work validates our score in the Spanish equity fund industry. We analyse one of the major mutual fund markets in the Eurozone. In accordance with the empirically validated hypothesis that overconfidence is enhanced in investors with good performance records, we find that our composite score permits the binary classification of overconfident managers with a great accuracy.

Our models also capture the following classification for the influence of past performance on overconfidence: First, top performers, then low performers are significantly more prone to show overconfidence management patterns, compared with mid performers. When it comes to low confidence, mid performers have a greater tendency to display low confidence levels, followed by low performers, then by top performers. We provide evidence supporting the hypothesis that the desperate search for better return records of poor performers might drive management patterns similar to the overconfidence of top performers.

Furthermore, our analysis reveals that the overconfidence of top performers leads to a deterioration of subsequent relative performance. However, the results of the Wilcoxon Test do not show that a high OCS is detrimental to low performing managers. Our results instead suggest that low performing managers who increase their active share, their turnover ratio and their equity exposure tend to perform better in subsequent quarters.

Finally, our study also provides some other interesting insights. First, Spanish managers' perception of Eurozone as a wider local investment universe than the domestic stock market could explain the positive impact of diversification and investment in Eurozone stocks on overconfidence. Second, coping mechanisms could explain why female managers are more prone to overconfidence than their male counterparts in a male dominated industry as is the Spanish mutual fund market. When it comes to other characteristics, we also find that managers who hold either a master's degree or a Chartered Financial Analyst designation are more prone to overconfidence, while industry experience does not seem to influence overconfidence.

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Appendix 1.1 Definition of Variables

Variables	Description
$Exc\_Ret_{p,t-1}$	Continuous variable that measures the average excess return of fund *p* with respect to a given benchmark during the previous 12-month period at the end of quarter *t-1*.
$Herf\_Index_{p,t}$	Continuous variable that measures the concentration of the portfolio holdings of fund *p* in quarter *t* using the Herfindahl-Hirschman Index.
$Fund\_Obj_{p,t}$	Dummy variable that is equal to 1 (0) for fund *p* with a primary investment objective in Eurozone (domestic) equities in quarter *t*.
$Bank_{p,t}$	Dummy variable that takes the value 1 when the management company of fund *p* is owned by a bank in quarter *t*, and 0 otherwise.
$TNA_{p,t}$	Logarithm of TNA under management of fund *p*'s company in quarter *t*.
$Flow_{p,t}$	Dummy variable that takes the value 1 for net inflows of fund *p* in quarter *t*, and 0 otherwise.
$Team_{p,t}$	Dummy variable that is equal to 1 (0) for fund *p* managed by a team (a solo-manager) in quarter *t*.
$Gender_{p,t}$	Dummy variable that is equal to 1 (0) for fund *p* managed by a male (a female) manager in quarter *t*.
$Education_{p,t}$	Dummy variable that takes the value 1 (0) for a fund *p* whose manager holds (does not hold) either a master's degree or a Chartered Financial Analyst designation in quarter *t*.
$Ind\_Exp_{p,t}$	Ordinal variable that orders the manager of fund *p* based on the percentile rank of their cumulative years of experience in quarter *t*.
$CL_{p,t}$	Confidence level measured by the first principal component of three proxies: turnover ratio, active share and equity exposure, estimated on the full sample and for the entire time period under study.
$Exc\_RetRanked_{p,t-1}$	Lagged ordinal variable that ranks the average excess return of fund *p* during the previous 12-month period at the end of quarter *t-1* into three categories: LOW for the bottom quintile, MID for the three middle quintiles and TOP for the uppermost quintile.
$OCS\_3_{p,t}$	Dummy variable that takes the value 1 for a fund *p* that is simultaneously in the top quartile of the three proxies (turnover ratio, active share, and equity exposure) in quarter *t* (OCS=3), and 0 otherwise.
$OCS\_0_{p,t}$	Dummy variable that takes the value 1 for a fund *p* that is simultaneously in the lowest quartile of the three proxies (turnover ratio, active share, and equity exposure) in quarter *t* (OCS=0), and 0 otherwise.
TR25	Dummy variable that takes the value 1 for a fund *p* that is in the top quartile of turnover ratio in quarter *t* and 0 otherwise.
AS25	Dummy variable that takes the value 1 for a fund *p* that is in the top quartile of active share in quarter *t* and 0 otherwise.
EE25	Dummy variable that takes the value 1 for a fund *p* that is in the top quartile of equity exposure in quarter *t* and 0 otherwise.

This appendix presents the definition of all the variables included in Equations [6] to [11]. The information about the management structure and gender is only available for 4,329 and 2,525 portfolios of our full sample, respectively.

Appendix 1.2 Logit results for managers who score 3 on the OCS

	OCS_3	OCS_3	OCS_3
Constant	0.652	0.035	0.909
Exc_RetRanked: MID	-0.326	-0.301	-0.163
	(0.025)	(0.005)	(0.030)
Exc_RetRanked: TOP	0.612	0.615	0.763
	(0.000)	(0.000)	(0.000)
Herf_Index	-0.082	-0.059	-0.055
	(0.003)	(0.003)	(0.000)
Fund_Obj	1.037	0.936	1.051
	(0.000)	(0.000)	(0.000)
Bank	-0.335	-0.542	-0.411
	(0.033)	(0.000)	(0.000)
TNA	-0.107	-0.071	-0.163
	(0.000)	(0.002)	(0.000)
Flow	-0.052	0.032	-0.051
	(0.630)	(0.698)	(0.403)
Gender	-0.305		
	(0.046)		
Education	0.995		
	(0.000)		
Ind_Exp	-0.960		
	(0.000)		
Team		-1.930	
		(0.054)	
Fund Fixed Effects	Yes	Yes	Yes
LR χ^2	294.28	306.34	694.10
χ^2 p-value	0.000	0.000	0.000
Pseudo R^2	0.1133	0.070	0.084
N	2525	4329	8408

This table is similar to Table 1.5, except for the selection of fund in the top median instead of the top quartile. It presents the results of the logit panel data model, first for solo managers, then for equity funds for which we have information about management structure and finally for the whole sample (results of Equations [9], [10] and [11] presented in columns 2, 3 and 4, respectively). The dependent variable is the dummy variable OCS_3 which takes the value of 1 for managers who are in the top median of the three proxies simultaneously. The independent variable is Excess Return (*Exc_RetRanked*) divided into top, mid and low performers, with low being the base. The control variables in the first column are defined in detail in Appendix 1. Estimated coefficients are given, with p-values in parentheses underneath.

Chapter 2: Do socially responsible investment funds sell losses and ride gains? The disposition effect in SRI funds[*]

"The irony of obsessive loss aversion is that our worst fears become realized in our attempts to manage them."

– Daniel Crosby

An increasing percentage of the total net assets under professional management is devoted to ethical investments. Socially responsible investment (SRI) funds have a dual objective: build an investment strategy based on environmental, social, and corporate governance (ESG) screens and provide financial returns to investors. In the current study, we investigate whether this dual objective has an influence on the behaviour of mutual fund managers in the realization of gains and losses. Evidence has shown that most investors in SRI funds invest in those funds primarily because of their social concerns. If the motivations of SRI managers align with those of SRI investors, SRI managers might then have more incentives than conventional managers to hold onto losing stocks if they feel their social value compensates for the economic loss. We hypothesize that SRI managers would be less prone to the disposition effect than conventional managers. Pertaining to the disposition effect, we do not find evidence of a difference in the behaviour of SRI fund managers compared with that of conventional fund managers. Our results hold, even when considering market trends, management structure, gender, and prior performance.

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2.1 Introduction

The demand for socially responsible investment (SRI) funds has grown exponentially in the last two decades in all major financial markets in the world. According to the Global Sustainable Investment Alliance (2018), in the five leading financial markets (Europe, United States, Japan, Canada, and Australia/New Zealand), sustainable investments rose from USD 22.8 trillion in 2016 to 30.6 trillion in 2018, a 34% increase in only two years. More recently, US SFI Foundation—The Forum for Sustainable and Responsible Investment (2020) reported a 42% increase in US-domiciled assets under management using SRI strategies over two years: from USD 12 trillion at the beginning of 2018 to USD 17.1 trillion at the start of 2020. Stated otherwise, this report affirms that ethical investments represented one in three dollars of the total value of assets under professional management in 2020 (USD 51.4 trillion). The increasing demand for ethical investments converted what was once a niche market into a mainstream investment class.

An extensive body of literature focuses on evaluating the performance of SRI mutual funds in different financial markets, especially compared with conventional funds or against benchmarks. Some studies find that SRI funds and conventional funds present no significant differences in terms of returns (Bauer et al., 2005; Kempf and Osthoff, 2008); others conclude that SRI funds earn higher returns (Kempf and Osthoff, 2007; Gil-Bazo et al., 2010); yet others find that they underperform (Renneboog et al., 2008).[1] Though it is true that SRI funds and conventional funds share similar financial objectives as they seek to find the optimum balance between risk and return, it is important to also look at the substantial difference between both types of funds. Besides the search for an adequate balance between risk and return, SRI mutual funds employ environmental, social, and corporate governance (ESG) screens to build their

[1] See Arefeen and Shimada (2020) for a global literature review and Cunha et al. (2020) for a global empirical analysis.

investment strategy. The dual objective of SRI mutual funds might have an influence, not only on their performance, but also on the behaviour of their managers (Kempf and Osthoff, 2008; Gil-Bazo et al., 2010; Benson et al., 2006).

Despite the long-standing arguments over the difference in performance of SRI funds and conventional funds, performance appears not to be the primary reason why retail investors hold SRI mutual funds. Riedl and Smeets (2017) tested and confirmed through experiments that investors hold SRI funds primarily because of intrinsic social motives, whereas financial reasons play an important, albeit limited role. Other examples of experimental studies that find similar results are Barreda-Tarazona et al. (2011), Apostolakis et al. (2018) and Lagerkvist et al. (2020).

Furthermore, Bollen (2007), Benson and Humphrey (2008) and Renneboog et al. (2011) found that SRI investors are less sensitive than conventional investors to lagged poor performance and more likely than conventional investors to keep their investment despite poor results. Durán-Santomil et al. (2019) determined that lagged sustainability scores significantly impact flows: Higher sustainability scores attract higher inflows into the fund. Similarly, Hartzmark and Susmann (2019) analysed US mutual funds and concluded that investors value sustainability, as they find a direct link between being classified as low sustainability and obtaining net outflows and inversely, being classified as high sustainability resulted in net inflows.

The implications of non-financial aspects of SRI mutual funds might go beyond performance, flows and persistence of flows, and drive not only the behaviour and expectations of retail investors, but also the behaviour and expectations of SRI mutual fund managers, their trading patterns, and investment styles.

Originally coined by Shefrin and Statman (1985), the term “disposition effect” refers to investors’ tendency to sell appreciated stocks (winners) too soon, while riding depreciated stocks (losers) too long. The purchase price is set as a reference point for appreciation or depreciation. The disposition effect is a robust and well-documented anomaly that was investigated both at investor level and at aggregate level, both empirically and experimentally (see Cici, 2012 for a pioneer study on the disposition effect of mutual fund managers; Summers and Duxbury, 2012 for an example of experimental study and Andreu et al., 2020 as an example of a recent empirical study). The disposition effect has also been investigated in financial markets worldwide, for example, in the United States by Cici (2012), in the United Kingdom by Richards et al. (2017), in France by Boolell-Gunesh et al. (2009), in Portugal by Leal et al. (2010), in Taiwan by Lee et al. (2013), and in China by Duxbury et al. (2015) and An et Al. (2019).

Pertaining to the causes of the disposition effect, Shefrin and Statman (1985) propose a theoretical framework that links the disposition effect to Kahneman and Tversky's (1979) prospect theory and to mental accounting. Shefrin and Statman (1985) propose regret aversion and a quest for pride as possible explanations for the disposition effect. Acknowledging that subsequent studies based on their work present prospect theory as the principal, if not the sole explanation behind the disposition effect, Shefrin (2007) insists on the fact that prospect theory is a basis for studying the disposition effect but cannot serve as a unique explanation for its occurrence. Shefrin (2007) warns against downplaying or disregarding the role of emotion-based explanations of the disposition effect, notably, the role of regret aversion.

Based on theoretical modelling, Barberis and Xiong (2009) and Hens and Vlcek (2011) reach the conclusion that prospect theory cannot explain the disposition effect. Although prospect theory is questioned in these works, they provide no alternative explanation. Summers and Duxbury (2012) carried out several experiments that lead to the conclusion that specific emotional states are the drivers of the disposition effect: regret after a paper loss drives holding losers, while elation after a paper gain leads to selling winners.

Because SRI investors value the social utility derived from stocks more than their financial utility (as shown by Riedl and Smeets, 2017; for example), SRI fund managers might be more willing to hold onto losing stocks if they feel that the social value compensates for the financial loss in the eyes of investors. Given that regret aversion drives holding losers and elation drives selling winners, if the priorities of managers of SRI funds are aligned with the priorities of their investors, in other words, if they value the social utility of stocks over financial utility similar to their investors, then the emotions derived from changes in prices of the stocks in their portfolio will be tempered. This will then lead to a lower disposition effect for SRI fund managers compared with conventional fund managers.

Furthermore, as supported by Kempf and Osthoff (2008) and Gil-Bazo et al. (2010), SRI fund managers trade less. As confirmed by Barber and Odean (2001), overconfidence is associated with high trading volumes. Given that SRI fund managers trade less, they might be less susceptible to behavioural biases linked to trading and thus we might expect SRI fund managers to be less subject to the disposition effect.

Akin to the title of the work of Benson et al. (2006): "Do socially responsible fund managers really invest differently?" is the question to know whether SRI fund managers trade differently. Are SRI mutual fund managers prone to hold capital losses over capital gains? How do they compare with conventional mutual funds?

Based on these interrogations, our study has several hypotheses. In the first null hypothesis, we expect that SRI fund managers would not be subject to the disposition effect. In this case, their proportion of gains realized (PGR) should not be different than the proportion of losses realized (PLR).

H1. *For SRI managers, proportion of gains realized = proportion of losses realized.*

Our second null hypothesis states that, for conventional managers, the proportion of gains (PGR) realized should be equal to the proportion of losses realized (PLR).

H2. *For conventional managers, proportion of gains realized = proportion of losses realized.*

The rejection of both H1 and H2 could lead to a potential disposition effect in both SRI and conventional managers, respectively, in the case that the proportion of gains realized were higher than the proportion of losses realized (PGR > PLR).

The third null hypothesis tests whether there are significant differences between the disposition effect of SRI managers and that of conventional managers. We hypothesize that the mean disposition spread (PGR-PLR) of SRI managers and conventional managers do not present significant differences.

H3. *Disposition spread of SRI managers = Disposition Spread of conventional managers.*

The rejection of H3 will conclude that the effect is different in SRI and conventional fund managers. In the case that H1 and H2 are not rejected, i.e., neither group of managers is found to exhibit the disposition effect, rejection of H3 would signify a difference in the realization of gains relative to losses across the two groups of managers, but not a difference in the strength of their disposition effects.

That we are aware of, the work of van Dooren and Galema (2018) is the only study that investigates the disposition effect of socially responsible investors. In their study, they analyse individual investors' portfolios and conclude that social preferences have an impact on trading behaviour. As far as we know, our study is the first to specifically investigate the disposition effect in SRI fund managers. Indeed, the literature has shown that the social inclinations of funds influence the trading volume of managers (Kempf and Osthoff, 2008; Gil-Bazo et al., 2010), that SRI funds investors prioritize the social utility of funds over their financial utility

(Riedl and Smeets, 2017) and that they are more likely to keep an investment despite poor performance (Bollen, 2007; Benson and Humphrey, 2008; Renneboog et al., 2011). It would then be interesting to know how well the behaviour of SRI fund managers compares with that of conventional fund managers and if the trading behaviour of SRI fund managers is influenced by the social inclinations of their investors.

The contribution of the current study to the existing literature is twofold. First, we contribute to the existing literature on behavioural biases, specifically the literature on the disposition effect by investigating whether the social orientation of funds has an impact on the trading behaviour of managers. The link between retail investors' social preferences and the disposition effect (van Dooren and Galema, 2018) cannot be extrapolated to fund managers without a thorough analysis.

Secondly, we improve on the existing literature that compares SRI with conventional funds of dissimilar characteristics (Kempf and Osthoff, 2008; Gil-Bazo et al., 2010). A similar methodology of creating a pool of conventional funds that match a sample of SRI funds is used by Gil-Bazo et al. (2010) and by Kempf and Osthoff (2008), SRI In the current study, each SRI fund analysed is matched with a conventional fund of similar characteristics (age, size, and global category). Though they do not match funds following a specific criterion, Kempf and Osthoff (2008) point out that SRI funds tend to be younger and smaller in size than the average conventional fund. These characteristics might have an incidence on the trading patterns of fund managers.

We do not find evidence of the impact of socially responsible strategy on the disposition effect. Pertaining to the disposition effect, our investigation does not support the hypothesis of a difference in behaviour for SRI fund managers, when compared with conventional fund managers. We obtain robust results, even when taking into consideration market trends, management structure, gender, and prior performance.

The remainder of the paper is organized as follows. Section 2 presents the data and the methodology used in the current study. Section 3 analyses the disposition effect of SRI and conventional fund managers. Section 4 concludes the paper.

2.2 Data and methodology

2.2.1 Data

Based on the data and the classification provided by Morningstar, we built a complete sample of US equity funds of the following four global categories: US Equity Large-Cap Blend, US Equity Large-Cap Growth, US Equity Large-Cap Value, and US Equity Mid-Cap. We use Morningstar's classification of sustainable investment to group funds into SRI funds or conventional funds. To carry out our analysis, we required a minimum of 5 consecutive monthly portfolios, which led to the exclusion of some SRI funds for not providing sufficient data for the analysis. Our analysis strictly required mutual funds that actively invest in equity; for this reason, index funds and funds of funds are excluded from the analysis. After applying the above filters, our database comprised 78 SRI mutual funds. For greater precision, we employed monthly portfolios to compute the disposition effect, hence, we exclude SRI funds that only report quarterly. According to Elton et al. (2010), using quarterly portfolio holdings for analysing the behaviour of equity mutual fund managers might result in distortions in the results obtained due to intra-quarter round trip trades. Our final sample of SRI funds consists of funds domiciled in the United States during the period January 2005 to December 2020 and is free of survivorship bias.

To assess the impact of socially responsible screening on the disposition effect, we built a pool of conventional funds. For this purpose, we carefully matched each SRI fund to a conventional fund. We required that the SRI fund and the conventional fund match in terms of global category, size (measured by the average total net assets of the fund during the entire period under study), and age (calculated from the inception date of the oldest share class). After filtering out SRI funds that do not report monthly portfolios, the final database comprised two sets of funds: 54 SRI mutual funds and 54 matched conventional funds.

Afterwards, we created a comprehensive database of the top 50 portfolio holdings with market values and numbers of shares for all the mutual funds in our sample and for each reporting period. These portfolio holdings employed are reported on a monthly basis. In their study, El Ghoul and Karoui (2017) demonstrated, when looking at the corporate social responsibility scores, that the top 10 holdings are representative of the entire portfolio. In this study, we decided to use the top 50 holdings, first to provide more robust results by analysing a wide range of holdings and secondly to avoid the bias of a potential window dressing effect. Indeed, given that the information about the top 10 holdings of funds is readily available to investors from financial media and from websites and brochures of asset management companies, it is more susceptible to portfolio manipulation, if any. Moreover, by employing the top 50 holdings and not the entire collection of holdings, we focused on the most representative stocks that might concurrently be the most significant to portfolio managers when building their strategy. Cash, cash equivalents, and derivative positions are excluded. The percentage of the top 50 portfolio holdings analysed is a significant portion of the funds' portfolio and, on average, represents 80.59% of the total net assets (TNA) value of the funds in our sample.

Table 2.1 provides the descriptive statistics of our sample of SRI funds and conventional funds for the period January 2005 to December 2020. The information is provided for each of the four investment categories analysed: US Equity Large-Cap Blend, US Equity Large-Cap Growth, US Equity Large-Cap Value and US Equity Mid-Cap, as well as the overall data for SRI funds and for conventional funds. In this study, we analyse more than 13,000 monthly portfolios, an average of more than 120 monthly portfolios per fund. The US Equity Large-Cap Blend category holds the highest mean total assets both for SRI funds and for conventional funds. Because of our methodical matching process, there are no significant differences in terms of average TNA neither within categories, nor between SRI funds and their conventional pair.

Table 2.1 Descriptive Statistics.

Global category	Num. of funds	Num. of portfolios	Mean total net assets (in USD million)	Mean Proportion of TNA controlled with top 50 holdings	Mean turnover ratio	Mean performance 3FF
US Equity Large-Cap Blend						
Non-SRI	26	3,346	1,201	75.53%	54.70%	-0.0048 (0.000)
SRI	26	3,483	1,159	75.62%	60.65%	-0.0043 (0.000)
US Equity Large-Cap Growth						
Non-SRI	12	1,488	763	84.35%	83.77%	-0.0045 (0.000)
SRI	12	1,573	691	90.09%	84.09%	-0.0041 (0.000)
US Equity Large-Cap Value						
Non-SRI	6	569	194	77.76%	54.37%	-0.0042 (0.000)
SRI	6	424	170	96.13%	66.90%	-0.0036 (0.000)
US Equity Mid-Cap						
Non-SRI	10	1,313	677	80.58%	79.38%	-0.0046 (0.000)
SRI	10	1,050	632	88.82%	49.46%	-0.0042 (0.000)
All categories						
Non-SRI	54	6,716	2,835	78.67%	66.16%	-0.0046 (0.000)
SRI	54	6,530	2,652	82.56%	64.88%	-0.0042 (0.000)

This table reports the descriptive statistics for our sample for the period January 2005—December 2020. The data is presented for SRI funds and non-SRI funds and according to the global categories: US Equity Large-Cap Blend, US Equity Large-Cap Growth, US Equity Large-Cap Value and US Equity Mid-Cap. This table also provides information about the total number of funds, the total number of portfolios, the average total net assets (TNA), the mean proportion of TNA controlled with the top 50 holdings and the mean monthly turnover ratio calculated as the lesser of purchases or sales, divided by average monthly net assets. The last column reports the three-factor model alphas, with p-value using Newey–West robust standard errors in parentheses.

Table 2.1 also provides information about the average monthly turnover ratio of the funds in our sample. This information is obtained from Morningstar and extracted from annual reports of funds. Contrary to Kempf and Osthoff (2008), and Gil-Bazo et al. (2010), our results show that SRI funds and conventional funds present almost similar turnover ratios on average. Moreover, we find that the difference between their turnover ratios is highly variable depending on the investment category. We also notice that SRI funds present slightly higher turnover ratios in all categories, except for US Equity Mid-Cap in which conventional funds exhibit a considerably higher average turnover ratio than SRI funds. In terms of average performance provided by Morningstar and based on the Fama and French (1993) three-factor model, alphas are negative and close to zero in all categories and for the subsets of SRI funds and conventional funds. The average alphas of SRI funds are, nonetheless, slightly higher than the average alphas of conventional funds in all categories.

2.2.2 Methods

To evaluate whether fund managers are subject to the disposition effect, we calculated the disposition spread. The disposition spread is the difference between the proportion of gains realized and the proportion of losses realized. If a fund manager is subject to the disposition effect, the proportion of gains realized will be greater than the proportion of losses realized, thus resulting in a positive disposition spread (i.e., PGR > PLR).

To compute the disposition spread, the first step is to determine, for every stock held in the portfolio, whether a sale occurs within the reporting period. Hence, we need to determine two crucial elements in our computation: the purchase price that we set as reference point and the sales price. The difference between the cost and the current price will determine whether a position is at gain or at loss. Because the information about the intra-period trading of funds is not available and therefore, the exact moment during the month when a given transaction takes place cannot be determined, studies on the disposition effect either assume trades to occur sometime during the reporting period or at the end of the reporting period. Previous studies such as that of Cici (2012) found consistent results when using average daily stock prices, based on the assumption that trades occur sometime during the reporting period and when using the stock prices at the end of the reporting period, assuming trades occurs at the end of the reporting period. Following Andreu et al. (2020), we suppose all trades occur at the end of the month. Thus, we assume the purchase price or the sales price to be the price at the end of the month. To calculate the sales price and the purchase price, we divide the reported market value of the specific stock by the number of shares, both values reported at the end of the month.

When final sales occur, i.e., when a fund exits the stock holding (Badrinath and Wahal, 2002), we have no market value to determine the sales price; we then proceed differently. First, we attempt to recover the sales price at the end of the given month from another fund that holds these shares. If this is not possible, we obtain the end-of-month price of the shares from the database of Eikon.

In the current study, additional purchases are factored in using the average purchase price as inventory method. Odean (1998) and Cici (2012) document that results of investigations on the disposition effect are consistent even when using other inventory methods such as first in, first out (FIFO), high in, first out (HIFO) or last in, first out (LIFO).

We followed the ratio-based approach proposed by Odean (1998) to compute the proportion of gains realized and the proportion of losses realized, for each fund and for each reporting period. The proportion of gains realized (PGR_t^i) and the proportion of losses realized (PLR_t^i) are computed as follows, with RG_t^i as realized capital gains, $UNRG_t^i$ as unrealized gains, RL_t^i as realized losses, and $UNRL_t^i$ as unrealized losses:

$$PGR_t^i = \frac{RG_t^i}{RG_t^i + UNRG_t^i} \quad [1]$$

$$PLR_t^i = \frac{RL_t^i}{RL_t^i + UNRL_t^i} \quad [2]$$

Computing PGR_t^i and PLR_t^i requires that their denominator be nonzero and that at least one sale takes place. The disposition spread (DISP) is the difference between the proportion of gains realized and the proportion of losses realized:

$$DISP_t^i = PGR_t^i - PLR_t^i \qquad [3]$$

A disposition spread greater (less) than zero implies that the manager has a propensity for selling gains (losses) more readily than losses (gains).

2.3 Empirical analysis

2.3.1 The disposition tendency: SRI fund managers vs non-SRI fund managers

Table 2.2 reports the mean proportion of gains realized (PGR), the mean proportion of losses realized (PLR) and the mean disposition spread (DISP) of our entire sample and of the subsets of SRI and non-SRI funds. PGR, PLR and DISP are computed for each fund monthly. In Panel A, the information is provided for the entire sample, and in Panel B, this same information is reported by category.

For the entire sample of funds in our study, we found a negative and significant average disposition spread (−0.033). Rather than suggesting a widespread disposition effect, these results imply that on average, equity mutual funds managers show a preference for realizing losses rather than gains. When the sample is divided into SRI funds and conventional funds, SRI funds appear to significantly realize losses more readily than gains, more specifically in the US Equity Large-Cap Blend category (−0.048).

Therefore, we reject hypothesis H1 that states that SRI fund managers realize gains and losses similarly. Given that SRI managers present a negative disposition spread, this behaviour is, however, not compatible with the disposition effect. On the other hand, we fail to reject hypothesis H2 that states that conventional managers display the same behaviour towards appreciated stocks and depreciated stocks. In other words, we do not find a difference in behaviour in the realization of gains and the realization of losses for conventional managers, but we find a clear pattern in SRI portfolios of the US Equity Large-Cap Blend category for the realization of losses over gains, which is just the reverse of a disposition effect.

Another important statistic provided by Table 2.2 is the percentage of funds with a mean positive disposition spread (26.9%). For the sample as a whole, less than one in three funds have a mean positive disposition spread. This is true for all categories except for US Equity Large-Cap Value funds, where the percentage of funds with a positive disposition spread peaks: 66.7% SRI funds belonging to this category present a mean disposition spread greater than 0. In terms of proportion of funds with a positive disposition spread, no significant difference is found between SRI and conventional funds, based on the Chi-Square Test in any of the categories.

Additionally, we found the differences between the disposition spreads of SRI fund managers and non-SRI fund managers to be negative (-0.028) for the sample as a whole and for two categories: US Equity Large-Cap Blend and US equity Large-Cap Growth, implying that in these cases, SRI fund managers display a stronger preference than non-SRI fund managers for realizing losses rather than gains. However, neither the positive differences nor the negative differences are statistically significant. We thus fail to reject hypothesis H3, indicating that there is an absence of difference between SRI fund managers and conventional fund managers in the realization of losses relative to gains.

Generally, our results are consistent with Cici (2012). By and large, we do not find evidence of disposition effect in equity mutual funds. Furthermore, by using higher frequency data than Cici (2012) and by differentiating between SRI and conventional funds, we find that there is no significant difference between the mean disposition spread of SRI funds and that of conventional funds, even when separating funds by investment categories. This absence of significant difference between the disposition spreads of SRI and non-SRI managers questions that alternative motives, such as social responsibility, significantly affect the elation (regret) felt by SRI fund managers in case of gains (losses) in comparison with conventional fund managers. Pertaining to the disposition effect, we do not find differences in trading behaviour between SRI fund managers and conventional fund managers.

Table 2.2 The disposition spreads of SRI and of Non-SRI funds.

Panel A: Full Sample			
	ALL funds	SRI	Non-SRI
PGR	0.257	0.236	0.277
PLR	0.288	0.282	0.295
DISP	-0.033 (0.003)	-0.047 (0.000)	-0.018 (0.320)
% funds > 0	26.9%	27.8%	25.9%
Chi-Square Test p-value		0.828	
DIFF DISP		-0.028 (0.167)	
Mann-Whitney		0.370	

Panel B: Global Category

U.S. Equity Large-Cap Blend				U.S. Equity Large-Cap Growth			
	ALL funds	SRI	Non-SRI		ALL funds	SRI	Non-SRI
PGR	0.279	0.247	0.310	PGR	0.254	0.241	0.266
PLR	0.302	0.293	0.311	PLR	0.306	0.310	0.301
DISP	-0.025 (0.200)	-0.048 (0.000)	-0.002 (0.975)	DISP	-0.054 (0.011)	-0.072 (0.071)	-0.036 (0.038)
% funds > 0	23.1%	19.2%	26.9%	% funds > 0	25%	33.3%	16.7%
Chi-Square Test p-value		0.510		Chi-Square Test p-value		0.346	
DIFF DISP		-0.046 (0.211)		DIFF DISP		-0.036 (0.374)	
Mann-Whitney		0.111		Mann-Whitney		0.908	

U.S. Equity Large-Cap Value				U.S. Equity Mid-Cap			
	ALL funds	SRI	Non-SRI		ALL funds	SRI	Non-SRI
PGR	0.212	0.221	0.204	PGR	0.230	0.214	0.247
PLR	0.213	0.218	0.208	PLR	0.276	0.258	0.295
DISP	-0.001 (0.968)	0.005 (0.906)	-0.0004 (0.849)	DISP	-0.047 (0.003)	-0.044 (0.086)	-0.050 (0.018)
% funds > 0	58.3%	66.7%	50%	% funds > 0	20%	20%	20%
Chi-Square Test p-value		0.558		Chi-Square Test p-value		1.000	
DIFF DISP		0.006 (0.865)		DIFF DISP		0.006 (0.849)	
Mann-Whitney		0.873		Mann-Whitney		0.821	

This table reports the general disposition data for the subsets of SRI funds and non-SRI funds: the mean proportion of gains realized (PGR), the mean proportion of losses realized (PLR) and the mean disposition spread (DISP) for our entire sample in Panel A and by category in Panel B. Additionally, for each panel and category, Table 2.2 provides information about the percentage of funds with a positive mean disposition spread, about the Chi-Square Test used to assess the difference in the proportion of funds with a DISP>0 for SRI and non-SRI subsets and about the difference between the mean disposition spread of SRI and non-SRI funds (DIFF DISP), with p-value of t-test in parentheses and in the last rows, p-value of Mann-Whitney test.

2.3.2 Internal, external and fund-related factors

Previous studies have established a link between the disposition effect and market trends (such as Leal et al., 2010), management characteristics (Cici, 2012, for instance), or prior performance (An et al., 2019, for example). In this part of our study, we examine through multiple lenses whether our results still hold, i.e., whether the null difference between the disposition spreads of SRI fund managers and conventional fund managers is robust when taking internal, external, and fund-related parameters into consideration.

2.3.2.1 Results structured by market trends

Kim and Nofsinger (2007) found evidence of differences in the behaviour of individual investors in bull periods compared with their behaviour in bear periods in the Japanese market. Investigating the impact of the state of the market could potentially unveil other aspects of the disposition effect. As suggested by Odean (1998), in a general scenario of rising prices, investors might tend to sell more winning stocks, because they have more opportunities to do so, given that several stocks in their portfolio have appreciated. In congruence with Odean's (1998) argument, Leal et al. (2010) expected momentum in bullish periods and contrarian behaviours in bearish periods, but they found evidence of stronger disposition effect during bull periods in the Portuguese market. Thus, a question arises in our analysis on the possibility of differences in the realization of gains and losses for SRI mutual fund managers compared with conventional managers under different market trends.

To successfully detect the bull/bear phases for the benchmark SandP500, we implemented the algorithm designed by Bry and Boschan (1971) and replicated in Pagan and Soussonov (2003). Based on this methodology, we identified the following bull periods for the time frame of the current study: January 2005 to October 2007, March 2009 to April 2011, October 2011 to May 2015, and October 2015 to December 2020. We also identify the following bear periods: November 2007 to February 2009, May 2011 to September 2011, and June 2015 to September 2015.

Panel A of Table 2.3 provides information about the state of the US equity market and the disposition effect for our entire sample. Our results suggest a general tendency to sell more losses than gains for both bullish and bearish markets. To be more specific, we obtain a disposition spread of −0.035 for bullish markets and −0.005 for bearish markets.

More interestingly, when discriminating between SRI funds and conventional funds, as per Table 2.3, Panel B, we find a disposition spread of −0.049, which implies that SRI funds exhibit a greater tendency to sell losses than gains and this tendency is strong and significant under bull market conditions. Conventional funds, on the other hand, do not present any significant pattern. However, the lack of significant difference in the disposition spreads of SRI and conventional funds remains under both market conditions.

Consequently, under bullish trends of the markets, we reject hypothesis H1 that supports that SRI managers display the same behaviour when faced with losses and when faced with gains. Given the negative disposition spread, this behaviour is however not consistent with the disposition effect. Conversely, we fail to reject H_2, the hypothesis of a difference in the realization of losses and gains for conventional fund managers in a scenario of general upward trend in stock prices. Finally, we fail to reject H_3, the hypothesis of a difference in behaviour between SRI fund managers and conventional fund managers in bullish trends.

On the other hand, under bearish trends, we fail to reject hypotheses H1, H2, and H3. Indeed, neither SRI fund managers nor conventional fund managers present significant differences in their realization of losses and gains and there is no significant difference between both groups in a scenario of general downward trend in stock prices.

Table 2.3 Disposition spreads by market trends.

Panel A: Full Sample				
	Bullish	Bearish		
PGR	0.255	0.293		
PLR	0.289	0.298		
DISP	-0.035 (0.001)	-0.005 (0.017)		
# months	108	78		
DIFF DISP	-0.031 (0.097)			
Mann-Whitney	0.088			
Panel B: Market trend and Investment Orientation				
	Bullish		Bearish	
	SRI	Non-SRI	SRI	Non-SRI
PGR	0.235	0.275	0.241	0.335
PLR	0.282	0.297	0.265	0.326
DISP	-0.049 (0.000)	-0.022 (0.232)	-0.024 (0.052)	0.012 (0.711)
DIFF DISP	-0.027 (0.198)		-0.036 (0.225)	
Mann-Whitney	0.503		0.506	

This table presents the mean proportion of gains realized (PGR), the mean proportion of losses realized (PLR) and the mean disposition spreads (DISP), for the entire sample in Panel A and for the subsets of SRI funds and non-SRI funds depending on the market trend in Panel B. This table also provides information about the number of months for each market trend and reports for each panel, the difference between the mean disposition spreads by market trend and for each subset, with p-values of t-test in parentheses and in the last rows, p-values of Mann-Whitney test.

2.3.2.2 Results structured by management characteristics

Pertaining to the relationship between the disposition effect and teams, as suggested by Cici (2012), two conflicting hypotheses arise. First, because of group objectivity, every single member of the team would feel less attached to the stocks held in the fund portfolio, thus leading to a mitigation of the disposition effect. Shefrin (2007) and Summers and Duxbury (2012) insist on the role of regret as a catalyst for the disposition effect. Contrarywise, based on the prime role of emotions in the onset of the disposition effect demonstrated by Summers and Duxbury (2012), it is possible that emotions become more extreme due to groupthink (Janis, 1972). Consequently, the behaviour of teams would be intensified compared with individuals and this would lead to a stronger disposition effect. Cici (2012) and Rau (2015) found evidence, in real life and in a laboratory-type experiment, respectively, that teams display a stronger disposition effect than individuals. Andreu et al. (2020), on the other hand, found no significant difference between the disposition effect in teams and in single managers.

In Panel A of Table 2.4, we report the statistics for the entire sample according to management structure. First, we notice that approximately two in three funds are managed by teams. We also find that, although teams present lower proportions of gains realized (0.260) and losses realized (0.295) than single managers (0.289 and 0.315, respectively), the former have a greater and stronger tendency to realize losses rather than gains. In addition, we observe that, although teams present a wider disposition spread than single managers, the difference between their disposition spreads (−0.010) is not statistically significant.

Panel B presents the statistics of team and single managers based on their investment orientation. Results are consistent with Panel A. Our findings suggest that SRI funds, especially team-managed SRI funds, are more reluctant to realize gains rather than losses. Nonetheless and consistent with our previous results, the difference between SRI and conventional funds in terms of disposition spread (−0.032) is not significant. In other words, SRI and conventional funds do not present any significant differences in disposition effect when considering management structure.

We reject hypothesis H1, as both team-managed and solo-managed portfolios reveal a tendency for SRI fund managers to realize more losses than gains. Consistent with our previous findings, the behaviour is not consistent with the disposition effect in SRI fund managers. We fail to reject hypothesis H2, suggesting that we do not find evidence of a difference in the realization of losses and gains for conventional managers in teams or individually. Finally, we fail to reject hypothesis H3, given that there is no evidence of a difference of behaviour between conventional managers and SRI managers when comparing based on management structure.

Pioneer studies in the field of behavioural finance have revealed different trading patterns for men and for women. Barber and Odean (2001), for instance, establish that men trade more frequently than women. Rau (2014) analyse gender differences in disposition effect and find that women present higher disposition effects than men, probably due to stronger loss aversion. Pertaining the disposition effect, Talpsepp (2013) does not find any significant differences between men and women.

From the statistics presented in Panel A, there is a gender asymmetry: Only one in ten funds in our sample is managed by a woman. Panel C shows that male fund managers, and especially male managers of SRI funds, might have a higher tendency to realize losses rather than gains. However, we do not find a significant difference when comparing male managers of SRI funds with male managers of conventional funds (−0.021). Contrary to Rau (2014), we do not find women to be reluctant to sell stocks below their reference prices. In the same manner as Talpsepp (2013), we do find not any significant difference in the disposition effect for our sample based on gender. More importantly, when looking at gender, SRI and conventional funds do not exhibit any significant differences in terms of disposition effect.

Therefore, when taking gender into account, we fail to reject hypotheses H1, H2, and H3. Based on our findings, neither male fund managers nor female fund managers, across both SRI and conventional groups, present significant differences in terms of the relative realization of gains and losses. Similarly, there appears to be no difference between male SRI fund managers and female SRI fund managers when compared with their respective counterparts.

Table 2.4 Disposition spreads by management structure and gender.

Panel A: Full Sample				
	Structure		Gender	
	TEAM	SOLO	MALE	FEMALE
PGR	0.260	0.289	0.288	0.241
PLR	0.295	0.315	0.313	0.292
DISP	-0.036 (0.002)	-0.026 (0.019)	-0.025 (0.030)	-0.052 (0.078)
# funds	99	55	52	6
DIFF DISP	-0.010 (0.522)		0.028 (0.342)	
Mann-Whitney	0.381		0.358	
Panel B: Management Structure and Investment Orientation				
	TEAM		SOLO	
	SRI	Non-SRI	SRI	Non-SRI
PGR	0.241	0.278	0.259	0.330
PLR	0.292	0.297	0.294	0.344
DISP	-0.052 (0.000)	-0.019 (0.329)	-0.037 (0.038)	-0.014 (0.291)
DIFF DISP	-0.032 (0.154)		-0.025 (0.246)	
Mann-Whitney	0.363		0.275	
Panel C: Gender and Investment Orientation				
	MALE		FEMALE	
	SRI	Non-SRI	SRI	Non-SRI
PGR	0.269	0.314	0.183	0.299
PLR	0.301	0.330	0.226	0.358
DISP	-0.034 (0.067)	-0.013 (0.265)	-0.043 (0.308)	-0.061 (0.278)
DIFF DISP	-0.021 (0.350)		0.018 (0.742)	
Mann-Whitney	0.374		0.275	

This table presents the mean proportion of gains realized (PGR), the mean proportion of losses realized (PLR) and the mean disposition spreads (DISP), for the entire sample in Panel A, for the subsets of SRI funds and non-SRI funds depending on management structure in Panel B and for the subsets of SRI funds and non-SRI funds depending on gender in Panel C. This table also provides information about the number of funds by management structure and by gender and reports for each panel, the differences between the mean disposition spreads of the subsets, with p-value of t-test in parentheses and in the last rows, p-values of Mann-Whitney test.

2.3.2.3 Prior performance and the disposition effect

Along the lines of the general state of the market, the performance of the entire portfolio might have an influence on the fund managers' behaviour and prompt them to sell gains more readily than losses. An et al. (2019) found a significant relationship between the disposition effect of retail investors and the performance of their portfolio. They found that when the portfolio is performing poorly, the investor is more likely to succumb to the disposition effect.

Duxbury et al. (2015) found that that house money effect (in the form of risk seeking/aversion following prior realized gains/losses) moderates the tendency of investors to succumb to the disposition effect.

To evaluate the relationship between prior performance and the disposition effect, we perform a logistic regression with the disposition effect as a dependent variable and 1-month lagged Fama and French (1993) alpha for the last 60 daily observations as an explanatory variable. The disposition effect is a dummy variable that takes the value 1 in the presence of disposition effect and 0 otherwise.

While our findings are not directly comparable to Duxbury et al. (2015), contrary to An et al. (2019), we do not find any significant relationship between the 3-month prior performance of mutual fund managers and the disposition effect, nor do we find a significant difference in the probability to succumb to the disposition effect when belonging either to SRI group, or to the conventional group. Our results are consistent when using 6-month prior performance. In other words, based on our results, we do not find any significant difference in the probability of SRI equity mutual fund managers to succumb to the disposition effect when compared with their conventional counterparts, even when taking prior performance into consideration. There is no evidence of a link between prior performance and the realization of gains relative to losses for SRI fund managers, nor for conventional managers.

Table 2.5 Logit regression of disposition effect and 3-month prior performance.

	ALL funds	SRI	Non-SRI
Panel A: Fixed effects: No			
Coef.	10.786 (0.364)	17.612 (0.268)	2.524 (0.888)
Num. of funds	107	53	54
Num. of portfolios	10,052	5,142	4,910
Panel B: Fixed effects: Yes			
Coef.	7.394 (0.552)	12.584 (0.482)	1.147 (0.951)
Num. of funds	75	38	37
Num. of portfolios	8,310	4,141	4,169

This table summarizes the output of our logistic regression model. Estimated coefficients are given, with p-values in parentheses. The reduced frequency in the number of funds and number of portfolios in the fixed effects models is due the fact that the model drops some funds because of all positive or all negative outcomes.

2.4 Conclusions

Ethical investments now represent both an increasing and important share of the investment markets in the United States. While several studies have investigated the difference in performance of Socially Responsible Investments (SRI) funds compared with conventional funds, performance appears not to be the prime reason why investors hold SRI funds. Many authors found evidence showing that investors of SRI funds are primarily motivated by their social responsibility, that they are less sensitive to poor performance and that they are more likely to keep an investment in a fund despite poor performance.

Do the social responsibility of their fund and the expectations of their investors influence how SRI fund managers realize losses and gains? In this study, we test several null hypotheses: there is no difference in the proportion of gains realized (PGR) and the proportion of losses realized (PLR), (H1) for SRI managers and (H2) for conventional managers. Finally, we also test the null hypothesis (H3) that SRI fund managers and conventional fund managers do not present significant differences in terms of disposition spreads (PGR-PLR).

Consistent with Cici (2012), we do not find evidence of a widespread disposition effect in equity mutual funds. Furthermore, the results of our investigation support the idea that there is no significant difference in the behaviour of SRI and conventional fund managers in terms of disposition effect. Interestingly, we do find that SRI fund managers might be more prone to realize losses rather than gains, especially in the US Equity Large-Cap Blend category. Despite their social responsibility, when compared with conventional fund managers, SRI mutual fund managers do not exhibit a significant different pattern of behaviour when facing losses and gains.

Based on our findings, we conclude that we reject hypothesis H1, given that SRI managers tend to realize more losses than they realize gains. This behaviour is, however, not consistent with the disposition effect. We also fail to reject hypothesis H2, as there is no evidence of differences in the realization of losses and gains for conventional managers. Finally, we fail to reject hypothesis H3: there is no significant difference between SRI managers and conventional managers, pertaining to the realization of losses and gains.

Our investigation confirms that, despite the added social preference of investors of SRI funds, SRI and conventional fund managers behave similarly when realizing losses and gains and thus might have the same motivation when taking trading decisions. The results obtained in the current study are robust for different investment categories and when taking into consideration market trends, management structure, gender, and prior performance.

More specific results could be obtained with monthly portfolios of all the SRI funds and the investigation was performed on the entire sample of SRI funds. Furthermore, more precise findings could be obtained with detailed information about the moment when trade takes place. Further analyses are warranted to determine whether the ESG scores of stocks influence the tendency to being disposed of them.

2.5 References

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Chapter 3: Sweepstakes: A Network DEA approach to mutual fund tournaments

"Investing isn't about beating others at their game. It's about controlling yourself at your own game."

– **Benjamin Graham**

Investors are attracted by well-performing funds to the point that the best performing fund, *the winner* receives a disproportionate percentage of inflows. This phenomenon, alongside other incentives such as status and monetary compensation, is the root of the tournament effect. Fund managers are said to alter the risk level of their portfolios in order to either catch up with others or to lock in their position. Data Envelopment Analysis (DEA) offers an interesting perspective to behavioural studies, given that it does not assume any pre-established functional form between the variables. In this study, we employ the DEA approach to assess how efficiently fund managers participate in the tournament. We propose and test a model divided in three phases: first, the reaction to mid-year rankings, then the recompense in terms of change in percent rank at the year-end and finally the reward in terms of inflows in the subsequent quarter. To our knowledge, this study is the first to use DEA to assess the behaviour of mutual fund managers. Our study reveals that the efficiency of fund managers in improving their year-end ranks compared to their mid-year ranks is strongly linked to how efficiently their change in rank will attract inflows. However, we find that efficiently altering the beta, the active share and the equity exposure of a portfolio is not correlated with the reward obtained at the end of the tournament. Our results are robust for an alternative time frame and for alternative variable specifications.

3.1 Introduction

The performance-chasing behaviour of mutual fund investors is a well-documented empirical phenomenon. Indeed, research has shown that investors tend to allocate capital based on the past performance of mutual funds. It is well-established that a superior relative performance for mutual funds is associated with subsequent greater money inflows (Ben-David et al., 2022; Berk & Green, 2004; Ferreira et al., 2012; Sirri & Tufano, 1998). For this reason, the significant growth spurt experienced by the mutual fund industry in the past few decades has exacerbated the competition among mutual funds managers for inflows and asset-based fees.[1]

The relationship between the performance of mutual funds and managers' subsequent attitude towards risk has received prime attention in literature worldwide. Several studies have documented that mutual fund managers actively alter the risk level of their portfolios based on their relative past performance. Some fundamental papers that provide evidence of this are Brown et al. (1996), Chevalier & Ellison (1997), Busse (2001), Huang et al. (2011) and Taylor (2003).

In their seminal research, Brown et al. (1996) concluded that mid-term losing managers, not having much more to lose, will gamble and increase the volatility of their fund portfolio, while mid-year winners will try to lock in their position and play it safe. Following this study, several authors reach a similar conclusion (Acker & Duck, 2006; Basak et al., 2008; Goriaev et al., 2005; Schwarz, 2012).

This tournament behaviour of fund managers is reinforced by the convex relationship between prior performance and money flows: While a disproportionate percentage of total

[1] In their extensive work, Khorana et al. (2005) presented a comparative study of the growth of the mutual fund industry worldwide. According to their research, in the 56 countries under study, the ratio of the total net assets of the mutual fund industry to gross domestic product (GDP) increased 7.9 points on average during the period 1996-2001. More recently, the Investment Company Institute (2020) revealed that the global assets in mutual funds hiked more than sevenfold in the last two decades, from USD 7 trillion in 2000 to USD 71 trillion in 2021.

inflows is dedicated to well performing funds, investors fail to withdraw money from underperforming mutual funds in the same proportion (Chevalier & Ellison, 1997; Gruber, 1996; Huang et al., 2007; Sirri & Tufano, 1998). Additionally, mutual fund managers have other concerns that could heighten their motivation to engage in annual tournaments: protecting their employment (Kempf et al., 2009; Khorana, 1996; Qiu, 2003), earning a higher salary (Farnsworth & Taylor, 2006; Kempf et al., 2009) or building up a reputation among their peers (Qiu, 2003).

However, contradictory findings to the expected *losers gamble while winners index* were reported by other empirical studies. There is evidence in literature that supports the notion that winners are more likely to gamble (Busse, 2001; Chevalier & Ellison, 1997; Qiu, 2003; Sheng et al., 2019; Taylor, 2003). Instead of viewing these findings as contradictory, there might be nuances to uncover in the tournament theory that has widely been studied both with parametric and non-parametric techniques. Our network approach aims to capture the actual tournament dynamics without any pre-established functional form between the main drivers of tournament behaviour.

The purpose of our study is to investigate the dynamics of tournament behaviour. Our study is part of the new sub-discipline called behavioural operational research. This sub-discipline was advocated by Hämäläinen et al. (2013) and analyses behavioural aspects with the help of operational research methods in modelling, problem solving and decision support. In accordance with on the research tasks considered by Becker (2016) as important to the new sub-discipline, our study is part of the application of operational research methods to behavioural finance within its own core paradigms.

To analyse tournament, we divide the tournament behaviour into three stages: first, how efficiently do mutual funds react to their past performance in terms of portfolio risk? Secondly, how efficiently do these risk changes impact on their subsequent performance?

And finally, how efficiently do these performance changes attract money inflows into the funds? To better analyse these tournament interactions, we employ a Network Data Envelopment Analysis (DEA). Given the complexity of modelling behavioural finance, the use of Network DEA models does not require any a priori establishment of functional forms between the explanatory factors could be especially useful in this area. For this reason, it is well suited to model complex behaviour patterns, such as tournament behaviour.

The network model of this study allows us to divide this overall interaction into single processes and thus better evaluate each stage. As summarized by Kao (2014), an overall system can be deemed efficient, even though its individual processes are, in reality, not efficient. Regarding the topic at hand, many tournament models are solely focused on mutual funds' reaction to earlier performance rankings and the subsequent performance consequences, but they omit the potential consequences in subsequent money flows. Our model overcomes this limitation by taking an overall approach to analyse the system.

To our knowledge, this study is the first to apply a Network DEA to evaluate tournament behaviour in the mutual fund industry. The current research fills the void in the existing literature on behavioural finance by using a Network DEA model to provide insights on the sequential and dynamic components within the tournament behaviour. In this study the main aim is to analyse the interaction between the tournament reaction, its recompense in terms of performance and the potential reward in the form of inflows.

We conduct our research on a comprehensive sample of Spanish equity mutual funds from January 2010 to December 2015. The characteristics of our sample are fit for a proper and complete application of our Network DEA model.

The remainder of this paper is organized as follows: Section 2 and Section 3 discuss the incentives for tournament behaviour and the DEA applications in the mutual fund industry, respectively. Section 4 presents the model and the variables. Section 5 contains the main empirical results. And finally, Section 6 concludes.

3.2 Incentives for tournament behaviour in the mutual fund industry

The literature on mutual fund tournaments mainly analyses the risk shifting behaviour of managers in relation to their mid-year performance. According to Brown et al. (1996), in the second part of the year, it is expected that mid-year losers, not having much to lose, will gamble and increase their volatility while mid-year winners will try to lock in their position and play it safe by reducing their volatility.

As suggested by Huang et al. (2011), there are two main reasons why managers could change their risk level. First, mutual fund managers and mutual fund companies, willing to maximize their profit by attracting more inflows into the fund, might reduce their risk-adjusted returns. In this regard, Ha and Ko (2017) reached the conclusion that an increase in fund risk is associated with an increase in subsequent net flows. Investors, on other hand, would rather prefer to maximize their risk-adjusted returns. This scenario unveils a potential agency conflict between mutual fund managers and investors. The second reason for employing risk shifting strategies might be to take advantage of time-sensitive investment opportunities. If risk shifting responds to superior active management abilities, one would expect funds that shift risk to subsequently perform better. However, Huang et al. (2011) found that funds that have a higher tendency to increase the risk level, subsequently obtain poorer results.

There are three crucial factors that come into play in the generation of tournament behaviour in the mutual fund industry. First and foremost, consistent evidence presents past performance rankings as one of the topmost decisive factors in investors' choice of a mutual fund (Capon et al., 1996; Sirri & Tufano, 1998). This, added to the fact that for their services to investors, mutual fund companies typically charge a fee that is calculated as a fixed percentage of the money invested into the fund (Gil-Bazo & Ruiz-Verdú, 2009), results in best performing funds subsequently attracting the highest money inflows and thus increasing their revenue (Chevalier & Ellison, 1997; Gruber, 1996; Sirri & Tufano, 1998). A recent study by Ben-David et al. (2022) concluded that investors rely more on simplistic performance indicators that are readily available such as fund rankings and ratings than on complex performance measures. This suggests that prior period fund rankings could a better predictor of subsequent inflows into funds and subsequent flows across funds than more complex performance measures.

Secondly, Kirchler et al. (2018) emphasized that mutual fund managers also have non-monetary incentives: an intrinsic incentive related to self-image and an extrinsic incentive related to the status derived from performing better than their peers. Relatedly, the results of O'Connell and Teo (2009) supported the view that professional investors' self-worth is more connected to their investment abilities; because they manage other people's account, and their past performance is often made public. Sheng et al. (2019) noticed that managers typically have two main monetary compensation incentives: an explicit incentive which is a fixed percentage of the assets under management and an implicit incentive which is derived from the future inflow attracted by their current performance. Thus, alongside non-monetary interests, managers have reasonable monetary interests in performing better than other managers in their field. Clearly, performing better than their peers will attract more money inflows into the mutual fund (Farnsworth & Taylor, 2006; Khorana, 1996) and will improve their self-image and manager status with respect to their peers (Qiu, 2003). The analysis of Kempf et al. (2009) suggested that when there is some prospect of employment risk, interim losers tend to decrease their risk compared with winning managers, in an attempt to secure their jobs. It also supports the idea that in the presence of low employment risk, compensation incentives become the main drivers of managers' behaviour.

Finally, empirical evidence shows that there is not a proportionate outflow of money in the poorest performing funds, clearly signifying an asymmetry in the prior performance-flow relationship (Chevalier & Ellison, 1997; Gruber, 1996; Huang et al., 2011; Sirri & Tufano, 1998). In other words, the penalization for interim losers is disproportionately lower than the gain in inflows derived by interim winners. This asymmetry then generates a stronger incentive for underperforming managers (interim losers) to gamble by increasing their volatility in order to catch up with better performing funds by year end.

Nevertheless, there is no consensus in literature on the level of performance that drives fund managers to increase the volatility of their portfolios. Chevalier and Ellison (1997) provided evidence of increase in tracking error of portfolios consistent with tournament theory, specifically in the last quarter of the year. Sheng et al. (2019) concluded that funds with a mid-year performance above the median have a greater tendency to hold risky assets in order to maintain the lead. It should be noted that Busse (2001), using the same data as Brown et al. (1996) but with a higher frequency, did not find evidence of interim losers changing their risk level. Taylor (2003), based on a theoretical model, suggested that when both managers compete against a publicly available benchmark, the winners are more likely to gamble. Qiu (2003), based on empirical evidence, showed that managers closer to the top are more likely than actual top performers to gamble because of the "winner takes all phenomenon" and that employment concerns curb underperformers' excess risk-taking behaviour. Relatedly, Keasey et al. (2000) investigated sub-units within organisations and found that being closer to the top increased the risk-seeking behaviour of managers of these sub-units.

Rather than viewing the mixed findings as contradictory, we believe there are more nuances to uncover in the tournament theory than the simplistic view that losers will gamble, and winners will index. Our Network DEA model does not assume any functional relationship between the variables in the tournament dynamics, thus it allows us to build a network approach that captures the actual tournament interactions without any pre-established functional forms.

3.3 DEA applications to mutual funds

DEA is a non-parametric frontier model that was first introduced by Charnes et al. (1978) to evaluate the efficiency of decision-making units (DMUs). Exhaustive reviews of real-world DEA applications confirm the wide use of this method in assessments in the financial industry (Cook & Seiford, 2009; Emrouznejad & Yang, 2018; Liu et al., 2013). In the mutual fund industry, one of the main DEA applications is the evaluation of mutual fund performance. This non-parametric frontier approach may be considered as an alternative to traditional performance measures such as risk-adjusted returns and alphas (Fama & French, 1993; Jensen, 1968; Sharpe, 1966).

Murthi et al. (1997) presented a pioneer study employing DEA to assess mutual fund performance. Murthi et al. (1997) stressed three main advantages of DEA over parametric performance models. First, DEA is flexible and enables the use of multiple inputs and outputs simultaneously. Secondly, DEA compares decision-making units with similar inputs and outputs against each other. In this regard, it allows not only the identification of inefficient units but also the evaluation of the magnitude of their inefficiency. Applied to the mutual fund industry, DEA maps the position of each fund relative to the frontier formed by the most efficient ones, revealing which funds are lagging behind in terms of the given inputs and outputs and which factors drive this inefficiency. Finally, DEA does not require any functional form in the multiple input-multiple output relationship. In this sense, it removes the obligation to set parametric connections between inputs and outputs.

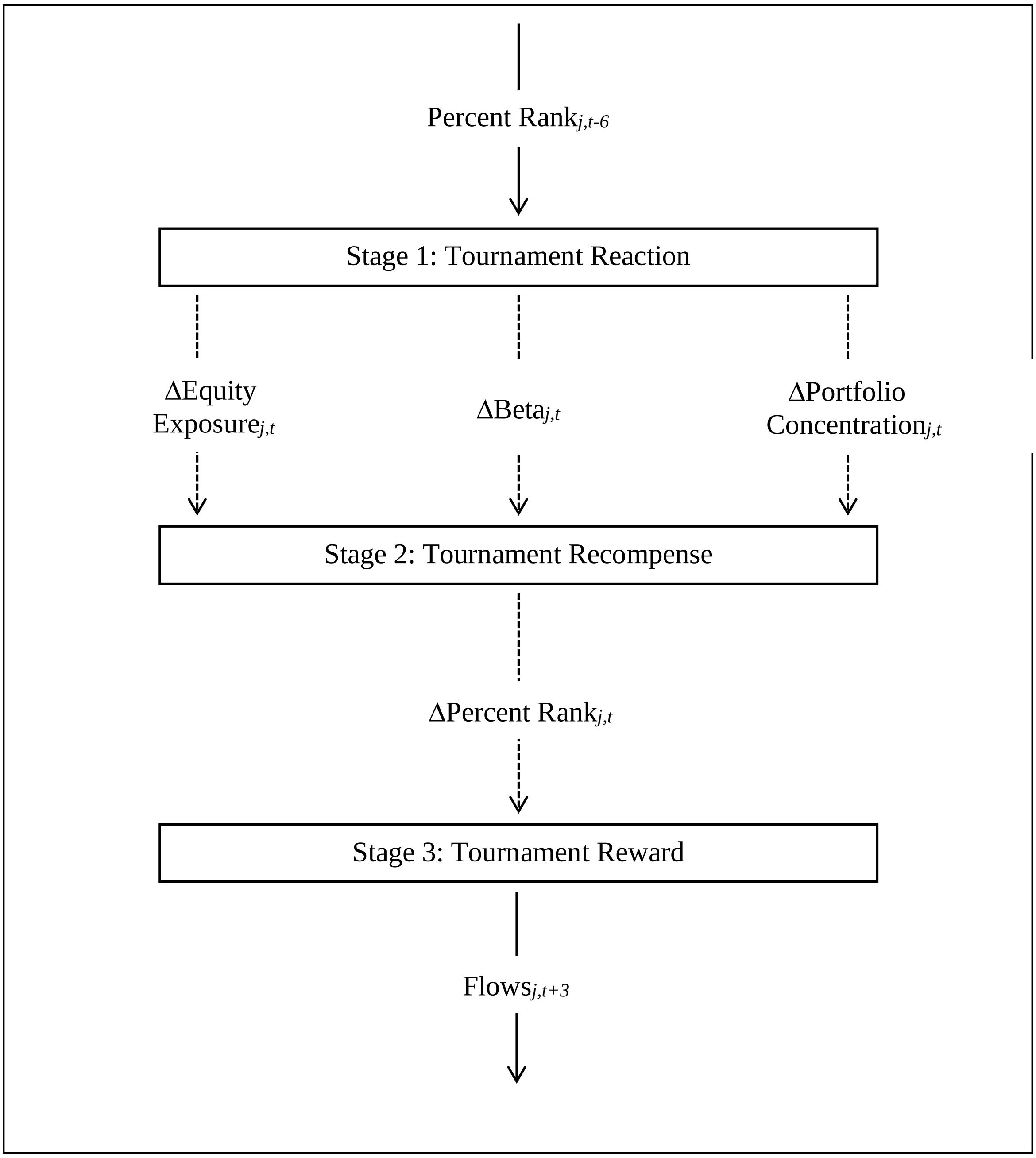
Based on these three advantages, many papers have extended the initial approach of Murthi et al. (1997) to assess mutual fund performance. Some examples of this increasing literature are Badrizadeh and Paradi (2020), Basso and Funari (2001, 2003, 2007), Chang (2004), Choi and Murthi (2001), Daraio and Simar (2006), Galagedera and Silvapulle (2002), Galagedera et al. (2018), Gregoriou (2006), Haslem and Scheraga (2003), Lamb and Tee (2012a), Lin and Li (2019), Lozano and Gutiérrez (2008), and McMullen and Strong (1998). Lamb and Tee (2012b) compensated for the lack of theoretical framework in the growing literature that employs DEA to construct return-risk ratios for mutual funds. Additionally, an increasing number of studies have used DEA to analyse other aspects of the mutual fund industry, such as mutual fund companies (Premachandra et al., 2012; Sánchez-Gónzalez et al., 2017), mutual fund managers (Andreu et al., 2019; Banker et al., 2016), the influence of size on performance (Basso & Funari, 2017; Tuzcu & Ertugay, 2020) and portfolio rebalancing (Zhou et al., 2018).

Despite the increasing DEA literature on mutual fund performance, there is a lack of DEA research on the behavioural dynamics of the mutual fund industry. Given the descriptive nature of the field of behavioural finance, defining a model can be complex in behavioural finance. DEA is especially relevant in this context as it does not require the establishment of any functional forms. Recent developments in the Network DEA methodology are leading to a new literature aiming to model complex behavioural patterns. Our paper aims to be part of this new literature.

3.4 Model and variables

3.4.1 Proposed network structure

Figure 3.1. Three-stage network of mutual fund tournaments.



This figure shows the tournament interactions in a mutual fund *j* as a three-stage network structure. *Percent Rank*$_{j,t-6}$ is the input variable at Stage 1: Tournament Reaction, and *Flows*$_{j,t+3}$ is the output variable at Stage 3: Tournament Reward. There are also four intermediate variables (dotted lines). *ΔEquity Exposure*$_{j,t}$, *ΔBeta*$_{j,t}$, and *ΔPortfolio Concentration*$_{j,t}$ are outputs at Stage 1: Tournament Reaction and are used as inputs at Stage 2: Tournament Recompense; *ΔPercent Rank*$_{j,t}$ is an output at Stage 2: Tournament Recompense that is considered as an input at Stage 3: Tournament Reward.

To the best of our knowledge, our approach is the first application of a Network DEA structure to analyse dynamic behaviour in the mutual fund industry. Our model (Figure 3.1) aims to capture the tournament interactions in a mutual fund *j* as a three-stage network structure. The three sequential stages are Tournament Reaction Stage, Tournament Recompense Stage and Tournament Reward Stage (hereafter also referred to as the Reaction Stage, the Recompense Stage, and the Reward Stage, respectively). At the Reaction Stage, our network approach captures the reaction of mutual fund managers as a change in the risk level of their portfolios in the second half on the year (from month *t-6* to month *t*), as a consequence of their relative performance in the first half of the year (measured at month *t-6*). At the Recompense Stage, our model evaluates the impact of this risk management on their year-end relative performance. That is, the Recompense Stage evaluates if there are changes in the relative performance of managers in the second half on the year as a consequence of the tournament behaviour. Finally, at the Reward Stage, our model evaluates the success of this tournament behaviour based on the money inflows into funds in the first trimester of the subsequent year (from month *t* to month *t+3*). Thus, our three-stage approach differentiates the timing of the tournament response of the manager to the prior relative performance of fund *j* and the potential consequences of that behaviour in terms of money flows, as they are not simultaneous.

In accordance with the review of Network DEA models in Kao (2014), Figure 3.1 corresponds to an extension of a basic two-stage into a basic three-stage network structure. Our network structure also includes a dynamic component and the different model variables correspond to sequential points in time to reflect the dynamic behaviour of mutual fund tournaments. The use of four intermediate variables as both outputs of Reaction Stage and inputs of the Recompense Stage might raise concerns related to the curse of dimensionality in our three-stage structure and special attention must therefore be paid to the DEA convention that the minimum number of decision-making units analysed, in this case mutual funds, should be greater than three times the number of variables (Coelli et al., 2005).

At the Reaction Stage, mutual fund *j* reacts to its performance ranking in the previous period from month *t-6* to month *t* by changing its risk level through three different mechanisms: 1) the percentage of the portfolio allocated to equity assets as representative of the most risky asset,[2] 2) the portfolio beta as representative of the systematic risk, and 3) the portfolio concentration as representative of the idiosynchratic risk. This timeline is consistent with the seminal paper of Brown et al. (1996) and subsequent studies such as Busse (2001), Goriaev et al. (2005) and Taylor (2003), to name a few.

Huang et al. (2011) identified three mechanisms through which mutual funds can shift risk: by modifying their liquidity ratio, by altering their exposure to systematic risk or by changing their exposure to idiosyncratic risk. Indeed, to increase the level of risk, mutual fund managers can reduce their cash holdings and/or increase their equity holdings, all other things being equal. They can also replace low beta stocks with high beta stocks, thus increasing their exposure to systematic risk. Finally, they can concentrate their holdings on fewer stocks or fewer industries, thus increasing their exposure to idiosyncratic risk.

The rationale behind this Reaction Stage is consistent with the seminal paper of Brown et al. (1996) who concluded that losing managers, not having much more to lose, will tend to gamble and increase their levels of portfolio risk, while winners will try to lock in their positions by playing it much safer than those managers at the bottom of performance ranking. Thus, a fund with a poor relative ranking in month *t-6* with significant increases in equity portfolio allocation, portfolio beta and portfolio concentration will lead to high DEA scores at the Reaction Stage, providing evidence of an important tournament response. On the other

[2] See Ibbotson and Harrington (2021) for an analysis of historical returns of the major asset classes of the US market.

hand, a fund with a poor relative ranking in month *t-6* with small changes in its portfolio risk will provide low DEA scores and thus a weak tournament response. Our model could even lead to lower DEA of winning funds compared to losing funds when the former tries to lock their previous performance positions with decisions on equity portfolio allocation, portfolio beta and portfolio concentration contrary to risk-shifting strategies. Further, the Reaction Stage also covers the scenario of winning funds gambling more than losers (Busse, 2001; Sheng et al., 2019). In this case, the values of the prior relative rankings (considered as inputs at this stage), and the magnitude of the subsequent changes in the portfolio risk (considered as outputs at this stage) will rank the intensity of the tournament reaction of both winners and losers and therefore the DEA score obtained in this stage.

At the Recompense Stage, our model evaluates how efficient the active risk management is. This efficiency is evaluated in terms of the impact of the tournament response on the subsequent performance rankings. The first aim of mutual fund managers who display tournament behaviour is to improve their previous performance ranks. The Recompense Stage evaluates whether the efforts of managers in the tournament have brought about any changes in their performance ranks. Thus, the outputs at the Reaction Stage are now the inputs of the Recompense Stage, building the first linking node in our network structure. Significant improvements in the subsequent performance ranking will lead to higher DEA scores with smaller increases of portfolio risk rather than with larger increases of portfolio risk. On the other hand, negative consequences in the subsequent performance ranking will be represented by lower DEA scores with larger risk-shifting strategies rather than with less important risk changes.

Finally, at the Reward Stage our model goes further still and evaluates how visible the impact of tournament behaviour has been in terms of money flows. Previous literature has extensively provided evidence for the "winner takes all phenomenon" in which winning funds capture a disproportionate share of total inflows (Chevalier & Ellison, 1997; Gruber, 1996; Huang et al., 2007; Qiu, 2003; Sirri & Tufano, 1998). The main aim of a tournament response to performance ranking is the improvement of the future performance ranking. Indeed this improvement is not only motivated by the need for good reputation, which could be really important for managers' own career plan, but it is also extremely important for mutual funds in terms of money flows, as these flows can be a relevant part of the fee structure of the mutual fund company.[3] Thus, the input of the Reward Stage is the output of the Recompense Stage, building the second linking node in our network structure. Those funds that obtain significantly higher flows as a consequence of minor changes in the performance ranking after tournament will lead to the highest DEA scores at the Reward Stage, while significantly lower flows after significant improvements in the performance ranking will lead the lowest DEA scores because this positive and significant impact of tournament behaviour is not importantly noticed by investors.

Our three-stage network structure is adequate to evaluate the tournament behaviour of a mutual fund as a whole through the screening of 1) the relevance of the tournament response in terms of risk management, 2) the impact of this response on the subsequent performance ranking, and 3) the visibility of this impact in terms of gains of money flows. Otherwise, a significant tournament response of a mutual fund with a significant positive impact on its relative performance could be far from valuable for the fund if this efficient tournament behaviour is not finally noticed and translated into money flows. Further, our three-stage approach also allows for the evaluation of each individual stage included in our network structure and overcomes the problems of overall systems that can be deemed efficient, even when its individual processes are not.

[3] This effect might be particularly relevant in mutual fund industries in which management fees are largely based on assets under management instead of performance-based fees, such as in the target market of our empirical analysis, Spain (Díaz-Mendoza et al., 2014).

3.4.2 Methodological approach

In this section, we describe the suitable procedure to model the network structure presented in Figure 3.1. We work with n funds (j = 1, …, n) consisting of 3 stages (k = 1, 2, 3). Let m_k and r_k be the numbers of inputs and outputs to stage k, respectively. The link from stage k to stage h is denoted by (k,h) and the set of links by L. The inputs of fund j at stage k are $\{x_j^k \in R_+^{m_k}\}$ and the outputs of fund j at stage k are $\{y_j^k \in R_+^{r_k}\}$, where (j=1,…, n; k= 1, 2, 3). The link variables from stage k to stage h are $\left\{z_j^{(k,h)} \in R_+^{t(k,h)}\right\}$ (j=1,…, n; $(k,h) \in L$), where $t_{(k,h)}$ is the number of items in link (k,h). $\lambda^k \in R_+^n$ is the intensity vector of stage k, and s^{k+} and s^{k-} are the non-negative vectors of input excesses and output shortfalls, respectively.

We follow the variable returns-to-scale (VRS) hypothesis because it evaluates efficiency better when not all the funds operate at optimal scale. Thus, the convex hull of the existing funds spans the production possibility set P.

$$P=\{(x^k,y^k,z^{(k,h)}) \setminus x^k \geq X^k\lambda^k,\ \ y^k \leq Y^k\lambda^k,\ \ z^{(k,h)}=Z^{(k,h)}\lambda^k,\ \ z^{(k,h)}=Z^{(k,h)}\lambda^h,\ \ e\lambda^k=1,\ \ \lambda^k \geq 0\} \qquad [1]$$

The exclusion of $e\lambda^k=1$ from Equation [1] would lead to the definition of the production possibility set P under the constant returns-to-scale (CRS) hypothesis.

We follow the widely used slacks-based measure (SBM) proposed by Tone (2001) to solve the network structure of tournaments proposed in Figure 3.1. SBM is a non-radial DEA model for measuring efficiency when inputs and outputs may change non-proportionally. SBM works with excess inputs and output shortfalls simultaneously and can be applied under CRS and VRS assumptions.

According to the non-oriented VRS approach of the SBM model, a target fund $\left\{x_o^k,\ y_o^k\right\}$ will be considered as efficient at stage k in terms of Pareto-Koopmans when it has no input excesses and no output shortfalls for any optimal solution, i.e., $\rho_o^{SBM_k}=1$.

$$\rho_o^{SBM_k}=\min_{\lambda^k,s^{k-},s^{k+}} \frac{1-\frac{1}{m_k}\left(\sum_{i=1}^{m_k}\frac{s_i^{k-}}{x_{io}^k}\right)}{1+\frac{1}{r_k}\left(\sum_{r=1}^{r_k}\frac{s_r^{k+}}{y_{ro}^k}\right)} \qquad [2]$$

subject to

$$X^k\lambda^k+s^{k-}=x_o^k$$
$$Y^k\lambda^k-s^{k+}=y_o^k$$
$$e\lambda^k=1$$
$$\lambda^k,s^{k-},s^{k+}\geq 0,$$

Where $X^k=\left(x_1^k,\cdots,x_n^k\right)\in R^{m_k\times n}$; $Y^k=\left(y_1^k,\cdots,y_n^k\right)\in R^{r_k\times n}$. In this approach, the link variables $Z^{(k,h)}$ and their slacks must be included in the sets of ordinary inputs X^k or outputs Y^k previously defined in our network structure (Figure 3.1). Let $\left(\lambda_o^{k*},s_o^{k-*},s_o^{k+*}\right)$ be an optimal solution of the model presented in Equation [2]. The reference set R_o to the target fund at stage k is defined as those funds corresponding to the positive values of the intensity vector.

$$R_o=\left\{j\backslash\ \lambda_j^{k*}>0,\ j=1,\ldots \mathrm{n}\right\} \qquad [3]$$

According to Tone (2001), the target fund $\left\{x_o^k,\ y_o^k\right\}$ can be projected in terms of the funds included in the reference set R_o at stage k, as follows:

$$\bar{x}_o^k=x_o^k-s_o^{k-*}=\sum_{j\in R_o}x_j\lambda_j^* \qquad \bar{y}_o^k=y_o^k+s_o^{k+*}=\sum_{j\in R_o}y_j\lambda_j^* \qquad [4]$$

Following Tone and Tsutsui (2009), there are two major alternatives for evaluating tournaments as represented in Figure 3.1: an SBM-based separation model and a Network SBM model. In the SBM-based separation approach, we could evaluate each of the three stages individually using intermediate variables as ordinary inputs or outputs as in the aforementioned SBM model (2), thereby omitting any continuity between the Reaction Stage, the Recompense Stage and the Reward Stage. However, we reject this SBM-based separation model as the main approach because it would not capture the interaction between the three stages proposed in our network dynamics of mutual fund tournaments.

In the NSBM approach, Tone and Tsutsui (2009) proposed the weighted SBM model (Cooper et al., 2007; Tsutsui & Goto, 2009) to decompose the overall score of the network structure into a weighted score of partial efficiencies where the weights are set exogenously. We follow one of the NSBM extensions proposed by Tone and Tsutsui (2009) to integrate the slacks of the link variables individually and independently into the NSBM objective function.

After setting exogenously the relative importance w^k of stage k in the overall efficiency measure, this NSBM approach evaluates the non-oriented overall efficiency of a target fund $\{x_o^k, y_o^k, z_o^{(k,h)}\}$ under the VRS assumption, including the slacks $s^{(f,k)-}$ of the intermediate input to stage k at link (f,k), and the slacks $s^{(k,h)+}$ of the intermediate output from stage k at link (k,h) as follows:

$$\rho_o^{NSBM} = \min_{\lambda^k, s^{k-}, s^{k+}, s^{(f,k)-}, s^{(k,h)+}} \frac{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{m_k + \sum_{f \in P_k} t_{(f,k)}} \left(\sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k} + \sum_{f \in P_k} \frac{s_f^{(f,k)-}}{z_{fo}^{(f,k)}} \right) \right]}{\sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k + \sum_{h \in F_k} t_{(k,h)}} \left(\sum_{r=1}^{r_k} \frac{s_r^{k+}}{y_{ro}^k} + \sum_{h \in F_k} \frac{s_h^{(k,h)+}}{z_{ho}^{(k,h)}} \right) \right]} \qquad [5]$$

subject to

$$\begin{array}{llll}
X^k \lambda^k + s^{k-} = x_o^k & Y^k \lambda^k - s^{k+} = y_o^k & e\lambda^k = 1 & (k=1,2,...,K) \\
Z^{(f,k)} \lambda^k + s^{(f,k)-} = z_o^{(f,k)} & Z^{(f,k)} \lambda^f = Z^{(f,k)} \lambda^k & \forall f,k & \\
Z^{(k,h)} \lambda^k - s^{(k,h)+} = z_o^{(k,h)} & Z^{(k,h)} \lambda^h = Z^{(k,h)} \lambda^k & \forall k,h & \\
\lambda^k, s^{k-}, s^{k+}, s^{(f,k)-}, s^{(k,h)+} \geq 0 & & \forall f,k,h &
\end{array}$$

Where P_k is the set of stages having the link $(f,k) \in L$ (predecessor of stage k), and $t_{(f,k)}$ is the number of intermediate variables in that link; and F_k is the set of stages having the link $(k,h) \in L$ (successor of stage k), and $t_{(k,h)}$ is the number of intermediate variables in that link. A company will be overall efficient under the NSBM model in Equation [5] when the optimal input and output slacks (s^{k-*}, s^{k+*}) together with optimal intermediate input and output slacks $(s^{(f,k)-*}, s^{(k,h)+*})$ result in $\rho_o^{NSBM} = 1$.

Our NSBM model is aligned with the cooperative approach proposed by Liang et al. (2008) to evaluate two-stage processes. According to the rationale of the network structure of mutual fund tournaments in Figure 3.1, we cannot assume leader or follower stages for the evaluation of the whole tournament dynamics because all of them are part of the success or failure of this mutual fund behaviour. For instance, could we consider as a tournament success a significant increase in the performance ranking after a risk-shifting strategy? The answer would depend on the improvement in subsequent money flows. On the contrary, a significant improvement of these money flows after a decrease in the performance ranking could respond to other mechanisms different from tournaments. This alignment with the cooperative rationale will result in a more centralized result of the intermediate variables as assumed by our NSBM approach. Further, the importance w^k of each stage k in the NSBM model presented in Equation [5] is exogenously defined to provide different weights compared with the equal weight assumption that assigns the same importance to all. This exogenous definition could be based on different criteria and should be justified in terms of importance for the model. In case of a neutral approach to tournament dynamics where the response, recompense a reward could have equal importance, an equal weight w^k for each stage k seems the most appropriate exogenous definition.

Our empirical application will analyse the SBM-based separation model and the Network SBM model (NSBM) previously described in this section to assess the robustness of our approach.

3.4.3 Inputs, intermediate variables and outputs

Table 3.1 lists and defines the inputs, outputs and intermediate variables used in our three-stage network representation of mutual fund tournaments in Figure 3.1.

These variables are obtained for three different sequential periods depending on when the tournament stage occurs each year, i.e., months *t-6*, *t* and *t+3*, thereby capturing the time dynamics of the model. We set the mid-year term (*t-6*=30th June) as the onset of managers comparison of their performance rankings against that of the rest of their peers and the starting point for the Reaction Stage. With reference to this, the subsequent period refers to the end of the year when the tournaments have taken place (*t*=31st December). This two-period model is based on the suggestion of Brown et al. (1996) and is similar to the one used in Karoui and Meier (2015) and Schwarz (2012). Finally, *t+3* refers to the end of the subsequent quarter (31st March) once the tournaments are over and when the short-term flows response to previous performance results is expected to have materialised. According to tournament (Brown et al., 1996) and flows literature (Berk and Green, 2004; Chevalier and Ellison, 1997; Sirri and Tufano, 1998) this baseline (June-December-March) covers the most accurate time sequence for tournaments within the year and short-term flows response. However, the empirical application of our model also allows for alternative specifications of this baseline time frame to get robust evaluations of the tournament behaviour for different time dynamics.

Where necessary and appropriate, variables listed in Table 3.1 are normalised in the range [0,1], in the same line as Sánchez-González et al. (2017) and Andreu et al. (2019).[4] This scaling down removes the potential time effects from tournaments and overcomes the problem of negative values of these variables in the NSBM model represented by Equation [5].

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[4] This rescaling subtracts the minimum value recorded for the variable from each fund's value in the variable and divides the result by the difference between the maximum and minimum value of the variable in the period.

Table 3.1 Inputs, outputs and intermediate variables.

Stage	Inputs	Outputs
Tournament Reaction	*Percent Rank$_{j,t-6}$* is the percentile rank of the cumulative gross return of fund *j* from 1st January to 30th June.	***ΔEquity Exposure$_{j,t}$*** is the normalised variation of fund *j* in its portfolio allocation to Equity from 30th June to 31st December. ***ΔBeta$_{j,t}$*** is the normalised variation in the CAPM beta of fund *j* from 30th June to 31st December. ***ΔPortfolio Concentration$_{j,t}$*** is the normalised variation in the Herfindahl-Hirschman index of portfolio of fund *j* from 30th June to 31st December.
Tournament Recompense	***ΔEquity Exposure$_{j,t}$*** is the normalised variation of fund *j* in its portfolio allocation to Equity from 30th June to 31st December. ***ΔBeta$_{j,t}$*** is the normalised variation in the CAPM beta of fund *j* from 30th June to 31st December. ***ΔPortfolio Concentration$_{j,t}$*** is the normalised variation in the Herfindahl-Hirschman index of portfolio of fund *j* from 30th June to 31st December.	***ΔPercent Rank$_{j,t}$*** is the normalised variation in the percentile rank of the cumulative gross return of fund *j* between 30th June and 31st December.
Tournament Reward	***ΔPercent Rank$_{j,t}$*** is the normalised variation in the percentile of the cumulative gross return rank of fund *j* between 30th June and 31st December.	*Flows$_{j,t+3}$* is the normalised value of the implied net money flows for fund *j* from 31st December to 31st March of the subsequent year.

This table shows the inputs, outputs and intermediate variables used in our three-stage network model of mutual fund tournaments and how they are computed. Intermediate variables are printed in bold.

3.5 Empirical analysis

3.5.1 Data

We choose the Spanish mutual fund market for the application of our tournament model. Spain is one of the most relevant Euro mutual fund industries and is characterised by an important concentration in terms of management: small and mostly independent mutual funds coexist with large and mostly bank-owned management companies.[5] Thus, the heterogeneity of the mutual funds to be analysed helps our network approach to capture the different tournament dynamics potentially present in this largely concentrated competition map.

The primary data used in this study are obtained from the Spanish Securities and Exchange Commission (CNMV). Our initial database includes open-end Spanish domiciled funds that were in operation during the period under study (January 2010 -December 2015). This sample period covers the years with the largest outflows of money from the Spanish fund industry in the two decades prior to 2012, alongside a significant and sharp recovery of money inflows in 2014-2015 (Inverco, 2016). This results in extremely different management contexts to identify tournament practices through our proposed model. The initial database comprises 551 funds. In total, 42 index funds are dropped given that they are not actively managed and only actively managed funds would qualify for the analysis of tournament behaviour. Our analysis is focused on the two main investment categories in the Spanish fund industry: Euro and Domestic Equity Funds, which represent a total of 184 funds. We obtained data on daily returns, monthly total net assets (TNA) and quarterly report of portfolio holdings.

[5] As of December 2016, Spain was the fifth largest Euro mutual fund industry in terms of the number of funds (Investment Company Institute, 2020). The top 5 and the top 10 of the 83 Spanish bank-owned fund companies controlled 58% and 78% of the total assets of the industry, respectively. The median size of the Euro and Domestic Equity funds registered in Spain is 22 million €, whereas the median size of the largest 25% funds is 151 million € (Inverco, 2016).

Finally, we also exclude a total of 35 funds from this simple because the reported information does not entirely fulfil the data availability required by our model (for instance, funds terminated before 31st December or funds not reporting subsequent money flows for the first quarter because they were terminated before 31st March). In order to obtain reliable results for tournament analysis, we require funds included in any given year in the study to exist in January and survive at least until March of the subsequent year, when flows are computed. Our final sample consists of a total of 149 distinct equity funds and a cumulative total of 624 fund year observations.

Table 3.2 reports the summary statistics of the sample of mutual funds analysed in this paper. The yearly fund observations steadily decrease from 135 at the beginning to 84 at the end of the sample period. This decreasing number of funds in our sample period is consistent with both the merger and acquisition process of some relevant Spanish bank-owned fund companies and the termination of small funds managed by small independent companies. Meanwhile, the cumulative TNA under management steadily increases during the period of study up to approximately the triple of the initial amount by the end of the period of study.

At aggregate level, the variables reported are relatively stable and no important annual disparities can be observed. The equity exposure is consistent with the legal requirement of the Spanish Securities and Exchange Commission (CNMV) which states that Spanish mutual funds should maintain a minimum of 75% in equity. Nonetheless, this average annual data is always maintained below 90%. The data reported in Table 3.2 generally indicate defensive portfolios and a high level of diversification for the entire sample, expressed by the average betas and average portfolio concentration respectively.

Table 3.2 Descriptive statistics.

	2010	2011	2012	2013	2014	2015
Total Number of Funds	135	119	107	88	91	84
Total Net Assets (in thousands)	34,868	36,110	44,104	66,637	86,585	96,975
Mid-year Equity Exposure (%)	84.70	83.85	88.80	86.12	85.49	88.75
Year-end Equity Exposure (%)	85.26	82.86	87.61	85.85	87.26	89.77
Mid-year Portfolio Beta	0.90	0.87	0.88	0.84	0.85	0.83
Year-end Portfolio Beta	0.88	0.92	0.83	0.84	0.87	0.90
Mid-year Portfolio Concentration	531	505	550	535	547	544
Year-end Portfolio Concentration	517	535	551	540	538	550
Mid-year Portfolio Return (%)	5.78	2.59	7.67	10.19	0.78	7.49
Year-end Portfolio Return (%)	6.28	1.90	1.93	2.32	0.53	5.99
Net Implied Flows (%)	1.29	-4.08	6.62	18.69	-1.76	-4.01

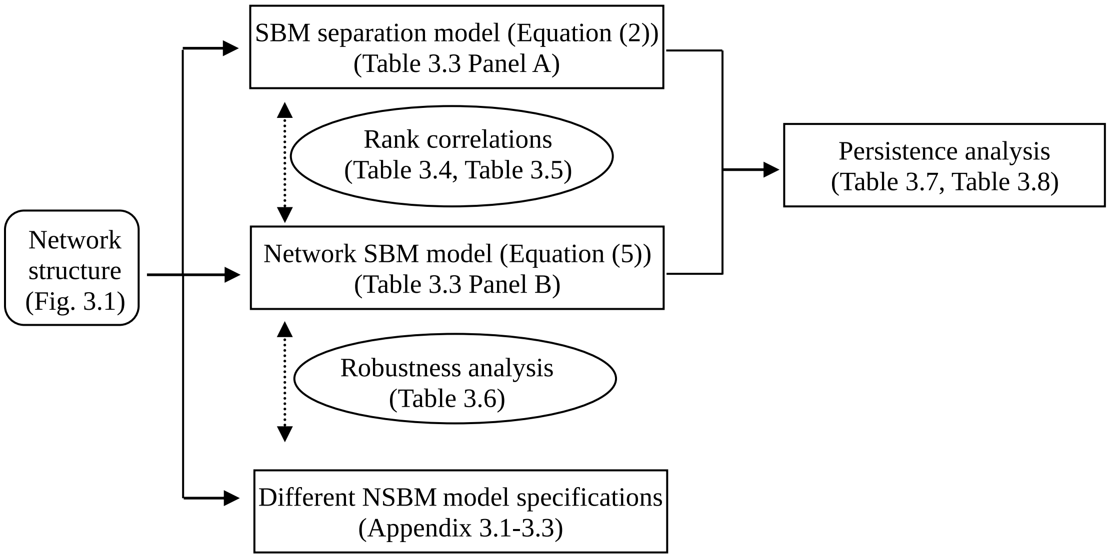
This table reports the descriptive statistics of the sample of mutual funds employed in this study. Total Number of Funds and Total Net Assets refer to year-end data. Equity Exposure, Portfolio Beta, Portfolio Concentration and Portfolio Return refer to the variables described by Table 3.1 and are reported at mid-year (30th June) and at year-end (31st December). Net Implied Flows refer to the data in the first quarter of the subsequent year.

3.5.2 Empirical results

3.5.2.1 Main models

Figure 3.2 shows the graphical outline of our three-stage network of mutual fund tournaments. First, we obtain the baseline results of the NSBM model proposed in Equation [5]. Thereafter, we compare these results with those obtained by the SBM-based separation models proposed in Equation [2] for each of the three tournament stages of the network displayed in Figure 3.1. Following this comparison, we apply nonparametric tests to check for the persistence of tournaments across time and across mutual funds. Subsequently, we run alternative NSBM models and variable specifications to provide robustness to our baseline findings.

Figure 3.2. Graphical outline of empirical analyses.



This figure shows the design of the empirical application of the three-stage network structure of mutual fund tournaments.

Table 3.3 presents the results of the SBM separation model (Panel A) in which the connection between the different tournament stages is not taken into account and the results of the NSBM model (Panel B) under VRS. Results are presented for each year of the sample period.[6] The equally weighted approach used, both in the SBM separation model and the NSBM model, ascribes equal importance to all three stages: the Reaction Stage, the Recompense Stage and the Reward Stage.

Panel A of Table 3.3 shows tournament scores assessed separately for each stage and the overall tournament data are provided by the arithmetic mean of the scores of individual stages. Meanwhile Panel B presents the tournament scores using the NSBM model that assumes a link between the distinct stages of tournament.

The number of funds singled out as efficient varies when comparing the SBM separation model and the NSBM model and neither do they follow similar patterns in the individual

[6] We obtained the efficiency scores of each of the funds included in our study and for both SBM separation and NSBM models. For the sake of brevity, the detailed results are not shown here and are available upon request.

stages, nor for the overall tournament analyses. Concerning the individual stages in the SBM separation model, the Reaction Stage generally appears to be the one with the highest number of tournament-efficient funds. This implies that though limited in number, some fund managers are proficient at reacting to their percent rank and at effectively altering the equity exposure, the beta, and the concentration of their portfolio as a result of their performance ranks. Ignoring the links between the individual stages also reveals that less fund managers are proficient in translating this shift in equity exposure, in beta, and in the concentration of their portfolio into better percent ranks in the second half of the year and that a change in percent rank is even less efficiently linked to inflows in the first quarter of the subsequent year.

Yet, the results of the NSBM model reveal that a fewer number of managers are efficient in altering the equity exposure, the volatility and the concentration of their portfolio as a result of their mid-year ranks. These results also reveal that managers who efficiently alter their year-end rank by changing the equity exposure, the volatility and the concentration of their portfolio also see their percent ranks efficiently translated into flows. In other words, when integrating the individual stages into a network model, we find that efficiently improving the percent rank of a fund at year-end compared with mid-year performance is strongly linked to how efficiently the fund will attract flows in the short term. This is a result of both the construction of our network model and the equally weighted distribution of the three stages of the model.[7]

Based on the annual standard deviations, the Reaction Stage scores consistently present the highest variability both for the SBM separation model and the NSBM model, meaning

[7] These results are in line with the structure described in Figure 1. We designed this structure based on the basic and tested relationship between flows and past performance (for instance, Chevalier & Ellison, 1997; Gruber, 1996 and Sirri & Tufano, 1998). This structure allows for the incorporation of additional inputs at the Reward Stage and for distinct weightings of the stages that logically influence the relationship between the Recompense Stage and the Reward Stage.

that the greatest disparity of tournament scores is at the Reaction Stage, the initial stage. These data suggest that reactions to mid-year rankings are disparate and could indicate that managers apply a variety of strategies as a response to their mid-year performance.

When looking at the overall tournament scores, in the SBM separation model no fund qualifies for efficiency. On the other hand, except for the year 2012, a couple of funds are considered efficient each year when employing links between the stages by applying the NSBM model. While many managers can efficiently react to their mid-year percent rank, leading an entirely successful and efficient tournament strategy is complex.

Table 3.3 Tournament scores: SBM separation and Network SBM models under VRS.

Panel A SBM separation model	2010	2011	2012	2013	2014	2015
Total number of mutual funds	135	119	107	88	91	84
Tournament Reaction						
Number of efficient mutual funds	15	10	10	11	11	9
Equally weighted score	0.245	0.172	0.147	0.217	0.168	0.204
(Standard deviation)	(0.313)	(0.293)	(0.289)	(0.328)	(0.290)	(0.290)
Tournament Recompense						
Number of efficient mutual funds	8	11	8	6	9	6
Equally weighted score	0.420	0.409	0.437	0.347	0.500	0.461
(Standard deviation)	(0.220)	(0.265)	(0.234)	(0.226)	(0.276)	(0.224)
Tournament Reward						
Number of efficient mutual funds	3	3	2	2	3	6
Equally weighted score	0.085	0.160	0.076	0.070	0.120	0.278
(Standard deviation)	(0.187)	(0.203)	(0.176)	(0.159)	(0.215)	(0.273)
Overall Tournament						
Number of efficient mutual funds	0	0	0	0	0	0
Equally weighted score	0.250	0.247	0.220	0.211	0.263	0.314
(Standard deviation)	(0.148)	(0.128)	(0.112)	(0.139)	(0.140)	(0.144)

Panel B Network SBM model	2010	2011	2012	2013	2014	2015
Tournament Reaction						
Number of efficient mutual funds	3	2	0	2	2	2
Equally weighted score	0.156	0.330	0.217	0.250	0.268	0.318
(Standard deviation)	(0.204)	(0.339)	(0.243)	(0.274)	(0.279)	(0.331)
Tournament Recompense						
Number of efficient mutual funds	4	4	4	4	4	8
Equally weighted score	0.459	0.887	0.565	0.640	0.670	0.915
(Standard deviation)	(0.190)	(0.095)	(0.193)	(0.184)	(0.187)	(0.116)
Tournament Reward						
Number of efficient mutual funds	4	4	4	4	4	8
Equally weighted score	0.459	0.887	0.562	0.640	0.670	0.914
(Standard deviation)	(0.190)	(0.095)	(0.193)	(0.184)	(0.187)	(0.116)
Overall Tournament						
Number of efficient mutual funds	3	2	0	2	2	2
Equally weighted score	0.358	0.702	0.448	0.510	0.536	0.716
(Standard deviation)	(0.166)	(0.129)	(0.167)	(0.171)	(0.177)	(0.141)

This table shows the total number of mutual funds and the number of tournament-efficient funds per stage and year. It also provides the equally weighted average of the tournament scores obtained by the SBM separation model (Panel A) and the Network SBM model (Panel B). The standard deviations of the scores are in brackets.

Tone and Tsutsui (2009) advocated against a direct comparison of the efficiency scores of the different stages, since they do not involve the same number of outputs and/or inputs. In this context, a comparison of the efficiency rankings provides a more accurate picture (Table 3.4). Panel A of Table 3.4 presents the rank correlations across tournament stages when the links between the stages are omitted. These results suggest that the stages are negatively correlated or independent, with the exception of the Overall Tournament results. This exception could be explained by the construct of the data which is an equally weighted average of the three stages.

The second model presented in Panel B of Table 3.4 provides a more accurate picture as it incorporates the link between the stages. It shows that while efficient tournament responses at the initial stage do not seem to affect efficient tournament responses at subsequent stages, efficiency at the Tournament Recompense stage is perfectly correlated with efficiency at the Tournament Reward stage. These findings imply that mutual fund managers who efficiently alter the equity exposure, the betas and the concentration of their portfolios to obtain better percent ranks are also efficient in obtaining higher inflows as a result of their change in percent rank. In other words, an efficient reaction of fund managers to their own percent rank does not directly influence subsequent inflows. On the contrary, how efficiently they succeed to alter their percent rank influences more the subsequent flows into their fund.[8]

[8] Kendall rank correlations applied to both the SBM separation model and NSBM model provide results consistent with the ones obtained using Spearman correlations presented in Table 3.4.

Table 3.4 Rank correlation across tournament stages.

Panel A: SBM separation model									
	2010			2011			2012		
	TRc	TRw	OT	TRc	TRw	OT	TRc	TRw	OT
Tournament Reaction (TR)	0.004	-0.107	0.602**	-0.092	-0.149	0.420**	0.003	-0.375**	0.337**
Tournament Recompense (TRc)	1	-0.520**	0.592**	1	-0.149	0.510**	1	-0.462**	0.521**
Tournament Reward (TRw)		1	-0.183**		1	0.227*		1	-0.175
Overall Tournament (OT)			1			1			1
	2013			2014			2015		
	TRc	TRw	OT	TRc	TRw	OT	TRc	TRw	OT
Tournament Reaction (TR)	0.070	-0.218*	0.712**	-0.133	0.042	0.331**	0.114	-0.0556	0.461**
Tournament Recompense (TRc)	1	-0.605**	0.5202**	1	-0.349**	0.604**	1	-0.3283	0.331**
Tournament Reward (TRw)		1	-0.313**		1	0.088		1	0.513**
Overall Tournament (OT)			1			1			1
Panel B: Network SBM model									
	2010			2011			2012		
	TRc	TRw	OT	TRc	TRw	OT	TRc	TRw	OT
Tournament Reaction (TR)	0.079	0.079	0.409**	-0.089	-0.089	0.881**	0.196*	0.201*	0.573**
Tournament Recompense (TRc)	1	1**	0.906**	1	1**	0.254**	1	1**	0.858**
Tournament Reward (TRw)		1	0.906**		1	0.254**		1	0.861**
Overall Tournament (OT)			1			1			1
	2013			2014			2015		
	TRc	TRw	OT	TRc	TRw	OT	TRc	TRw	OT
Tournament Reaction (TR)	0.135	0.135	0.592**	0.205	0.205	0.621**	0.193	0.193	0.878**
Tournament Recompense (TRc)	1	1**	0.813**	1	1**	0.834**	1	1**	0.551**
Tournament Reward (TRw)		1	0.813**		1	0.834**		1	0.551**
Overall Tournament (OT)			1			1			1

Panel A of this table shows the Spearman rank correlations across the tournament rankings obtained by the SBM separation model under VRS for the different tournament stages. Panel B provides similar information corresponding to the tournament rankings obtained by the Network SBM model under VRS. * 5% significance level; ** 1% significance level.

To further analyse the difference between the SBM separation model and the NSBM model, we apply Spearman correlations to the efficiency ranks resulting from both models.[9] The results are shown in Table 3.5 and indicate a high correlation between both models for the overall tournament, except for the year 2010. Regarding the individual stages, Table 3.5 shows significant correlations between the Reaction Stage and the Reward Stage, the first

[9] Kendall rank correlations applied to the same sample provide results consistent with the ones obtained using Spearman correlations presented in Table 3.5.

stage and the last stage of each model. However, the Recompense Stages of both models are either not to significantly correlated or negatively correlated when significant. These results reinforce the hypothesis that the Recompense Stage is a necessary link to fully capture the tournament phenomenon within the mutual fund industry, as described in Figure 3.1.

Table 3.5 Rank correlation: SBM separation vs Network SBM models under VRS.

	2010	2011	2012	2013	2014	2015
Tournament Reaction	0.729**	0.516**	0.470**	0.581**	0.387**	0.613**
Tournament Recompense	-0.481**	0.026	0.105	-0.055	-0.253*	-0.172
Tournament Reward	0.954**	0.839**	0.618**	0.622**	0.941**	0.883**
Overall Tournament	0.133	0.749**	0.629**	0.470**	0.477**	0.836**

This table shows Spearman rank correlations between the tournament scores obtained by the SBM separation and the Network SBM models under VRS. This information is provided per each tournament stage and year.
* 5% significance level; ** 1% significance level.

3.5.2.2 Robustness analysis

Our findings show that the NSBM model that links the distinct stages captures better the tournament behaviour of mutual fund managers. To test for robustness, we apply the NSBM model and the SBM separation model to alternative variable specifications: for the time splitting (*t-3, t, t+3*) in line with Chevalier and Ellison (1997) and for the use of the percentile rank of the implied net money flows from 31st December to 31st March instead of variable $Flows_{j,t+3}$. We further test for the use of the normalised value of the cumulative gross return of fund *j* from 1st January to 30th June instead of $Percent\ Rank_{j,t-6}$ and the normalised variation in the cumulative gross return of fund *j* between 30th June and 31st December instead of $\Delta Percent\ Rank_{j,t}$.[10]

[10] The results of the efficiency scores of alternative model specifications SBM separation and Network SBM models under VRS are presented in Appendix A: for Tournament Reaction stage covering the period year-start to September instead of year-start to mid-year (Table A3.1), for the use of percentile rank of the implied net money flows from 31st December to 31st March instead of the variable $Flows_{j,t+3}$ (Table A3.2) and for the normalised value of the cumulative gross return of fund *j* from 1st January to 30th June instead of $Percent\ Rank_{j,t-6}$ and the normalised variation in the cumulative gross return of fund *j* between 30th June and 31st December instead of $\Delta Percent\ Rank_{j,t}$ (Table A3.3).

In Table 3.6, we assess the correlation between the results obtained in the main NSBM models and the ones obtained using alternative variable specifications. By and large, they reveal that our findings on tournament behaviours are consistent when modelling for tournament reaction covering the period year-start to September instead of year-start to mid-year (Panel A of Table 3.6), when employing percent ranks of the implied net money flows from 31st December to 31st March instead of the variable $Flows_{j,t+3}$ (Panel B of Table 3.6) and when using the normalised value of the cumulative gross return of fund *j* from 1st January to 30th June instead of $Percent\ Rank_{j,t-6}$ (Panel C of Table 3.6).

We also obtain results consistent with the ones presented in Table 3.6 for a similar Spearman rank correlation test applied to rankings obtained using the SBM separation model and alternative variable specifications.[11]

[11] For the sake of brevity, results are not presented here.

Table 3.6 Rank correlation across different NSBM models and variable specifications.

Panel A: NSBM (*t-6, t, t+3*) vs NSBM (*t-3, t, t+3*)	2010	2011	2012	2013	2014	2015
Tournament Reaction (TR)	0.5875**	0.3636**	0.4989**	0.5102**	0.5442**	0.4079**
Tournament Recompense (TRc)	0.8023**	0.6575**	0.8491**	0.7831**	0.8429**	0.7922**
Tournament Reward (TRw)	0.8023**	0.6575**	0.8491**	0.7831**	0.8429**	0.7922**
Overall Tournament (OT)	0.7297**	0.3928**	0.7109**	0.5673**	0.8375**	0.5543**
Panel B: NSBM (*t-6, t, t+3*) vs NSBM (*t-6, t, t+3*) RankFlows	2010	2011	2012	2013	2014	2015
Tournament Reaction (TR)	0.9293**	0.9161**	0.9703**	0.9591**	0.9606**	0.9041**
Tournament Recompense (TRc)	0.8137**	0.8361**	0.9059**	0.9083**	0.9508**	0.9441**
Tournament Reward (TRw)	0.8137**	0.8361**	0.9083**	0.9083**	0.9508**	0.9441**
Overall Tournament (OT)	0.7737**	0.5606**	0.8832**	0.8632**	0.9102**	0.7784**
Panel C: NSBM (*t-6, t, t+3*) vs NSBM (*t-6, t, t+3*) Returns	2010	2011	2012	2013	2014	2015
Tournament Reaction (TR)	0.8946**	0.9673**	0.9292**	0.9289**	0.8829**	0.9574**
Tournament Recompense (TRc)	0.8848**	0.8969**	0.9474**	0.8957**	0.9310**	0.9420**
Tournament Reward (TRw)	0.8848**	0.8969**	0.9461**	0.8957**	0.9310**	0.9420**
Overall Tournament (OT)	0.8867**	0.9388**	0.9358**	0.9004**	0.8975**	0.9503**

Panel A of this table shows the Spearman rank correlations of the tournament rankings obtained by the NSBM model under VRS for the temporal specification (*t-6, t, t+3*) against the tournament rankings obtained by the NSBM model under VRS for the temporal specification (*t-3, t, t+3*). Panel B of this table shows the Spearman rank correlations of the tournament rankings obtained by the NSBM model under VRS (*t-6, t, t+3*) against the tournament rankings obtained by the same NSBM model specification using the percentile rank of the implied net money flows from 31st December to 31st March instead of variable $Flows_{j,t+3}$ (see Table 3.1). Panel C of this table shows the Spearman rank correlations of the tournament rankings obtained by the NSBM model under VRS (*t-6, t, t+3*) against the tournament rankings obtained by the same NSBM model specification using the normalised value of the cumulative gross return of fund *j* from 1st January to 30th June instead of $Percent\ Rank_{j,t-6}$ (see Table 3.1), and the normalised variation in the cumulative gross return of fund *j* between 30th June and 31st December instead of $\Delta Percent\ Rank_{j,t}$ (see Table 3.1). * 5% significance level; ** 1% significance level.

3.5.2.3 Persistence analysis

Are efficient tournament responses limited to a given year or are they sustained across time? To analyse the persistence of efficient tournament responses, we employ a k-means clustering technique to form 4 groups: Top Winners, Winners, Losers and Bottom Losers, in descending order of efficiency.

Table 3.7 presents the average NSBM scores and the total number of funds for each cluster. This table confirms that fund managers do not efficiently react to their mid-year performance ranks, given that the Bottom Losers cluster is by far the largest each year at the Reaction Stage. Nevertheless, fund managers appear to be more efficient in obtaining changes in their percent ranks as a result of their change in strategy and these changes in percent ranks are usually efficiently rewarded by investors.

The overall tournament data suggest that, except for the last year of study, most fund managers fail in efficiently carrying out a tournament strategy. These results further confirm that leading a tournament strategy successfully and efficiently is complicated. Future studies investigating the determinants of mutual fund performance could use the model proposed here as a benchmark to evaluate the impact of these management practises on return.

Table 3.7 Summary statistics of the tournament-efficiency clusters.

	2010	2011	2012	2013	2014	2015
Tournament Reaction						
Top Winners	0.95 (05)	0.87 (29)	0.68 (14)	0.91 (06)	0.81 (14)	0.89 (19)
Winners	0.38 (22)	0.54 (08)	0.46 (20)	0.63 (10)	0.51 (10)	0.38 (10)
Losers	0.15 (29)	0.24 (23)	0.15 (16)	0.47 (10)	0.25 (17)	0.18 (17)
Bottom Losers	0.04 (79)	0.07 (59)	0.04 (57)	0.09 (62)	0.07 (50)	0.07 (38)
Tournament Recompense						
Top Winners	0.84 (18)	0.97 (22)	0.95 (12)	0.96 (10)	0.89 (23)	0.98 (26)
Winners	0.52 (44)	0.90 (72)	0.65 (38)	0.76 (22)	0.67 (48)	0.92 (47)
Losers	0.36 (58)	0.82 (24)	0.47 (51)	0.60 (41)	0.48 (16)	0.79 (10)
Bottom Losers	0.21 (15)	0.03 (01)	0.14 (06)	0.36 (15)	0.13 (04)	0.03 (01)
Tournament Reward						
Top Winners	0.84 (18)	0.97 (22)	0.94 (12)	0.88 (20)	0.94 (14)	0.98 (26)
Winners	0.54 (32)	0.90 (72)	0.65 (36)	0.67 (35)	0.75 (27)	0.92 (47)
Losers	0.40 (46)	0.82 (24)	0.47 (52)	0.52 (25)	0.61 (39)	0.79 (10)
Bottom Losers	0.28 (39)	0.03 (01)	0.17 (07)	0.28 (08)	0.32 (11)	0.03 (01)
Overall Tournament						
Top Winners	0.90 (07)	0.90 (26)	0.76 (11)	0.85 (09)	0.87 (11)	0.94 (16)
Winners	0.48 (30)	0.75 (21)	0.61 (16)	0.59 (30)	0.60 (33)	0.73 (27)
Losers	0.33 (59)	0.63 (71)	0.44 (48)	0.46 (31)	0.45 (38)	0.64 (40)
Bottom Losers	0.21 (39)	0.03 (01)	0.27 (32)	0.29 (18)	0.23 (09)	0.02 (01)

This table illustrates the average NSBM scores per cluster and year for each different stage. The number of funds for each cluster is in brackets.

To determine the persistence of tournament response, we employ contingency tables. These tables are constructed based on the aforementioned clusters. First, we check for mobility across clusters within a stage. Panel A of Table 3.8 shows the results of various mobility ratios: Immobility Ratio (IR), the percentage of funds with improved performance (MU) and the percentage of funds with worsened performance (MD). Largely, this table does not present any clear patterns. The Immobility Ratios at the Reaction Stage tend to be high, suggesting that funds that inefficiently react to their percent rank tend to stay inefficient a year later. These data are, however, not significant.

Panel B of Table 3.8 presents the transition probability matrices derived from the contingency tables. These matrices compare any given year to the year immediately subsequent, for the distinct tournament stages and overall. Generally, here also we only sporadically find significant values. Consequently, it can be concluded that there is general absence of persistence both in the case of tournament-efficient clusters and inefficient clusters. In line with our findings in the previous panel, it appears that at the Reaction Stage, the highest transition probability is obtained by the Bottom Losers cluster. This implies that funds in this cluster tend to remain in this same category in the subsequent year. These data are only occasionally significant.

To conclude, adopting an efficient strategy does not follow a persistent pattern. This highlights the complexity and the difficulty of developing systematic tournament efficient behaviours. Efficient behaviours are more sporadic rather than persistent.

Table 3.8 Persistence analysis.

Panel A: Mobility ratios and chi-square tests

	Tournament Reaction				*Tournament Recompense*				*Tournament Reward*				*Overall Tournament*			
	IR	MU	MD	χ2	IR	MU	MD	χ2	IR	MU	MD	χ2	IR	MU	MD	χ2
2010-2011	0.41	0.41	0.18	14.5	0.27	0.51	0.22	10.2	0.20	0.60	0.20	6.0	0.28	0.53	0.18	8.5
2011-2012	0.42	0.26	0.32	15.1	0.35	0.16	0.49	2.6	0.34	0.16	0.50	2.8	0.35	0.20	0.45	18.6*
2012-2013	0.47	0.19	0.34	7.1	0.37	0.19	0.44	15.7	0.40	0.36	0.24	14.5	0.30	0.47	0.23	15.8
2013-2014	0.31	0.27	0.42	11.4	0.23	0.62	0.15	14.6	0.50	0.30	0.20	7.1	0.33	0.38	0.28	3.9
2014-2015	0.40	0.37	0.23	7.3	0.49	0.28	0.23	6.8	0.40	0.37	0.23	8.1	0.39	0.33	0.28	4.9

Panel B: Transition probability matrices

	Tournament Reaction				*Tournament Recompense*				*Tournament Reward*				*Overall Tournament*			
2011 / 2010	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL
TW	0.00	0.00	0.75**	0.25	0.13	0.67	0.20	0.00	0.13	0.67	0.20	0.00	0.17	0.17	0.67	0.00
W	0.31	0.06	0.13	0.50	0.19	0.56	0.26	0.00	0.19	0.53	0.28	0.00	0.30	0.11	0.56	0.04
L	0.33	0.14	0.19	0.33	0.11	0.73*	0.14	0.02	0.19	0.68	0.11	0.03	0.25	0.15	0.60	0.00
BL	0.21	0.05	0.16	0.57	0.36	0.36*	0.29	0.00	0.16	0.59	0.25	0.00	0.11	0.26	0.63	0.00
2012 / 2011	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL
TW	0.18	0.23	0.23	0.36	0.15	0.30	0.50	0.05	0.15	0.30	0.50	0.05	0.16	0.11	0.26	0.47
W	0.14	0.29	0.43*	0.14*	0.11	0.37	0.46	0.06	0.11	0.35	0.46	0.08	0.25*	0.05	0.40	0.30
L	0.05	0.27	0.14	0.55	0.10	0.33	0.52	0.05	0.10	0.33	0.52	0.05	0.05*	0.18	0.51	0.26
BL	0.15	0.11	0.09	0.65*	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00*	0.00	0.00
2013 / 2012	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL
TW	0.11	0.22	0.11	0.56	0.25	0.58**	0.08**	0.08	0.58**	0.25	0.08	0.08	0.00	0.33	0.44	0.22
W	0.17	0.11	0.11	0.61	0.11	0.19	0.52	0.19	0.19	0.46	0.31	0.04	0.33**	0.33	0.25	0.08
L	0.11	0.00	0.11	0.78	0.08	0.18	0.55	0.20	0.15*	0.37	0.34	0.15	0.13	0.41	0.31	0.15
BL	0.02*	0.11	0.13	0.74	0.25	0.25	0.25	0.25	0.50	0.25	0.25	0.00	0.00*	0.26	0.35	0.39*
2014 / 2013	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL
TW	0.17	0.17	0.33	0.33	0.20	0.30	0.40*	0.10	0.25	0.20	0.35	0.20	0.11	0.56	0.22	0.11
W	0.11	0.33*	0.22	0.33	0.27	0.59	0.09	0.05	0.20	0.31	0.43	0.06	0.14	0.36	0.39	0.11
L	0.00	0.00	0.22	0.78	0.36*	0.46	0.13	0.05	0.09	0.30	0.43	0.17	0.13	0.32	0.48	0.06
BL	0.18	0.08	0.15	0.60	0.00*	0.73	0.27	0.00	0.00	0.38	0.50	0.13	0.11	0.28	0.44	0.17
2015 / 2014	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL	TW	W	L	BL
TW	0.29	0.14	0.21	0.36	0.36	0.55	0.09	0.00	0.38	0.62	0.00	0.00	0.27	0.36	0.36	0.00
W	0.44	0.11	0.22	0.22	0.27	0.62	0.09	0.02	0.35	0.50	0.12	0.04	0.16	0.35	0.45	0.03
L	0.21	0.21	0.21	0.36	0.23	0.46	0.31*	0.00	0.20	0.66	0.14	0.00	0.21	0.26	0.53	0.00
BL	0.16	0.09	0.20	0.56*	0.50	0.50	0.00	0.00	0.38	0.38	0.25	0.00	0.00	0.33	0.67	0.00

Panel A provides the following data based on the probability matrices: *Immobility Ratio* (IR), *the percentage of funds with improved performance* (MU) and *the percentage of funds with worsened performance* (MD). A chi-square test χ2 is applied to check for the persistence hypothesis. Panel B reports the transition probability matrices for each sub-sample period and tournament stage. Each element p_{ij} of each transition matrix corresponds to the probability of transiting from cluster *i* to cluster *j*, i.e., the number of funds in cluster *i* of year *t-1* that are now part of cluster *j* of year *t* in relation to the total of funds included in the transition matrix for that sub-sample period. The significance is based on Haberman adjusted residues. * 5% significance level; ** 1% significance level.

3.6 Conclusions

This study provides a more nuanced tournament model for the mutual fund industry and analyses how efficiently managers react to their interim performance ranks, how efficiently they alter their portfolio to improve their year-end performance ranks and, finally, how efficiently these changes in performance ranks are rewarded by investors through flows into the fund in the subsequent quarter. To the best of our knowledge, this study is the first to employ Network Data Envelopment Analysis (DEA) to model behavioural dynamics in the mutual fund industry.

Applying our model to a real market, provides empirical results that sustain our initial assumptions. Our results confirm how complicated it is for fund managers to apply a strategy that can efficiently improve their year-end performance in relation to their peers. Indeed, fund managers can adopt a wide range of strategies and it appears from our results that the Reaction Stage is not correlated with the Reward Stage. Meaning that, efficiently altering the equity exposure, the beta and the concentration of the portfolio as a result of interim performance ranks is not significantly correlated with subsequent flows into the fund.

Consistent with the literature on flows, how well fund managers improve their performance ranks by altering the equity exposure, the volatility and the concentration of their portfolio is a determinant of how well they will attract flows in the subsequent quarter. Thus, success at the Recompense Stage, successfully improving year-end performance, is a determinant in the final tournament results. These findings reinforce the validity of the model we propose in this study. Our results are robust even when employing alternative variable specifications. Finally, we do not find persistence in tournament-efficiency at the individual stages and also overall. Our results support the idea that following a persistent and systematically efficient tournament strategy is difficult and complex.

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Appendix 3.1 SBM separation and Network SBM models under VRS (alternative time splitting: *t-3, t, t+3*).

Panel A SBM separation model	2010	2011	2012	2013	2014	2015
Total number of mutual funds	135	119	107	88	91	84
Tournament Reaction						
Number of efficient mutual funds	15	15	15	7	10	6
Equally weighted score	0.184	0.281	0.265	0.193	0.193	0.140
(Standard deviation)	(0.314)	(0.330)	(0.326)	(0.299)	(0.321)	(0.280)
Tournament Recompense						
Number of efficient mutual funds	5	4	8	11	11	6
Equally weighted score	0.474	0.417	0.367	0.581	0.547	0.400
(Standard deviation)	(0.196)	(0.185)	(0.235)	(0.222)	(0.258)	(0.205)
Tournament Reward						
Number of efficient mutual funds	3	2	3	2	5	3
Equally weighted score	0.0253	0.058	0.092	0.0736	0.216	0.149
(Standard deviation)	(0.170)	(0.142)	(0.180)	(0.169)	(0.241)	(0.187)
Overall Tournament						
Number of efficient mutual funds	0	0	0	0	0	0
Equally weighted score	0.237	0.252	0.241	0.283	0.319	0.230
(Standard deviation)	(0.142)	(0.131)	(0.124)	(0.108)	(0.153)	(0.107)

Panel B Network SBM model	2010	2011	2012	2013	2014	2015
Tournament Reaction						
	0	2	2	1	4	2
Equally weighted score	0.092	0.332	0.233	0.254	0.289	0.341
(Standard deviation)	(0.148)	(0.330)	(0.218)	(0.217)	(0.296)	(0.361)
Tournament Recompense						
	4	6	5	3	6	6
Equally weighted score	0.429	0.903	0.547	0.557	0.686	0.917
(Standard deviation)	(0.176)	(0.095)	(0.198)	(0.173)	(0.186)	(0.116)
Tournament Reward						
	4	6	5	3	6	6
Equally weighted score	0.429	0.903	0.547	0.557	0.686	0.917
(Standard deviation)	(0.176)	(0.095)	(0.198)	(0.173)	(0.186)	(0.116)
Overall Tournament						
	0	2	2	1	4	2
Equally weighted score	0.316	0.712	0.442	0.456	0.554	0.725
(Standard deviation)	(0.135)	(0.137)	(0.169)	(0.144)	(0.186)	(0.157)

This table is similar to Table 3.3 but for the use of the alternative time framework (*t-3, t, t+3*). It shows the total number of mutual funds and the number of tournament-efficient funds per stage and year. It also provides the equally weighted average of the tournament scores obtained by the SBM separation model (Panel A) and the Network SBM model (Panel B). The standard deviations of the scores are in brackets.

Appendix 3.2 SBM separation and Network SBM models under VRS (alternative variable: $Flows_{j,t+3}$)

Panel A SBM separation model	2010	2011	2012	2013	2014	2015
Total number of mutual funds	135	119	107	88	91	84
Tournament Reaction						
Number of efficient mutual funds	15	10	10	11	9	9
Equally weighted score	0.245	0.172	0.147	0.217	0.168	0.204
(Standard deviation)	(0.313)	(0.293)	(0.289)	(0.328)	(0.289)	(0.290)
Tournament Recompense						
Number of efficient mutual funds	8	11	8	6	11	6
Equally weighted score	0.420	0.409	0.437	0.347	0.500	0.461
(Standard deviation)	(0.220)	(0.265)	(0.234)	(0.226)	(0.276)	(0.224)
Tournament Reward						
Number of efficient mutual funds	3	4	4	3	6	6
Equally weighted score	0.135	0.176	0.105	0.143	0.165	0.269
(Standard deviation)	(0.256)	(0.230)	(0.196)	(0.260)	(0.276)	(0.277)
Overall Tournament						
Number of efficient mutual funds	0	0	0	0	0	0
Equally weighted score	0.267	0.252	0.229	0.236	0.278	0.311
(Standard deviation)	(0.154)	(0.131)	(0.113)	(0.142)	(0.153)	(0.145)

Panel B Network SBM model	2010	2011	2012	2013	2014	2015
Tournament Reaction						
Number of efficient mutual funds	3	2	0	2	3	2
Equally weighted score	0.231	0.241	0.262	0.260	0.272	0.251
(Standard deviation)	(0.276)	(0.277)	(0.310)	(0.302)	(0.308)	(0.304)
Tournament Recompense						
Number of efficient mutual funds	5	6	8	7	7	8
Equally weighted score	0.684	0.686	0.691	0.702	0.690	0.709
(Standard deviation)	(0.274)	(0.274)	(0.275)	(0.281)	(0.278)	(0.270)
Tournament Reward						
Number of efficient mutual funds	5	6	6	7	7	8
Equally weighted score	0.684	0.686	0.688	0.702	0.690	0.709
(Standard deviation)	(0.274)	(0.274)	(0.274)	(0.281)	(0.278)	(0.270)
Overall Tournament						
Number of efficient mutual funds	3	2	0	2	3	2
Equally weighted score	0.533	0.537	0.547	0.555	0.550	0.557
(Standard deviation)	(0.226)	(0.225)	(0.233)	(0.236)	(0.246)	(0.241)

This table is similar to Table 3.3 but for the use of the percentile rank of the implied net money flows from 31st December to 31st March instead of the variable $Flows_{j,t+3}$ (see Table 3.1). It shows the total number of mutual funds and the number of tournament-efficient funds per stage and year. It also provides the equally weighted average of the tournament scores obtained by the SBM separation model (Panel A) and the Network SBM model (Panel B). The standard deviations of the scores are in brackets.

Appendix 3.3 SBM separation and Network SBM models under VRS (alternative variables: *Percent Rank$_{j,t-6}$*, *ΔPercent Rank$_{j,t}$*)

Panel A SBM separation model	2010	2011	2012	2013	2014	2015
Total number of mutual funds	135	119	107	88	91	84
Tournament Reaction						
Number of efficient mutual funds	13	8	10	6	7	4
Equally weighted score	0.342	0.197	0.152	0.207	0.217	0.273
(Standard deviation)	(0.292)	(0.286)	(0.289)	(0.285)	(0.266)	(0.241)
Tournament Recompense						
Number of efficient mutual funds	7	9	7	6	10	6
Equally weighted score	0.398	0.387	0.441	0.411	0.558	0.540
(Standard deviation)	(0.181)	(0.235)	(0.226)	(0.210)	(0.242)	(0.203)
Tournament Reward						
Number of efficient mutual funds	3	2	2	2	3	4
Equally weighted score	0.030	0.035	0.072	0.079	0.114	0.384
(Standard deviation)	(0.148)	(0.131)	(0.157)	(0.165)	(0.206)	(0.282)
Overall Tournament						
Number of efficient mutual funds	0	0	0	0	0	0
Equally weighted score	0.257	0.206	0.221	0.233	0.296	0.399
(Standard deviation)	(0.123)	(0.109)	(0.110)	(0.124)	(0.115)	(0.135)

Panel B Network SBM model	2010	2011	2012	2013	2014	2015
Tournament Reaction						
Number of efficient mutual funds	2	0	0	2	2	35
Equally weighted score	0.179	0.387	0.264	0.279	0.413	0.404
(Standard deviation)	(0.164)	(0.291)	(0.208)	(0.200)	(0.217)	(0.287)
Tournament Recompense						
Number of efficient mutual funds	4	4	3	3	5	5
Equally weighted score	0.396	0.875	0.551	0.559	0.654	0.915
(Standard deviation)	(0.161)	(0.094)	(0.178)	(0.175)	(0.179)	(0.115)
Tournament Reward						
Number of efficient mutual funds	4	4	3	3	5	5
Equally weighted score	0.396	0.875	0.551	0.559	0.654	0.915
(Standard deviation)	(0.161)	(0.094)	(0.178)	(0.175)	(0.179)	(0.115)
Overall Tournament						
Number of efficient mutual funds	2	0	0	2	2	3
Equally weighted score	0.323	0.713	0.455	0.466	0.574	0.745
(Standard deviation)	(0.143)	(0.119)	(0.158)	(0.154)	(0.172)	(0.133)

This table is similar to Table 3.3 but for the use of the normalised value of the cumulative gross return of fund *j* from 1st January to 30th June instead of *Percent Rank$_{j,t-6}$* (see Table 3.1), and the normalised variation in the cumulative gross return of fund *j* between 30th June and 31st December instead of *ΔPercent Rank$_{j,t}$* (see Table 3.1). It shows the total number of mutual funds and the number of tournament-efficient funds per stage and year. It also provides the equally weighted average of the tournament scores obtained by the SBM separation model (Panel A) and the Network SBM model (Panel B). The standard deviations of the scores are in brackets.

General conclusions

In this final section, we provide a general summary of the conclusions and contributions of the analyses carried out in this thesis. The main aim of this thesis was to contribute to the field of behavioural finance by providing further insights into the biases and heuristics to which professional fund managers are subject.

The findings of this work are relevant to the main participants of the mutual fund industry. This work is useful to investors as it raises awareness about the potential behavioural biases that affect the performance of funds in which they invest. This work is also especially relevant to mutual fund managers in that, only by deepening their understanding of behavioural biases can they design effective strategies to avoid them or to curb the impact of these biases on the performance of their portfolio. Finally, this work is also of significance to market supervisors as it could provide support in strengthening existing laws and enacting new ones with the aim of increasing investors' protection and improving market transparency.

Overconfidence, the central theme of Chapter 1 of the current study, is a robust and well-document behavioural bias. Several empirical studies have confirmed the pre-eminence and the ubiquity of this bias. Indeed, both amateurs and professionals in the field of finance and in other fields are prone to display this bias. In the finance industry, many studies have resorted to the use of a proxy in order to capture as closely as possible overconfidence. The issue with this approach is that the most common proxies are used in isolation, despite the fact that these same proxies have been used to capture phenomena different from overconfidence. To this date, properly gauging overconfidence has been the principal question in many studies. The aim of this chapter was to provide a method of identifying overconfident mutual fund managers with a greater degree of certainty.

It is the contention of our study that managers who, in relation to their peers, simultaneously trade the most, deviate the most from their benchmark and hold the highest percentage of their portfolio in equity can be said to be overconfident with greater accuracy. We proposed that by combining the three most used proxies in literature: turnover ratio, active share and equity exposure, we would be able to more accurately identify overconfident managers.

We employed the Principal Component Analysis to merge all three proxies into one unique variable. This variable allowed us to first determine the proportion of the contribution of each proxy into the final result and also to carry out a preliminary analysis of the influence of past performance on the confidence level of fund managers. Our results showed that the greater the past performance, the more confident the mutual fund manager.

Based on the results of this preliminary analysis, we designed our Overconfidence Composite Score: fund managers that are simultaneously in the top quartile of all three measures are singled out as overconfident by our scoring system. We then applied a logistic regression to determine whether top-performing managers were more prone than low-performing managers to display overconfidence.

Generally, our results were consistent with the overconfidence hypothesis. We found that fund managers had a higher probability of displaying overconfidence after outstanding performance. Through a robustness check, we confirmed that the use of the composite score should be preferred over the use of single proxies. Finally, we found that overconfidence had a negative impact on the subsequent performance of top-performing managers. Interestingly, low performers who traded the most, deviated the most from their benchmark and held a higher percentage of their portfolio in equity later performed better. We believe that these changes could respond to a Bayesian learning process in which low performers corrected their errors.

But overconfidence is not the only bias to which mutual fund managers are subject. The disposition effect is a behavioural bias that has also been amply tested. However, we shed some new light by exploring the following question in Chapter 2 of this thesis: How do SRI fund managers compare to non-SRI fund managers in terms of the disposition effect? Indeed, empirical studies have shown that investors of SRI funds value the social utility of these funds more than their financial utility. Does this affect how SRI fund managers trade compared with non-SRI fund managers? More specifically, do SRI fund managers realise gains more readily than losses? How does their behaviour compare with the behaviour of non-SRI fund managers?

From a sample of SRI funds of the four main categories of US equity funds, we built a matching pool of non-SRI funds. The criteria used were the global category, the TNA under management and the age of the fund. We used the disposition spread to determine whether fund managers in each group were subject to the disposition effect. To calculate the disposition spread, we employed a formula that permitted us to minimise the impact of flow-induced trading, given that only voluntary trading would qualify in the evaluation of the disposition effect.

Our study failed to accept the hypothesis of the existence of the disposition effect, either in the pool of SRI funds or in the group of non-SRI funds for the period under study. Interestingly, we found traces of reverse disposition effect in SRI funds: Some SRI fund managers appear to realize losses more readily than gains. Our study also revealed that there are no significant differences in the behaviour of SRI fund managers compared with non-SRI fund managers.

Because earlier studies had found a link between the disposition effects and other factors such as market trends, managers' characteristics, and prior performance, we replicate our analysis taking these factors into accounts. The results of our study remained consistent and robust, even when taking these factors into account.

Finally, in Chapter 3 our aim was to capture the dynamics of the tournament behaviour of mutual fund managers. The interest in this phenomenon raises from the fact that investors are constantly chasing well-performing funds, to the extent that the *winner* of the annual tournament takes the largest share. Indeed, mutual funds with outstanding past performance receive disproportionately larger inflows. For this reason, it was hypothesised and empirically tested in some studies that losing managers would gamble, while winners will try to lock in their position. Nonetheless, other empirical studies have hypothesised that winners are more likely to gamble to secure their position.

In the current study, we employed Data Envelopment Analysis as it allows us to investigate how efficiently fund managers take part into this tournament without any pre-established functional form between the variables involved in tournament behaviour. To our knowledge this study is the first to employ Network DEA to model behaviour in the mutual funds industry. This study is part of the new sub-discipline of Behavioural Operational Research that aims to investigate behaviour with the help of operational research techniques.

For a more thorough analysis, we divided each annual tournament into three stages. First, we analysed how efficiently fund managers reacted to their mid-year performance rankings. In this first stage, we evaluated how efficiently fund managers altered the equity exposure, the beta, and the concentration of their portfolio in relation to their mid-year percent rank. Secondly, we focused on how efficiently these changes in equity exposure, in beta, in portfolio concentration generated changes in year-end percent rankings. And finally, we investigated how efficiently these changes in year-end rankings attracted inflows in the subsequent quarter.

By dividing the tournament into three stages, we were able to obtain some interesting results. First, our results reveal that though a limited number of managers can efficiently alter the equity exposure, the beta, and the concentration of their portfolio as a result of their mid-year rankings, a fewer number of them can translate these changes into improved year-end rankings. We also found that efficiently altering the beta of a portfolio in relation to mid-year performance did not predict future flows into the fund. Based on our results, future inflows are more linked to how well managers can improve their year-end ranks compared with their mid-year ranks.

Resumen y conclusiones

Los principios fundamentales de los modelos financieros clásicos presentan a unos agentes racionales que interactúan en mercados eficientes. En la práctica, estas premisas, aunque deseables, casi nunca se cumplen. De hecho, los inversores operan en un entorno en el que hay numerosas noticias que procesar, además de opiniones divergentes, interpretaciones distintas y una asimetría de la información. Aun así, el entorno es sólo una parte de la ecuación, ya que los inversores tienen que lidiar también con sus propios sesgos y heurísticas, y están sujetos a fallos de razonamiento, a errores y a sus propias emociones.

Las finanzas conductuales no sólo incorporan en el diseño de sus modelos la maximización de la utilidad y la aversión al riesgo, sino que también toman en consideración las heurísticas, los sesgos, los atajos cognitivos y las emociones, factores a los que estamos todos sujetos. El objetivo de las finanzas conductuales es tender un puente entre la teoría y la práctica. Las finanzas conductuales son el subcampo de la economía conductual que investiga cómo los factores y sesgos psicológicos afectan al comportamiento de los inversores minoristas, a los profesionales de las finanzas y al mercado en su conjunto. Como tal, las finanzas conductuales se centran en proporcionar información no sólo a los inversores particulares, sino también a los profesionales. De hecho, se ha demostrado que los sesgos no se limitan a los inversores particulares, sino que son inherentes al comportamiento humano.

Corrigiendo sus sesgos, los gestores profesionales de fondos de inversión pueden ser más eficientes y, dado el tamaño de las carteras que gestionan, sus sesgos podrían tener un gran impacto en los mercados financieros. Los errores cognitivos, los sesgos y las falacias forman parte del comportamiento humano y el primer paso para evitar caer presa de ellos es tomar conciencia de su existencia.

Dada la considerable proporción del mercado financiero que administran los gestores profesionales de fondos, las conclusiones de esta tesis revisten importancia tanto para la investigación académica como para el sector financiero.

Esta tesis responde también al considerable y duradero interés de los inversores por los fondos de inversión como instrumento de ahorro. En efecto, existe una fuerte demanda de fondos de inversión y los flujos hacia dichos fondos han crecido exponencialmente en la última década. El patrimonio neto total gestionado en fondos regulados se multiplicó por siete en dos décadas y, solo en el periodo comprendido entre finales de 2020 y finales de 2021, el patrimonio neto total de los fondos de inversión pasó de 63,0 billones de USD a 71,1 billones de USD en todo el mundo (Investment Company Institute, 2022).

Paralelamente al rápido crecimiento de la demanda de fondos de inversión, se ha producido un aumento de la demanda de tipos específicos, como los fondos de Inversión Socialmente Responsable (ISR). En tan solo cuatro años, la Global Sustainable Investment Alliance (2020) informó de un aumento del 55% en el total de activos gestionados de inversiones sostenibles globales gestionadas profesionalmente, alcanzando los 35,3 billones de USD a principios de 2020.

Las finanzas conductuales son un campo de estudio bien establecido. Sin embargo, hay varias cuestiones relacionadas con las finanzas conductuales que siguen sin explorarse. En este trabajo se han identificado tres cuestiones merecedoras de atención, que se abordarán en capítulos separados:

1. Dado que la evidencia ha demostrado que el sesgo de exceso de confianza tiene un impacto potencialmente negativo en el rendimiento, ¿cómo podemos detectar a los gestores de fondos con exceso de confianza? ¿Cuáles son las características de los gestores de fondos más propensos a este sesgo?

2. Basándonos en la literatura previa, sabemos que los inversores en inversiones socialmente responsables (ISR) tienen una doble motivación, tanto financiera como social. Entonces, ¿los gestores de fondos ISR operan de forma diferente en comparación con los gestores de fondos convencionales? ¿Ambos grupos presentan diferencias en cuanto a un sesgo como el sesgo de disposición?

3. Puesto que se ha demostrado empíricamente que el "mejor fondo se lo lleva todo" en términos de captación de inversores, ¿hasta qué punto son eficientes los gestores de fondos cuando reaccionan a su clasificación de resultados a mitad de año? ¿Cuán eficientes son los gestores de fondos en el torneo en su conjunto?

Así pues, el objetivo del Capítulo 1 es diseñar una medida que pueda identificar a los gestores de fondos excesivamente confiados con mayor precisión que las aproximaciones utilizadas de forma aislada en la literatura. La principal contribución de este trabajo es la medida compuesta de exceso de confianza y las recomendaciones sobre la elección y la calibración de los indicadores utilizados en esta medida.

En el capítulo 2, el objetivo es encontrar pruebas del sesgo de disposición en un grupo de fondos ISR y un grupo equivalente de fondos no ISR. Este estudio complementa otros estudios que comparan el comportamiento de los gestores de fondos ISR con el comportamiento de los gestores no ISR. Además, llena el vacío existente en la literatura al investigar el sesgo de disposición en los fondos ISR.

Por último, el Capítulo 3 pretende dilucidar la dinámica del torneo en el sector de los fondos de inversión. Proponemos un modelo de tres etapas y empleamos un Análisis Envolvente de Datos en Red (Network DEA) para evaluar la eficiencia de los gestores de fondos de inversión en el torneo. Hasta donde sabemos, nuestro estudio es el primero que emplea el DEA en red para evaluar el comportamiento en el sector de los fondos de inversión.

Capítulo 1: Un nuevo sistema de medición del exceso de confianza en gestores de fondos de inversión

1.1 Introducción

El exceso de confianza es un sesgo de comportamiento robusto y bien documentado. En general, se dice que existe exceso de confianza cuando la percepción que tienen las personas de sus capacidades es superior a su rendimiento objetivo. Este concepto, procedente de la psicología, se ha extendido a otros campos de estudio en la última década. Debido a su prevalencia, el exceso de confianza se presenta a menudo como la causa subyacente de muchos acontecimientos, desde guerras (Johnson, 2004) hasta huelgas (Neale y Bazerman, 1985), desde altas tasas de nuevas empresas a pesar de notables fracasos empresariales (Van Zant y Moore, 2013) hasta colapsos y burbujas financieras (Michailova y Schmidt, 2016). Moore y Healy (2008) presentaron una revisión exhaustiva de trabajos en esta línea. En palabras de Griffin y Tversky (1992, p. 432): "Difícilmente puede exagerarse la importancia del exceso de confianza para la gestión de los asuntos del ser humano".

Varios estudios empíricos realizados en la población general revelan el predominio de este sesgo. Un ejemplo popular es el análisis realizado por Svenson (1981). Basándose en una muestra de estudiantes estadounidenses, el autor ofrece una clara ilustración: Más del 80% de los estudiantes encuestados creían estar entre el 30% de los mejores en cuanto a seguridad vial. En el campo de las finanzas y la inversión, James Montier (2006) realizó un estudio similar sobre un grupo de 300 gestores de fondos profesionales. Los resultados del estudio revelaron que el 74% de los gestores de fondos consideraba que su rendimiento en el trabajo estaba por encima de la media y el 26% juzgaba que su rendimiento estaba en la media, quedando un 0% que se consideraba por debajo de la media. Estos estudios ilustran claramente lo que se ha dado en llamar el sesgo " por encima de la media".

Aunque la prevalencia y la ubicuidad del exceso de confianza están bien establecidas, existe un vacío en la literatura en relación con la identificación empírica del exceso de confianza. Algunos estudios recurren al uso de experimentos de laboratorio para medir el exceso de confianza por no haberse establecido aún la validez de los proxies (por ejemplo, Duxbury, 2015), otros estudios recurren al uso de proxies de exceso de confianza para superar la posible falta de un componente real en los experimentos de laboratorio (por ejemplo, Puetz y Ruenzi, 2011). Los principales proxies utilizados en la literatura para detectar el exceso de confianza son la frecuencia de operaciones (Barber & Odean, 2000; Barber & Odean, 2001; Glaser & Weber, 2007; Odean, 1999; Puetz & Ruenzi, 2011), la gestión activa (Choi & Lou, 2010) y la exposición al riesgo (O'Connell & Teo, 2009), siendo la frecuencia de operaciones uno de los proxies más utilizados.

Sin embargo, el uso de un único proxy podría dar lugar a estimaciones sesgadas, ya que se podrían estar captando otros fenómenos, por ejemplo, la compraventa inducida por el flujo y los comportamientos de torneo (Coval & Stafford, 2007; Kempf et al., 2009). Además, en algunos mercados las variables sustitutivas generalmente utilizadas en la literatura podrían no ser muy eficaces debido a sus niveles relativamente bajos de variación entre los distintos fondos de inversión. Por ejemplo, Beckmann et al. (2008) han demostrado que los gestores de activos en países con una cultura de rechazo a la incertidumbre tienden a desviarse menos de su índice de referencia. En tales mercados, el coeficiente de actividad (active share) podría ser relativamente bajo y no presentar mucha variación entre los distintos fondos.

Detectar adecuadamente el exceso de confianza reviste una importancia primordial por sus posibles consecuencias en el mercado financiero. Daniel Kahneman considera que el exceso de confianza es "el más perjudicial" de los sesgos de comportamiento (Shariatmadari, 2015, párr. 4). De hecho, varias investigaciones empíricas son coherentes con la idea de que el exceso de confianza puede ser dañino para el rendimiento de los fondos de inversión (Choi y Lou, 2010; Cuthbertson et al., 2016; Puetz y Ruenzi, 2011). En este sentido, la hipótesis del sesgo de atribución autocomplaciente sugiere que los gestores con exceso de confianza solo prestarán atención a las señales confirmatorias e ignorarán las señales no confirmatorias, lo que conducirá a una mala asignación de la cartera y, en consecuencia, a peores resultados (Choi & Lou, 2010).

El objetivo de este estudio es diseñar una medida compuesta de exceso de confianza (OCS, por sus siglas en inglés) que pueda ayudar a identificar el exceso de confianza en los gestores de fondos de inversión. En este estudio, combinamos la ratio de rotación, el active share y la exposición a la renta variable para construir una puntuación que mida el nivel de confianza de los gestores de fondos de inversión. Sostenemos que los gestores de fondos de inversión que simultáneamente negocian más, se desvían más de su índice de referencia y mantienen el mayor porcentaje de su patrimonio neto total en renta variable pueden considerarse excesivamente confiados.

La combinación de varios indicadores tiene varias ventajas. En primer lugar, no está exactamente claro que lo que captan los indicadores individuales sea el exceso de confianza y no otro acontecimiento o fenómeno. Por ejemplo, la ratio de rotación también se ha empleado para investigar el efecto maquillaje de cartera, también conocido como "window-dressing" (Elton et al., 2010; Ortiz et al., 2015). Mediante la combinación de proxies, proporcionamos un método mejorado de detección del exceso de confianza en los gestores de fondos de inversión. Finalmente, al permitir asignar diferentes pesos a cada proxy, nuestro OCS podría ser mucho más flexible y adaptable a cada mercado que el uso de un único indicador.

Este estudio utiliza el Análisis de Componentes Principales ("PCA", por sus siglas en inglés) para evaluar la influencia de la rentabilidad pasada en el nivel de confianza (CL) de los gestores de fondos. La función del PCA es establecer los puntos en común entre las tres proxies más utilizadas: la ratio de rotación, el active share y la exposición a renta variable. En una segunda fase, nuestro estudio valida esta novedosa puntuación compuesta que incluye simultáneamente los tres proxies y su relación con los resultados destacados anteriores.

Una aportación adicional de nuestro estudio es el uso de niveles relativos de confianza en lugar de valores absolutos de confianza. Los niveles absolutos de exceso de confianza podrían no ser muy informativos para los sectores en los que los participantes ya tienen un nivel de confianza más alto o en los que se les exige tener cierta confianza en sus capacidades para realizar su trabajo. Schulz y Thöni (2016), al analizar el vínculo entre el exceso de confianza y la elección de carrera, encontraron diferencias significativas entre los campos de estudio y llegaron a la conclusión de que los estudiantes de campos relacionados con los negocios mostraban los mayores niveles de confianza. Por este motivo, resulta más apropiado utilizar una medida relativa del exceso de confianza que compare a los gestores de fondos de inversión con sus homólogos. Además, el uso de medidas relativas permitiría la calibración en función del mercado.

En resumen, nuestro enfoque pretende calibrar el nivel de confianza de los gestores de fondos en relación con sus homólogos y, a continuación, proporcionar una puntuación de exceso de confianza que pueda calibrarse y adaptarse a diferentes contextos y mercados de fondos. Nuestro análisis principal está orientado hacia la detección del exceso de confianza de los gestores de fondos de inversión. Posteriormente, utilizamos este análisis inicial para identificar las características de los gestores de fondos con exceso de confianza, en concreto, el género, la educación y la experiencia. Posteriormente, comprobamos la solidez y la coherencia de nuestra medida. Por último, investigamos el impacto del exceso de confianza en el rendimiento posterior.

1.2 Datos y metodología

La base de datos inicial se compone de datos trimestrales de participaciones en cartera, valor liquidativo y total de patrimonio neto (TNA) de todos los fondos de renta variable registrados en España. Esta información, disponible públicamente para los inversores y para el público en general, fue proporcionada por la Comisión Nacional del Mercado de Valores (CNMV). El uso de información disponible públicamente es especialmente apropiado en este estudio porque estamos midiendo el sesgo "por encima de la media": Los gestores de fondos podrían tener un exceso de confianza cuando, basándose en la información disponible para todo el mundo, se clasifican mejor que sus homólogos.

El periodo de estudio abarca el periodo comprendido entre diciembre de 1999 y diciembre de 2016. Acotamos nuestro análisis a las dos categorías de inversión en renta variable más relevantes en España en términos de TNA: fondos de renta variable nacional y fondos de renta variable euro, que representan el 32% del TNA gestionado en la industria de fondos de renta variable en el año 2016. Al final de todo el proceso de selección, obtenemos un total de 279 fondos de renta variable y 9.831 carteras trimestrales. La muestra está libre tanto del sesgo de supervivencia como del sesgo de anticipación. De hecho, todos los fondos que entran en la base de datos se tienen en cuenta en el análisis, aunque en algún momento dentro del periodo de tiempo estudiado hayan dejado de existir.

Excluimos de la muestra final las carteras de fondos indexados, dado que no proceden de una gestión activa. En consecuencia, éstos no pueden reflejar adecuadamente el nivel de confianza de los gestores de fondos. Sólo la gestión activa sería válida para calibrar el exceso de confianza. También controlamos las fusiones y adquisiciones dentro de la muestra de fondos para garantizar que las variaciones en el TNA reflejen la actividad no excepcional del fondo. Por último, excluimos 16 fondos por no proporcionar información durante al menos 5 trimestres consecutivos. Este periodo mínimo es necesario para calcular los datos de rendimiento anual. gestores de fondos en relación con sus homólogos y, a continuación, proporcionar una puntuación de exceso de confianza que pueda calibrarse y adaptarse a diferentes contextos y mercados de fondos. Nuestro análisis principal está orientado hacia la detección del exceso de confianza de los gestores de fondos de inversión. Posteriormente, utilizamos este análisis inicial para identificar las características de los gestores de fondos con exceso de confianza, en concreto, el género, la educación y la experiencia. Posteriormente, comprobamos la robustez y la coherencia de nuestra medida. Por último, investigamos el impacto del exceso de confianza en el rendimiento posterior.

Con el objetivo de determinar adecuadamente las características de los gestores excesivamente confiados, construimos dos submuestras a partir de nuestra muestra inicial. En primer lugar, obtenemos una submuestra más reducida compuesta únicamente por fondos gestionados por un único gestor. En este conjunto, agrupamos los fondos para los que disponemos de información sobre las características personales de los gestores, a saber, sexo, educación y duración de la experiencia en el sector. La información sobre la experiencia en el sector, sobre los nombres completos de los gestores y sobre la estructura de gestión de los fondos de inversión se obtiene de Morningstar, y la información sobre el nivel de estudios de los gestores se recoge manualmente de páginas web oficiales y redes sociales profesionales. El género se asigna manualmente a partir de los nombres de pila de los gestores de fondos.

A continuación, diseñamos una segunda submuestra más amplia compuesta por todos los fondos de los que tenemos información sobre la estructura de gestión. Incluimos tanto los fondos gestionados en solitario como los gestionados en equipo. En total, la submuestra de fondos gestionados por un único gestor, la muestra más pequeña, comprende 114 fondos de renta variable y 2.717 carteras trimestrales; la segunda submuestra comprende 173 fondos de renta variable y 4.650 carteras.

Para comparar los fondos nacionales y los fondos de la Eurozona con su índice de referencia, utilizamos las ponderaciones trimestrales de los componentes del índice de referencia español Ibex35 y del índice de referencia de la Eurozona EuroStoxx50, respectivamente. Ambos conjuntos de datos proceden de Datastream.

Mientras que la ratio de rotación, la participación activa y la exposición a acciones utilizadas de forma aislada podrían caracterizar otros patrones de gestión y de comportamiento diferentes, su uso combinado podría proporcionar una medida más precisa.

En efecto, la mayoría de los estudios mencionados han recurrido al empleo de una única variable sustitutiva. Al utilizar un único indicador, se podrían captar otras conductas de gestión y comportamiento distintas del exceso de confianza. Por ejemplo, la ratio de rotación también se ha empleado para probar el escaparatismo (Elton et al., 2010; Ortiz et al., 2015); el active share se ha utilizado sobre todo para predecir el rendimiento (Cremers & Petajisto, 2009); y la exposición a la renta variable se ha utilizado para evaluar el cambio de nivel de riesgo (Huang et al., 2011). En nuestra opinión, el uso de la contribución acumulada de los tres indicadores nos permite identificar a los gestores excesivamente confiados con un alto nivel de certeza. Puede decirse que los gestores de fondos que simultáneamente realizan más operaciones, se desvían más de su índice de referencia y mantienen un porcentaje de cartera más alto en renta variable en comparación con sus homólogos están sujetos al exceso de confianza con un alto nivel de certeza. No obstante, hay que reconocer también que una posible desventaja de utilizar tres indicadores simultáneamente es el carácter restrictivo de este método y, en consecuencia, podríamos dejar fuera a algunos gestores que tienen exceso de confianza pero que no se sitúan simultáneamente en los primeros puestos de las tres medidas.

Inicialmente, siguiendo el método utilizado por Adebambo y Yan (2016), nuestra primera metodología consiste en utilizar el Análisis de Componentes Principales (CPA, por sus siglas en inglés). El CPA se utiliza para identificar los puntos en común entre los tres proxies. Sobre la base de la hipótesis explicada anteriormente, se podría argumentar que se trata del nivel de confianza de los directivos. El CPA se utiliza para determinar la relación entre los resultados anteriores y el posterior nivel de confianza obtenido por los gestores de fondos de inversión.

Basándonos en los resultados del CPA, construimos una puntuación compuesta de exceso de confianza en la que todos los indicadores se ponderan en función de sus eigenvalores. La puntuación compuesta sirve como herramienta para clasificar a los gestores de fondos en cada trimestre como excesivamente confiados o no, según un umbral específico.

1.3 Resultados y conclusiones

Este estudio construye una puntuación para evaluar el exceso de confianza de los gestores profesionales basándose en el Análisis de Componentes Principales ("PCA", por sus siglas en inglés). Esta puntuación de exceso de confianza se basa en la calibración independiente de tres proxies en función de los rangos relativos de los gestores de fondos. Los gestores de fondos que simultáneamente realizan más operaciones, que se desvían más de su índice de referencia y mantienen el mayor porcentaje de sus activos en renta variable se consideran excesivamente confiados. Nuestra puntuación de exceso de confianza puede adaptarse a otros sectores de fondos de inversión o a otros mercados de fondos de renta variable recalibrando las variables en función de los resultados del ACP.

Este trabajo valida nuestra puntuación en la industria española de fondos de renta variable. Analizamos uno de los principales mercados de fondos de inversión de la zona euro. De acuerdo con la hipótesis empíricamente validada de que el exceso de confianza aumenta en los gestores con buenos rendimientos, encontramos que nuestra medida compuesta permite la clasificación binaria de los gestores con exceso de confianza con una gran precisión.

Nuestros modelos también reflejan la clasificación siguiente de la influencia de los resultados anteriores en el exceso de confianza: En primer lugar, los gestores de alto rendimiento y, a continuación, los de bajo rendimiento son significativamente más propensos a mostrar patrones de exceso de confianza en la gestión, en comparación con los de rendimiento medio. En lo que respecta a la baja confianza, los trabajadores con un rendimiento medio tienen una mayor tendencia a mostrar bajos niveles de confianza, seguidos de los trabajadores con un rendimiento bajo y, a continuación, de los trabajadores con un rendimiento alto. Aportamos pruebas que apoyan la hipótesis de que la búsqueda desesperada de mejores rendimientos por parte de los gestores con rendimientos bajos podría impulsar patrones de gestión similares al exceso de confianza de los gestores con alto rendimiento.

Además, nuestro análisis revela que el exceso de confianza de los gestores con mejores resultados conduce a un deterioro del rendimiento relativo posterior. Sin embargo, los resultados de la prueba de Wilcoxon no demuestran que un OCS elevado perjudique a los directivos de bajo rendimiento. Por el contrario, nuestros resultados sugieren que los gestores de bajo rendimiento que aumentan su active share, su ratio de rotación y su exposición a renta variable tienden a obtener mejores resultados en los trimestres siguientes.

Por último, nuestro estudio también ofrece otras conclusiones interesantes. En primer lugar, la percepción de los gestores españoles de la Eurozona como un universo de inversión local más amplio que el mercado de valores nacional podría explicar el impacto positivo de la diversificación y la inversión en valores de la Eurozona sobre el exceso de confianza. En segundo lugar, los mecanismos de afrontamiento podrían explicar por qué las mujeres gestoras son más propensas al exceso de confianza que sus homólogos masculinos en un sector dominado por los hombres como es el mercado español de fondos de inversión. En lo que se refiere a otras características, también encontramos que los gestores que poseen un máster o la designación de Chartered Financial Analyst son más propensos al exceso de confianza, mientras que la experiencia en el sector no parece influir en el exceso de confianza.

Capítulo 2: El sesgo de disposición en los fondos ISR

2.1 Introducción

La demanda de fondos de inversión socialmente responsable (ISR) ha crecido exponencialmente en las dos últimas décadas en los principales mercados financieros del mundo. Según la Global Sustainable Investment Alliance (2018), en los cinco principales mercados financieros (Europa, Estados Unidos, Japón, Canadá y Australia/Nueva Zelanda), las inversiones sostenibles pasaron de 22,8 billones de USD en 2016 a 30,6 billones en 2018, lo que supone un aumento del 34 % en solo dos años. Más recientemente, US SFI Foundation-The Forum for Sustainable and Responsible Investment (2020) informó de un aumento del 42% en los patrimonios gestionados y domiciliados en Estados Unidos que utilizan estrategias ISR en dos años: de 12 billones USD a principios de 2018 a 17,1 billones USD a principios de 2020. Dicho de otro modo, este informe afirma que las inversiones éticas representaron uno de cada tres dólares del patrimonio total de activos bajo gestión profesional en 2020 (51,4 billones USD). La creciente demanda de inversiones éticas convirtió lo que antes era un nicho de mercado en una clase de inversión dominante.

Un amplio corpus de literatura se centra en evaluar el rendimiento de los fondos de inversión ISR en diferentes mercados financieros, especialmente en comparación con los fondos convencionales o frente a índices de referencia. Algunos estudios concluyen que los fondos ISR y los fondos convencionales no presentan diferencias significativas en términos de rendimientos (Bauer et al., 2005; Kempf y Osthoff, 2008); otros concluyen que los fondos ISR obtienen rendimientos más elevados (Kempf y Osthoff, 2007; Gil-Bazo et al., 2010); y otros constatan que obtienen rendimientos inferiores (Renneboog et al., 2008). Si bien es cierto que los fondos ISR y los fondos convencionales comparten objetivos financieros similares, ya que buscan encontrar el equilibrio óptimo entre riesgo y rentabilidad, también es importante analizar la diferencia sustancial entre ambos tipos de fondos. Además de la búsqueda de un equilibrio adecuado entre riesgo y rentabilidad, los fondos de inversión ISR emplean criterios medioambientales, sociales y de gobierno corporativo (ASG) para elaborar su estrategia de inversión. El doble objetivo de los fondos de inversión ISR podría influir, no sólo en sus resultados, sino también en el comportamiento de los gestores (Kempf and Osthoff, 2008; Gil-Bazo et al., 2010; Benson et al., 2006).

Pese a los argumentos que se sostienen desde hace años acerca de la diferencia de rentabilidad entre los fondos ISR y los fondos convencionales, la rentabilidad no parece ser la razón principal por la que los inversores minoristas mantienen fondos de inversión ISR. Riedl y Smeets (2017) comprobaron y confirmaron mediante experimentos que los inversores mantienen fondos ISR principalmente por motivos sociales intrínsecos, mientras que los motivos financieros desempeñan un papel también importante, aunque limitado. Otros ejemplos de estudios experimentales que encuentran resultados similares son Barreda-Tarazona et al. (2011), Apostolakis et al. (2018) y Lagerkvist et al. (2020).

Además, Bollen (2007), Benson y Humphrey (2008) y Renneboog et al. (2011) encontraron que los inversores ISR son menos sensibles que los inversores convencionales a los malos resultados y más propensos que los inversores convencionales a mantener su inversión a pesar de los malos resultados. Durán-Santomil et al. (2019) determinaron que las calificaciones de sostenibilidad afectan significativamente a los flujos: Las puntuaciones de sostenibilidad más altas atraen mayores flujos de entrada al fondo. Del mismo modo, Hartzmark y Susmann (2019) analizaron fondos de inversión estadounidenses y concluyeron que los inversores valoran la sostenibilidad, ya que encuentran una relación directa entre ser clasificado como de "baja sostenibilidad" y obtener salidas netas e, inversamente, ser clasificado como de "alta sostenibilidad" resultó en entradas de capital netas.

Las implicaciones de los aspectos no financieros de los fondos de inversión ISR podrían ir más allá del rendimiento, los flujos y la persistencia de los flujos, e impulsar no sólo el comportamiento y las expectativas de los inversores minoristas, sino también el comportamiento y las expectativas de los gestores de fondos de inversión ISR, sus pautas de realización y sus estilos de inversión.

Acuñado originalmente por Shefrin y Statman (1985), el término "sesgo de disposición" se refiere a la tendencia que tienen los inversores a vender acciones apreciadas (ganadoras) demasiado pronto, mientras que mantienen acciones depreciadas (perdedoras) durante demasiado tiempo. El precio de compra se fija como punto de referencia para la apreciación o la depreciación. El sesgo de disposición es una anomalía robusta y bien documentada que se investigó tanto a nivel de inversor como a nivel agregado, tanto empírica como experimentalmente (véase Cici, 2012 para un estudio pionero sobre el sesgo de disposición de los gestores de fondos de inversión; Summers y Duxbury, 2012 para un ejemplo de estudio experimental y Andreu et al., 2020 como ejemplo de un estudio empírico reciente). El sesgo de disposición también se ha investigado en mercados financieros de todo el mundo, por ejemplo, en Estados Unidos por Cici (2012), en el Reino Unido por Richards et al. (2017), en Francia por Boolell-Gunesh et al. (2009), en Portugal por Leal et al. (2010), en Taiwán por Lee et al. (2013), y en China por Duxbury et al. (2015) y An et Al. (2019).

En cuanto a las causas del sesgo de disposición, Shefrin y Statman (1985) proponen un marco teórico que vincula el sesgo de disposición con la teoría prospectiva de Kahneman y Tversky (1979) y con la contabilidad mental. Shefrin y Statman (1985) proponen la aversión al arrepentimiento y la búsqueda del orgullo como posibles explicaciones del sesgo de disposición. Reconociendo que estudios posteriores basados en su trabajo presentan la *prospect theory* como la principal, si no la única, explicación del sesgo de disposición, Shefrin (2007) insiste en el hecho de que la *prospect theory* es una base para estudiar el sesgo de disposición, pero no puede servir como explicación única de su aparición. Shefrin (2007) advierte que no se debe restar importancia o ignorar el papel de las explicaciones del sesgo de disposición basadas en las emociones, en particular, el papel de la aversión al arrepentimiento.

Basándose en modelos teóricos, Barberis y Xiong (2009) y Hens y Vlcek (2011) llegan a la conclusión de que la teoría de las perspectivas no puede explicar el sesgo de disposición. Aunque en estos trabajos se cuestiona la *prospect theory*, no aportan ninguna explicación alternativa. Summers y Duxbury (2012) llevaron a cabo varios experimentos que llevan a la conclusión de que estados emocionales específicos son los impulsores del sesgo de disposición: el arrepentimiento tras una pérdida de papel impulsa a mantener a las acciones perdedoras, mientras que la euforia tras una ganancia de papel lleva a vender a las acciones ganadoras.

2.2 Datos y metodología

A partir de los datos y la clasificación facilitados por Morningstar, hemos construido una muestra completa de fondos de renta variable estadounidense de las cuatro categorías globales siguientes: US Equity Large-Cap Blend, US Equity Large-Cap Growth, US Equity Large-Cap Value y US Equity Mid-Cap. Utilizamos la clasificación de inversión sostenible de Morningstar para agrupar los fondos en fondos ISR o fondos convencionales. Para llevar a cabo nuestro análisis, requerimos un mínimo de 5 carteras mensuales consecutivas, lo que llevó a la exclusión de algunos fondos ISR por no proporcionar datos suficientes para el análisis. Nuestro análisis requería estrictamente fondos de inversión que invirtieran activamente en renta variable; por este motivo, los fondos indexados y los fondos de fondos quedan excluidos del análisis. Tras aplicar los filtros anteriores, nuestra base de datos comprendía 78 fondos de inversión ISR. Para mayor precisión, empleamos carteras mensuales para calcular el sesgo de disposición, por lo que excluimos los fondos ISR que sólo informan trimestralmente. Según Elton et al. (2010), el uso de carteras trimestrales para analizar el comportamiento de los gestores de fondos de inversión de renta variable podría dar lugar a distorsiones en los resultados obtenidos debido a las operaciones de ida y vuelta intratrimestrales. Nuestra muestra final de fondos ISR se compone de fondos domiciliados en Estados Unidos durante el periodo comprendido entre enero de 2005 y diciembre de 2020 y está libre de sesgo de supervivencia.

Para evaluar el impacto de la selección socialmente responsable en el sesgo de disposición, construimos un conjunto de fondos convencionales. Para ello, emparejamos cuidadosamente cada fondo ISR con un fondo convencional. Exigimos que el fondo ISR y el fondo convencional coincidan en términos de categoría global, tamaño (medido por el patrimonio neto total medio del fondo durante todo el periodo estudiado) y antigüedad (calculada a partir de la fecha de inicio de la clase de acciones más antigua). Tras filtrar los fondos ISR que no informan mensualmente de sus carteras, la base de datos final constaba de dos conjuntos de fondos: 54 fondos de inversión ISR y 54 fondos convencionales.

Posteriormente, creamos una base de datos exhaustiva de las 50 participaciones principales de cartera en términos de valores de mercado y número de acciones para todos los fondos de inversión de nuestra muestra y para cada periodo de información. Estas participaciones de cartera empleadas se comunican mensualmente. En su estudio, El Ghoul y Karoui (2017) demostraron, al examinar las puntuaciones de responsabilidad social corporativa, que las 10 principales tenencias son representativas de toda la cartera. En este estudio, decidimos utilizar las 50 principales participaciones, en primer lugar para proporcionar resultados más robustos mediante el análisis de una amplia gama de participaciones y, en segundo lugar, para evitar el sesgo de un posible sesgo de maquillaje de cartera. En efecto, dado que la información sobre las 10 principales participaciones de los fondos está fácilmente a disposición de los inversores en los medios de comunicación financieros y en los sitios web y folletos de las sociedades de gestión de activos, son más susceptible de manipulación, en caso de que tenga lugar. Además, al emplear las 50 participaciones principales y no la colección completa de participaciones, nos centramos en los valores más representativos que, al mismo tiempo, podrían ser los más significativos para los gestores de cartera a la hora de elaborar su estrategia. Se excluyen el efectivo, los equivalentes de efectivo y las posiciones en derivados. El porcentaje de las 50 principales participaciones analizadas es una parte significativa de la cartera de los fondos y, por término medio, representa el 80,59% del valor del patrimonio neto total (TNA) de los fondos de nuestra muestra.

Para evaluar si los gestores de fondos están sujetos al sesgo de disposición, calculamos el margen de disposición. El margen de disposición es la diferencia entre la proporción de ganancias realizadas y la proporción de pérdidas realizadas. Si un gestor de fondos está sujeto al efecto de disposición, la proporción de ganancias realizadas será mayor que la proporción de pérdidas realizadas, lo que se traduce en un margen de disposición positivo (es decir, PGR > PLR).

Para calcular el margen de disposición, el primer paso consiste en determinar, para cada acción mantenida en la cartera, si se produce una venta dentro del período de referencia. Por lo tanto, necesitamos determinar dos elementos cruciales en nuestro cálculo: el precio de compra que fijamos como punto de referencia y el precio de venta. La diferencia entre el precio de coste y el precio actual determinará si una posición está en ganancias o en pérdidas. Dado que no se dispone de información sobre las transacciones entre períodos de los fondos y, por lo tanto, no puede determinarse el momento exacto del mes en que tiene lugar una transacción determinada, los estudios sobre el sesgo de disposición suponen que las transacciones se producen en algún momento del período de referencia o al final del mismo. Estudios anteriores como el de Cici (2012) encontraron resultados consistentes cuando se utilizan los precios medios diarios de las acciones, basándose en el supuesto de que las operaciones se producen en algún momento durante el período de información y cuando se utilizan los precios de las acciones al final del período de información, presuponiendo que las operaciones se producen al final del período de información. Siguiendo a Andreu et al. (2020), suponemos que todas las operaciones se producen al final del mes. Por lo tanto, asumiremos que el precio de compra o el precio de venta es el precio al final del mes. Para calcular el precio de venta y el precio de compra, dividimos el valor de mercado comunicado de la acción específica por el número de acciones, ambos valores comunicados a final de mes.

Cuando se producen las ventas finales, es decir, cuando un fondo deja de poseer unas determinadas acciones (Badrinath y Wahal, 2002), no tenemos valor de mercado para determinar el precio de venta; entonces procedemos de forma diferente. En primer lugar, intentamos recuperar el precio de venta al final del mes en cuestión de otro fondo que posea esas acciones. Si esto no es posible, obtenemos el precio de fin de mes de las acciones a partir de la base de datos de Eikon.

En el presente estudio, las compras adicionales se tienen en cuenta utilizando el método del precio medio de compra como inventario. Odean (1998) y Cici (2012) documentan que los resultados de las investigaciones sobre el sesgo de disposición son coherentes incluso cuando se utilizan otros métodos de inventario como primero en entrar, primero en salir (FIFO), primero en entrar, primero en salir (HIFO) o último en entrar, primero en salir (LIFO).

Seguimos el enfoque basado en ratios propuesto por Odean (1998) para calcular la proporción de ganancias realizadas y la proporción de pérdidas realizadas, para cada fondo y para cada periodo de información.

2.3 Resultados y conclusiones

Las inversiones éticas representan actualmente una parte creciente e importante de los mercados de inversión en Estados Unidos y en el mundo. Aunque varios estudios han investigado la diferencia de rendimiento de los fondos de Inversión Socialmente Responsable (ISR) en comparación con los fondos convencionales, el rendimiento no parece ser la razón principal por la que los inversores mantienen fondos ISR. Muchos autores han encontrado pruebas que demuestran que los inversores de fondos ISR están motivados principalmente por su responsabilidad social, que son menos sensibles a los malos resultados y que es más probable que mantengan una inversión en un fondo a pesar de los malos resultados.

¿Influyen la responsabilidad social de su fondo y las expectativas de sus inversores en la forma en que los gestores de fondos ISR obtienen pérdidas y ganancias? En este estudio, contrastamos varias hipótesis nulas: no existe diferencia en la proporción de ganancias realizadas (PGR) y la proporción de pérdidas realizadas (PLR), (H1) para los gestores ISR y (H2) para los gestores convencionales. Por último, también probamos la hipótesis nula (H3) de que los gestores de fondos ISR y los gestores de fondos convencionales no presentan diferencias significativas en términos de márgenes de disposición (PGR-PLR).

En consonancia con Cici (2012), no encontramos evidencia de un sesgo de disposición generalizado en los fondos de inversión de renta variable. Además, los resultados de nuestra investigación apoyan la idea de que no existen diferencias significativas en el comportamiento de los gestores de fondos ISR y convencionales en términos de sesgo de disposición. Curiosamente, sí observamos que los gestores de fondos ISR podrían ser más propensos a realizar pérdidas en lugar de ganancias, especialmente en la categoría de renta variable estadounidense de gran capitalización mixta. A pesar de su responsabilidad social, en comparación con los gestores de fondos convencionales, los gestores de fondos de inversión ISR no muestran un patrón de comportamiento significativamente diferente a la hora de afrontar pérdidas y ganancias.

Basándonos en nuestros resultados, rechazamos la hipótesis H1, dado que los gestores ISR tienden a realizar más pérdidas que ganancias. Sin embargo, este comportamiento no es coherente con el sesgo de disposición. Tampoco rechazamos la hipótesis H2, ya que no hay pruebas de diferencias en la realización de pérdidas y ganancias para los gestores convencionales. Por último, no rechazamos la hipótesis H3: no existen diferencias significativas entre los gestores ISR y los gestores convencionales en cuanto a la realización de pérdidas y ganancias.

Nuestra investigación confirma que, a pesar de la preferencia social añadida de los inversores de fondos ISR, los gestores de fondos ISR y convencionales se comportan de forma similar a la hora de realizar pérdidas y ganancias y, por lo tanto, podrían tener la misma motivación a la hora de tomar decisiones de negociación. Los resultados obtenidos en el presente estudio son robustos para diferentes categorías de inversión y cuando se tienen en cuenta las tendencias del mercado, la estructura de gestión, el género y los resultados anteriores.

Podrían obtenerse resultados más específicos con carteras mensuales de todos los fondos ISR y la investigación se realizó sobre toda la muestra de fondos ISR. Además, podrían obtenerse resultados más precisos con información detallada sobre el momento en que tiene lugar la negociación. Se justifican nuevos análisis para determinar si las puntuaciones ASG de las acciones influyen en la tendencia a desprenderse de ellas.

Capítulo 3: Un enfoque Network DEA para los torneos de fondos de inversión

3.1 Introducción

El afán por obtener rentabilidad de los inversores en fondos de inversión es un fenómeno empírico bien documentado. De hecho, la investigación ha demostrado que los inversores tienden a asignar capital basándose en el rendimiento pasado de los fondos de inversión. Está bien establecido que un rendimiento relativo superior de los fondos de inversión se asocia con mayores entradas de dinero posteriores (Ben-David et al., 2022; Berk & Green, 2004; Ferreira et al., 2012; Sirri & Tufano, 1998). Por este motivo, el importante crecimiento experimentado por el sector de los fondos de inversión en las últimas décadas ha agudizado la competencia entre los gestores de fondos de inversión por las entradas de dinero y las comisiones basadas en los activos.

La relación entre el rendimiento de los fondos de inversión y la posterior actitud de los gestores hacia el riesgo ha recibido una atención primordial en la literatura internacional. Varios estudios han documentado que los gestores de fondos de inversión modifican activamente el nivel de riesgo de sus carteras en función de su rendimiento relativo en el pasado. Algunos trabajos fundamentales que aportan pruebas de ello son Brown et al. (1996), Chevalier & Ellison (1997), Busse (2001), Huang et al. (2011) y Taylor (2003).

En su investigación seminal, Brown et al. (1996) llegaron a la conclusión de que los gestores perdedores a medio plazo, al no tener mucho más que perder, apostarán y aumentarán la volatilidad de su cartera de fondos, mientras que los ganadores a medio año intentarán fijar su posición y jugar sobre seguro. Tras este estudio, varios autores llegan a una conclusión similar (Acker & Duck, 2006; Basak et al., 2008; Goriaev et al., 2005; Schwarz, 2012).

Este comportamiento de torneo de los gestores de fondos se ve reforzado por la relación convexa entre el rendimiento previo y los flujos de dinero: Mientras que un porcentaje desproporcionado de las entradas totales se dedica a los fondos con buenos resultados, los inversores no retiran el dinero de los fondos de inversión con malos resultados en la misma proporción (Chevalier y Ellison, 1997; Gruber, 1996; Huang et al., 2007; Sirri y Tufano, 1998). Además, los gestores de fondos de inversión tienen otras preocupaciones que podrían aumentar su motivación para participar en torneos anuales: proteger su empleo (Kempf et al., 2009; Khorana, 1996; Qiu, 2003), ganar un salario más alto (Farnsworth & Taylor, 2006; Kempf et al., 2009) o labrarse una reputación entre sus colegas (Qiu, 2003).

Sin embargo, estudios empíricos han revelado resultados contradictorios con respecto a la expectativa de que los perdedores apuestan mientras que los ganadores indexan. Existen pruebas en la literatura que apoyan la noción de que los ganadores son más propensos a apostar (Busse, 2001; Chevalier & Ellison, 1997; Qiu, 2003; Sheng et al., 2019; Taylor, 2003). En lugar de ver estos hallazgos como contradictorios, podría haber matices que descubrir en la teoría del torneo que ha sido ampliamente estudiada tanto con técnicas paramétricas como no paramétricas. Nuestro enfoque en red pretende captar la dinámica real del torneo sin que exista ninguna forma funcional preestablecida entre los principales impulsores del comportamiento del torneo.

El objetivo de nuestro estudio es investigar la dinámica del comportamiento de los torneos. Nuestro estudio forma parte de la nueva subdisciplina denominada investigación operativa del comportamiento. Esta subdisciplina fue preconizada por Hämäläinen et al. (2013) y analiza aspectos del comportamiento con la ayuda de métodos de investigación operativa en modelización, resolución de problemas y apoyo a la toma de decisiones. De acuerdo con las tareas de investigación que Becker (2016) considera importantes para la nueva subdisciplina, nuestro estudio forma parte de la aplicación de los métodos de investigación operativa a las finanzas conductuales dentro de sus propios paradigmas básicos.

Para analizar el torneo, dividimos el comportamiento del torneo en tres etapas: en primer lugar, ¿con qué eficiencia reaccionan los gestores de fondos de inversión a su rendimiento pasado en términos de riesgo de cartera? En segundo lugar, ¿con qué eficacia repercuten estos cambios de riesgo en su rendimiento posterior? Y, por último, ¿con qué eficacia atraen estos cambios de rendimiento entradas de dinero a los fondos? Para analizar mejor estas interacciones entre torneos, empleamos un Análisis Envolvente de Datos (DEA) en red. Dada la complejidad de la modelización de las finanzas comportamentales, el uso de modelos DEA en red, que no requieren el establecimiento a priori de formas funcionales entre los factores explicativos, podría ser especialmente útil en este ámbito. Por este motivo, resulta muy adecuado para modelizar patrones de comportamiento complejos, como el comportamiento en los torneos.

El modelo de red de este estudio nos permite dividir esta interacción global en procesos individuales y así evaluar mejor cada etapa. Como resume Kao (2014), un sistema global puede considerarse eficiente, aunque sus procesos individuales no lo sean, en realidad. En cuanto al tema que nos ocupa, muchos modelos de torneos se centran únicamente en la reacción de los fondos de inversión a las clasificaciones de rendimiento anteriores y las consecuencias de rendimiento posteriores, pero omiten las posibles consecuencias en los flujos de dinero posteriores. Nuestro modelo supera esta limitación adoptando un enfoque global para analizar el sistema.

Que sepamos, este estudio es el primero que aplica una DEA en red para evaluar el comportamiento de los torneos en el sector de los fondos de inversión. La presente investigación llena el vacío existente en la literatura sobre finanzas conductuales utilizando un modelo DEA en red para proporcionar información sobre los componentes secuenciales y dinámicos del comportamiento de los torneos. En este estudio, el objetivo principal es analizar la interacción entre la reacción al torneo, su recompensa en términos de rendimiento y la recompensa potencial en forma de entradas.

Llevamos a cabo nuestra investigación sobre una amplia muestra de fondos de inversión de renta variable española desde enero de 2010 hasta diciembre de 2015. Las características de nuestra muestra son adecuadas para una correcta y completa aplicación de nuestro modelo DEA en red.

3.2 Datos y metodología

Elegimos el mercado español de fondos de inversión para la aplicación de nuestro modelo de torneo. España es una de las industrias de fondos de inversión más relevantes del euro y se caracteriza por una importante concentración en términos de gestión: fondos de inversión pequeños y mayoritariamente independientes coexisten con sociedades gestoras de propiedad bancaria grandes y mayoritarias. Así pues, la heterogeneidad de los fondos de inversión que se van a analizar ayuda a nuestro enfoque de red a captar las diferentes dinámicas de torneo potencialmente presentes en este mapa de competencia ampliamente concentrado.

Los datos primarios utilizados en este estudio se obtienen de la Comisión Nacional del Mercado de Valores (CNMV). Nuestra base de datos inicial incluye los fondos abiertos domiciliados en España que estuvieron en funcionamiento durante el periodo de estudio (enero de 2010 a diciembre de 2015). Este periodo muestral abarca los años con mayores salidas de dinero de la industria de fondos española en las dos décadas anteriores a 2012, junto a una significativa y fuerte recuperación de las entradas de dinero en 2014-2015 (Inverco, 2016). Esto da lugar a contextos de gestión extremadamente diferentes para identificar las prácticas del torneo a través de nuestro modelo propuesto. La base de datos inicial comprende 551 fondos. En total, se descartan 42 fondos indexados dado que no son de gestión activa y solo los fondos de gestión activa cumplirían los requisitos para el análisis del comportamiento de los torneos. Nuestro análisis se centra en las dos principales categorías de inversión de la industria española de fondos: Fondos de Renta Variable Euro y Renta Variable Nacional, que representan un total de 184 fondos. Obtuvimos datos sobre rendimientos diarios, activos netos totales (TNA) mensuales e informes trimestrales de participaciones en cartera.

Finalmente, también excluimos un total de 35 fondos de esta simple porque la información reportada no cumple totalmente con la disponibilidad de datos requerida por nuestro modelo (por ejemplo, fondos terminados antes del 31 de diciembre o fondos que no reportan flujos de dinero posteriores para el primer trimestre porque fueron terminados antes del 31 de marzo). Con el fin de obtener resultados fiables para el análisis del torneo, exigimos que los fondos incluidos en un año determinado en el estudio existan en enero y sobrevivan al menos hasta marzo del año siguiente, cuando se computan los flujos. Nuestra muestra final consta de un total de 149 fondos de renta variable distintos y un total acumulado de 624 observaciones de años de fondos.

Nuestro modelo pretende captar las interacciones de torneo en un fondo de inversión j como una estructura de red de tres etapas. Las tres etapas secuenciales son la Etapa de Reacción del Torneo, la Etapa de Recompensa del Torneo y la Etapa de Recompensa del Torneo (en lo sucesivo, Etapa de Reacción, Etapa de Recompensa y Etapa de Retribución, respectivamente). En la Etapa de Reacción, nuestro enfoque de red capta la reacción de los gestores de fondos de inversión como un cambio en el nivel de riesgo de sus carteras en la segunda mitad del año (del mes t-6 al mes t), como consecuencia de su rendimiento relativo en la primera mitad del año (medido en el mes t-6). En la Etapa de Recompensa, nuestro modelo evalúa el impacto de esta gestión del riesgo sobre su rentabilidad relativa al final del año. Es decir, la Etapa de Recompensa evalúa si hay cambios en el rendimiento relativo de los gestores en la segunda mitad del año como consecuencia del comportamiento del torneo. Por último, en la Etapa de Recompensa, nuestro modelo evalúa el éxito de este comportamiento de torneo basándose en las entradas de dinero en los fondos en el primer trimestre del año siguiente (del mes t al mes t+3). Así, nuestro enfoque en tres etapas diferencia el momento de la respuesta de torneo del gestor al rendimiento relativo previo del fondo j y las posibles consecuencias de ese comportamiento en términos de flujos de dinero, ya que no son simultáneos.

De acuerdo con la revisión de los modelos DEA en red en Kao (2014), la Figura 3.1 corresponde a una ampliación de una estructura de red básica de dos etapas a una estructura de red básica de tres etapas. Nuestra estructura de red también incluye un componente dinámico y las distintas variables del modelo corresponden a puntos secuenciales en el tiempo para reflejar el comportamiento dinámico de los torneos de fondos de inversión. El uso de cuatro variables intermedias tanto como salidas de la Etapa de Reacción como entradas de la Etapa de Recompensa podría plantear problemas relacionados con la maldición de la dimensionalidad en nuestra estructura de tres etapas, por lo que debe prestarse especial atención a la convención DEA según la cual el número mínimo de unidades de decisión analizadas, en este caso los fondos de inversión, debe ser superior a tres veces el número de variables (Coelli et al., 2005).

En la Etapa de Reacción, el fondo de inversión j reacciona a su clasificación de rendimiento en el periodo anterior, desde el mes t-6 hasta el mes t, modificando su nivel de riesgo a través de tres mecanismos diferentes: 1) el porcentaje de la cartera asignado a activos de renta variable como representante del activo más arriesgado, 2) la beta de la cartera como representante del riesgo sistemático, y 3) la concentración de la cartera como representante del riesgo idiosincrático. Esta cronología es coherente con el trabajo seminal de Brown et al.

(1996) y estudios posteriores como Busse (2001), Goriaev et al. (2005) y Taylor (2003), por citar algunos.

Huang et al. (2011) identificaron tres mecanismos a través de los cuales los fondos de inversión pueden desplazar el riesgo: modificando su coeficiente de liquidez, alterando su exposición al riesgo sistemático o cambiando su exposición al riesgo idiosincrásico. En efecto, para aumentar el nivel de riesgo, los gestores de fondos de inversión pueden reducir sus tenencias de efectivo y/o aumentar sus tenencias de acciones, en igualdad de condiciones. También pueden sustituir valores de beta baja por valores de beta alta, aumentando así su exposición al riesgo sistemático. Por último, pueden concentrar sus participaciones en menos valores o menos sectores, aumentando así su exposición al riesgo idiosincrático.

El razonamiento que subyace a esta etapa de reacción es coherente con el trabajo seminal de Brown et al. (1996), que concluyeron que los gestores perdedores, al no tener mucho más que perder, tenderán a apostar y a aumentar sus niveles de riesgo de cartera, mientras que los ganadores tratarán de afianzar sus posiciones jugando mucho más seguro que los gestores situados en la parte inferior de la clasificación de rendimiento. Así pues, un fondo con una mala clasificación relativa en el mes t-6 con aumentos significativos en la asignación de la cartera de renta variable, la beta de la cartera y la concentración de la cartera dará lugar a puntuaciones DEA elevadas en la Etapa de Reacción, proporcionando pruebas de una importante respuesta de torneo. Por otra parte, un fondo con una mala clasificación relativa en el mes t-6 con pequeños cambios en el riesgo de su cartera proporcionará puntuaciones DEA bajas y, por tanto, una débil respuesta del torneo. Nuestro modelo podría incluso llevar a una DEA más baja de los fondos ganadores en comparación con los fondos perdedores cuando los primeros intentan fijar sus posiciones de rendimiento anteriores con decisiones sobre la asignación de la cartera de renta variable, la beta de la cartera y la concentración de la cartera contrarias a las estrategias de desplazamiento del riesgo. Además, la Etapa de

Reacción también cubre el escenario de los fondos ganadores que apuestan más que los perdedores (Busse, 2001; Sheng et al., 2019). En este caso, los valores de las clasificaciones relativas previas (considerados como inputs en esta etapa), y la magnitud de los cambios posteriores en el riesgo de la cartera (considerados como outputs en esta etapa) clasificarán la intensidad de la reacción al torneo tanto de los ganadores como de los perdedores y, por tanto, la puntuación DEA obtenida en esta etapa.

En la Etapa de Recompensa, nuestro modelo evalúa la eficiencia de la gestión activa del riesgo. Esta eficiencia se evalúa en términos del impacto de la respuesta al torneo en las clasificaciones de rendimiento posteriores. El primer objetivo de los gestores de fondos de inversión que muestran un comportamiento de torneo es mejorar su clasificación de resultados anterior. La Etapa de Recompensa evalúa si los esfuerzos de los gestores en el torneo han provocado algún cambio en sus clasificaciones de rendimiento. Así pues, los resultados de la fase de reacción son ahora las entradas de la fase de recompensa, lo que constituye el primer nodo de enlace de nuestra estructura de red. Las mejoras significativas en la clasificación de rendimiento posterior darán lugar a puntuaciones DEA más altas con incrementos menores del riesgo de la cartera en lugar de con incrementos mayores del riesgo de la cartera. Por otro lado, las consecuencias negativas en la clasificación de rendimiento posterior estarán representadas por puntuaciones DEA más bajas con estrategias de cambio de riesgo mayores en lugar de con cambios de riesgo menos importantes.

Por último, en la fase de retribución, nuestro modelo va más allá y evalúa hasta qué punto el impacto del comportamiento en los torneos ha sido visible en términos de flujos monetarios. La literatura anterior ha aportado numerosas pruebas del fenómeno "el ganador se lo lleva todo", en el que los fondos ganadores captan una parte desproporcionada de las entradas totales (Chevalier & Ellison, 1997; Gruber, 1996; Huang et al., 2007; Qiu, 2003; Sirri & Tufano, 1998). El principal objetivo de una respuesta de torneo a la clasificación de rendimiento es la mejora de la clasificación de rendimiento futura. De hecho, esta mejora no sólo está motivada por la necesidad de una buena reputación, que podría ser realmente importante para el propio plan de carrera de los gestores, sino que también es extremadamente importante para los fondos de inversión en términos de flujos monetarios, ya que estos flujos pueden ser una parte relevante de la estructura de comisiones de la sociedad de fondos de inversión. Así, la entrada de la Etapa de Recompensa es la salida de la Etapa de Retribución, construyendo el segundo nodo de enlace en nuestra estructura de red. Aquellos fondos que obtengan flujos significativamente mayores como consecuencia de cambios menores en la clasificación de rendimiento después del torneo darán lugar a las puntuaciones DEA más altas en la Etapa de Recompensa, mientras que los flujos significativamente menores después de mejoras significativas en la clasificación de rendimiento darán lugar a las puntuaciones DEA más bajas porque este impacto positivo y significativo del comportamiento del torneo no es notado de forma importante por los inversores.

Nuestra estructura de red de tres etapas es adecuada para evaluar el comportamiento de torneo de un fondo de inversión en su conjunto a través del cribado de 1) la relevancia de la respuesta de torneo en términos de gestión de riesgos, 2) el impacto de esta respuesta en la posterior clasificación de rendimiento, y 3) la visibilidad de este impacto en términos de ganancias de flujos monetarios. De lo contrario, una respuesta de torneo significativa de un fondo de inversión con un impacto positivo importante en su rendimiento relativo podría estar lejos de ser valiosa para el fondo si este comportamiento de torneo eficiente no se percibe finalmente y no se traduce en flujos monetarios. Además, nuestro enfoque de tres etapas también permite evaluar cada etapa individual incluida en nuestra estructura de red y supera los problemas de los sistemas globales que pueden considerarse eficientes, aunque sus procesos individuales no lo sean.

3.3 Resultados y Conclusiones

Este estudio proporciona un modelo de torneo más matizado para el sector de los fondos de inversión y analiza la eficacia con la que los gestores reaccionan a sus clasificaciones provisionales de rentabilidad, la eficacia con la que modifican su cartera para mejorar sus clasificaciones de rentabilidad a final de año y, por último, la eficacia con la que los inversores recompensan estos cambios en las clasificaciones de rentabilidad a través de los flujos hacia el fondo en el trimestre siguiente. Hasta donde sabemos, este estudio es el primero que emplea el Análisis Envolvente de Datos en red (DEA) para modelizar la dinámica de comportamiento en el sector de los fondos de inversión.

La aplicación de nuestro modelo a un mercado real arroja resultados empíricos que corroboran nuestras hipótesis iniciales. Nuestros resultados confirman lo complicado que resulta para los gestores de fondos aplicar una estrategia capaz de mejorar eficientemente sus resultados de fin de año en relación con los de sus homólogos. De hecho, los gestores de fondos pueden adoptar una amplia gama de estrategias y de nuestros resultados se desprende que la Etapa de Reacción no está correlacionada con la Etapa de Recompensa. Esto significa que la modificación eficaz de la exposición a la renta variable, la beta y la concentración de la cartera como resultado de los rangos de rentabilidad provisionales no está correlacionada de forma significativa con los flujos posteriores hacia el fondo.

En consonancia con la bibliografía sobre flujos, el grado en que los gestores de fondos mejoran su clasificación de rentabilidad modificando la exposición a la renta variable, la volatilidad y la concentración de su cartera es un factor determinante de su capacidad para atraer flujos en el trimestre siguiente. Así pues, el éxito en la Etapa de Retribución, mejorando con éxito el rendimiento a final de año, es determinante en los resultados finales del torneo. Estas conclusiones refuerzan la validez del modelo que proponemos en este estudio. Nuestros resultados son robustos incluso cuando empleamos especificaciones de variables alternativas. Por último, no encontramos persistencia en la eficiencia de los torneos en las fases individuales ni tampoco en general. Nuestros resultados apoyan la idea de que seguir una estrategia de torneo persistente y sistemáticamente eficiente es difícil y complejo.