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Assessing Overconfidence among Professional Investors

Autora

Beatrice Carole Boumda

Directora

Dra. Cristina Ortiz Lázaro

Facultad de Economía y Empresa

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Abstract

This study examines overconfidence among managers of Spanish equity mutual funds between December 1999 and June 2014. Using quarterly turnover ratio as a proxy for overconfidence and a database free of both the survivorship bias and the look-ahead bias, we do not find strong evidence of overconfidence among mutual fund managers. Indeed, the impact of performance on subsequent turnover ratio is not statistically significant. However, when separating performance in quintiles, we find strong evidence of increase in turnover ratio subsequent to poor performance. We conjecture that this phenomenon could be related to a possible risk-shifting behavior.

En este estudio, se examina el sesgo de exceso de confianza en gestores de fondos de inversión de renta variable nacional de España entre diciembre de 1999 y junio de 2014. Empleando una base de datos libre del sesgo de supervivencia y del sesgo *look-ahead*, y usando el índice trimestral de rotación de los fondos como proxy, no hemos hallado sólidas evidencias de exceso de confianza en dichos gestores. Efectivamente, no se ha hallado un impacto estadísticamente significativo de la rentabilidad pasada sobre el índice de rotación. No obstante, cuando se divide la rentabilidad en quintiles, se encuentra evidencia de aumento del índice de rotación después de una rentabilidad baja. Se conjetura que este resultado puede estar debido a un fenómeno de cambio de nivel de riesgo conocido como *risk-shifting behavior*.

1. Introduction

Overconfidence is a robust and well-documented behavioral bias. Originally from the field of psychology, the concept has grown even more influential in other fields of study in the recent years.[1] A number of studies conducted on the general population reveal the predominance of this bias. Svenson (1981), based on a sample of US students, provides a clear illustration: a little more than 80% of the students surveyed believed to be among the top 30% in terms of driving safety.

Due to its prevalence, overconfidence is presented as the root cause behind many events, from wars to strikes, from high rates of new start-ups despite notable entrepreneurial failure to financial crashes and bubbles (see Moore and Healy, 2008 for a review of papers in this line). In Griffin and Tversky's words: "the significance of overconfidence to the conduct of human affairs can hardly be overstated" (1992, p. 432). In fact, overconfidence is not solely limited to the lay person. According to Kyle and Wang (1997), experts display more overconfidence than novices. Indeed, investigations have evidenced overconfidence in different categories of professionals including and not limited to engineers, lawyers, clinical psychologists, investment advisors, security analysts, fund managers and entrepreneurs (see Moore and Healy, 2008; Kyle and Wang, 1997; Griffin and Tversky, 1992).

In essence, this paper seeks to examine whether professional investors, specifically equity mutual funds managers in Spain, are prone to overconfidence after a good performance. This research follows the work of Puetz and Ruenzi (2011) on overconfidence among equity mutual fund managers in the US.

This investigation is important for many reasons. The central axioms of classic finance models are those of rational agents and efficient markets. These assumptions, though desirable, hardly ever hold in practice. In fact, professional investors evolve in an environment where there are numerous pieces of information to process, combined with diverging opinions and interpretations and information asymmetry. As pointed out by Eshraghi and Taffler (2012: p4), investment managers have "to rely to a large extent on subjective judgment, intuition and *gut feeling*". Yet, environment is only one part of the equation as professional investors have to deal with their own biases, heuristics and fallacies. Given such a setting, analyzing investors' psychology appears to be of uttermost importance in order to capture the dynamics of financial markets. Focusing on professional investors is of even more importance as they are often expected to behave rationally, at least more than

[1]On the 17 September 2015, a rapid search of the keyword *overconfidence* in the Science Direct database yielded 4536 results, of which more than 60% were published during the past decade.

laypeople. A possible justification for this belief is that professional investors generally possess more experience and have more financial knowledge than a lay person.

Prior literature has identified self-serving attribution bias as the cause of overconfidence (Eshraghi and Taffler, 2012; Puetz and Ruenzi, 2011). The self-serving attribution bias leads investors to attribute successes to their own dispositions and skills, while they tend to attribute poor performance to chance or external forces. As a result, after a good performance, investors become more overconfident, but following a poor performance, they do not become less overconfident.

Three types of overconfidence are commonly differentiated in literature: Overprecision in the accuracy of one's belief or *miscalibration,* overestimation of one's performance or *illusion of control* and over placement of one's performance in relation to others' or *better-than-average effect* (see Glaser, Langer and Weber, 2005; Moore and Healy, 2008; Glaser and Weber, 2007). Usually, researchers implicitly or explicitly assume the different types of overconfidence to be interchangeable, as documented by Moore and Healy (2008). Glaser and Weber (2007) have highlighted the importance of distinguishing between the types of overconfidence, as they have disparate consequences and thus are measured through different experiments and distinct proxies. As pointed out by Moore and Healy (2008) confounding the varieties of overconfidence results in empirical inconsistencies and methodological problems. Our study is geared towards the analysis of both overestimation of one's performance or illusion of control.

Eshraghi and Taffler (2012) observed that most studies use laboratory-type experiments. Broihanne, Merli and Roger (2014), for instance, measured overconfidence through a questionnaire given to a sample of different categories of finance professionals. They principally focused on assessing miscalibration and the better-than-average effect. The results of this study show that finance professionals are overconfident both on the general and the finance domains. According to Eshraghi and Taffler (2012), only a few laboratory-type experiments are robust due to issues related to ecological validity. To avoid these issues, many studies resort to the use of proxies. In their own study, the latter authors investigated to what extent overconfidence affects professional investors' performance. To measure overconfidence, they used both direct testing and proxies. The direct testing implied a content analysis of the narratives of reports written by mutual fund managers to their investors. They conclude that excessive overconfidence is robustly related to diminished investment returns in the 12 months subsequent to the report.

The two main proxies used in financial literature to gauge overconfidence are active share and trading activity. Active share, a measure introduced by Cremers and Petajisto (2009), refers to the percentage or proportion of a portfolio stock holding that differ from the benchmark index. In the presence of overconfidence, a good performance will lead to increase in active share. Chou and Loi (2010) used absolute deviations from the benchmark and conclude that mutual fund managers increase their active share after a good performance but do not decrease it after a poor performance. They also find this bias to be more pronounced in novice investors than in more experienced investors.

Trading activity, on the other hand, is a more frequently used proxy to estimate overconfidence. Various studies demonstrate that the higher the level of confidence of an investor, the greater their trading activity (Barber & Odean, 2000; Barber, 2001; Gervais & Odean, 2001; Glaser & Weber, 2007; Moore & Healy, 2008; Odean, 1998a; Odean, 1998b). This phenomenon is considered by Odean (1998b) as “the most robust effect of overconfidence” (p. 1888). Consistent with these theories, Puetz and Ruenzi (2011) and Statman, Thorley, and Vorkink (2006) find high trading volumes subsequent to good performance.

While trading activity is a common measure of overconfidence, it should be carefully used. Glaser and Weber (2007) correlated overconfidence scores and trading measures. They conclude that investors who think they are better than average tend to trade more, while miscalibration does not appear to be related to trading volume.

There is little consensus over the effect of overconfidence on subsequent results. Because overconfidence serves as a motivation to trade more aggressively (Barber and Odean, 2001); it may result in higher expected profits (Kyle and Wang, 1997). Zhou (2015) modeled competition among identically and asymmetrically informed agents. The author concludes that overconfidence is a virtue given that the imperfectly informed agent can earn more than their rational imperfectly informed colleagues. Moreover, under certain specific conditions the imperfectly informed agents yield better results when overconfident than when they behave rationally. However, this same model concludes that no matter how confident, a less informed agent cannot earn more than a better informed agent.

Contrary to what these models predict, empirical investigations conclude that overconfidence leads to poorer performances (Eshraghi and Taffler, 2012; Puetz and Ruenzi 2011). Eshraghi and Taffler (2012) conclude that the relationship between overconfidence and subsequent returns has an inverted-U shape: both excessive confidence and underconfidence negatively impact performance. This can be explained the fact that excess trading leads to poorer performance as shown by Barber and Odean (2000).

In this paper, we test the following null hypothesis: there is no significant evidence of individual fund managers' overconfidence after a good past performance. To measure investor's overconfidence we use trading activity as a proxy, more specifically we use the fund's turnover ratio. The formula used to calculate the turnover ratio permits us minimize the effect of flow-induced trading. Among other findings, this study does not find strong evidence for the fact that managers increase their turnover ratio in the period subsequent to a top performance. However, our results confirm that the relationship between past performance and turnover ratio, though not statistically significant, is not linear but U-shaped. When separating performance in quintiles, we find strong evidence for increase in turnover ratio after poor performance. This can be explained by a change of strategy in funds with the lowest performance and is no evidence for overconfidence. This result could be an indicative of a possible risk-shifting behavior on the part of managers with poor performance. Indeed the motivation for risk-shifting is high for poor performing managers: large payoff if among top performing funds against small penalty if fund falls further in rankings. Brown et al (1996) provide robust empirical evidence to support this theory.

A few methodological concerns can be raised. A recent study by Ortiz, Ramírez and Vicente (2015) suggests that when using quarterly data instead of monthly data, 38% of the trade is missed. Thus, the robustness of the present study could be increased by the use of fund's monthly stock holding data. The main difficulty rises from the fact that this information is not publicly available. Another amelioration that could be brought to this study is the examination of the relationship between change in performance and subsequent change in turnover ratio.

This paper contributes to two main areas of the existing literature. First, our study is part of the strand of literature that explores behavioral biases and investor's psychology. More specifically, we focus on overconfidence of professionals investors. The latter constitute a less studied group. Our study is also related to other investigations that share as a common feature the analysis of the lead-lag relationship between trading volume and returns, specifically, studies that analyze the relationship between returns and subsequent trading volumes.

The remainder of this paper is organized as follows. In section 2 we introduce our equity mutual fund database, provide some descriptive statistics and describe the computation of the proxy used to gauge overconfidence. Section 3 includes the empirical analysis and presents the results. Finally, Section 4 concludes the paper.

2. Methodology

2.1. Sample

Our initial dataset consists of monthly and quarterly holdings reports of all domestic equity mutual funds. From this initial database, we eliminate funds that held less than 75% of their assets in cash and stocks listed in Spanish stock exchange market. Thus our selection is restricted solely to domestic equity mutual funds. We also control for mergers and acquisitions within the sample of funds.

The final dataset consists of 144 equity mutual funds. A total number of 45,910 quarterly observations were used to estimate the linear model and the quadratic model of this investigation. The time period under study starts in December 1999 and ends in June 2014. Quarterly data of funds are publicly available as fund managers in Spain are required to disclose their portfolios to investors on a quarterly basis. This means that fund managers can infer their relative positions on a quarterly basis and thus adjust their strategy according to this information.

Our database is free of both the survivor bias and the look-ahead bias. Survivor bias results from restricting the sample to surviving funds and eliminating all dead funds from the database. To avoid the survivor bias, all funds that enter the database remain even if at some point in the time period they cease to exist. The least survival period of a fund in the final database is six months. The percentage of dead funds during the sample period is approximately 55.6%. Look-ahead bias is a consequence of using information outside the simulation period. The database used in this study is free of this bias.

To compute the turnover ratio, as explained in details in the next section, we used average price of each stock included in the funds' portfolio over the quarter. A detailed database of funds' quarterly portfolios was supplied by the Spanish Securities and Exchange Commission (CNMV). It is also worth mentioning that the daily prices of close to 90% of the stocks in the funds' portfolio were controlled. Our extensive stock database, supplied by DataStream, comprises a total number of 3,188,039 daily observations of stock prices, including domestic stocks, other European stocks and foreign stocks.[2] All of those prices were controlled for splits and reverse splits. Each stock was carefully identified by its security number to take into account mergers and takeovers. Based on these daily prices we computed quarterly average prices of each stock.

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[2] We consider as domestic stocks, stocks listed in the Spanish stock market. Other European stocks are stocks listed in countries belonging to the European Union excluding Spain. Foreign stocks refer to all other stocks.

2.2. Computation of turnover ratios

Trading activity is the most used proxy for overconfidence. Theories and empirical analysis conclude that the higher the confidence level of an investor, the more likely they are to trade heavily. Trading activity is a good proxy for gauging retail investors' confidence level but for institutional investors, some adjustments have to be made. Indeed fund managers often have to trade because of flows. The effect of this flow-induced trading ought to be minimized as only voluntary trading would be a sound proxy for overconfidence. Similarly, exclusions of stock from the market were not considered as sales.

To minimize flow-induced trading, we compute the turnover ratio in line with the definition of Elton et al. (2010, p. 914) "the lesser of purchases or sales (excluding all securities with maturities less than one year) divided by the average monthly net asset value". Consistent with Elton et al. (2010), we use the following equation:

$$C_j^+ = \sum_i \left(N_{i,j} - N_{i,j-1}\right)\bar{P}_{i,j} \text{ for all } i\text{, where } \left(N_{i,j} - N_{i,j-1}\right) \geq 0 \quad (1)$$

$$C_j^- = \sum_i \left(N_{i,j} - N_{i,j-1}\right)\bar{P}_{i,j} \text{ for all } i\text{, where } \left(N_{i,j} - N_{i,j-1}\right) < 0 \quad (2)$$

where: $N_{i,j}$ is the number of shares of stock *i* held at the end of the quarter *j*

$\bar{P}_{i,j}$ is the average price of stock *i* over quarter *j*.

The equation from Elton et al. (2010) was slightly modified. First, we use quarterly information instead of monthly data. Again, in order to approximate with more accuracy the total purchases (C_j^+) or sales (C_j^-), we use average stock price over the quarter instead of average of the prices of stock at the beginning and end of period. The turnover ratio of a fund is then:

$$TR_j = \frac{\min(C_j^+, C_j^-)}{\overline{\mathrm{TNA}}_j} \quad (3)$$

where: TR_j is the turnover ratio

$\overline{\mathrm{TNA}}_j$ is the quarterly average of the Total Net Assets of the fund in period *j*

Table 1

Descriptive Statistics

Year	Number of funds	Average quarterly TNA (Euros)	Quarterly Turnover Ratio		
			Mean	Min	Max
2000	102	76,942,862	12.46%	0.00%	66.85%
2001	101	62,027,876	9.37%	0.00%	50.35%
2002	92	51,770,887	8.53%	0.00%	46.72%
2003	93	46,911,897	7.49%	0.00%	42.85%
2004	95	66,336,152	7.67%	0.00%	48.19%
2005	97	84,294,441	8.58%	0.00%	37.97%
2006	101	89,281,897	9.67%	0.00%	52.48%
2007	100	89,886,327	9.92%	0.00%	72.64%
2008	97	43,907,938	8.39%	0.01%	43.74%
2009	85	30,786,455	10.57%	0.00%	66.31%
2010	77	31,981,160	9.77%	0.01%	56.09%
2011	70	32,512,974	10.26%	0.00%	52.94%
2012	45	30,184,854	7.87%	0.14%	33.80%
2013	35	50,327,181	7.40%	0.15%	30.37%
06/2014	34	81,759,798	9.21%	0.29%	63.38%

Notes:
This table presents the descriptive statistics of our sample of funds. Funds that do not invest at least 75% of their total asset in domestic stocks were eliminated. Second column refers to the number of funds active during at least a quarter of the year. The average quarterly Total Net Assets of each year is contained in the third column. Finally, the mean, minimum and maximum of quarterly turnover ratios of each year are contained in the three last columns.

Table 1 presents the descriptive statistics of our sample. Given that we need at least 3-month data to compute quarterly turnover ratio and quarterly average total net assets, the table starts in 2000. Column 2 of Table 1 reports, for each year, the number of funds active at least during a quarter. The number of funds is relatively stable until 2008. During the period 2009-2014, we observe a drastic fall in the total number of funds. This can be explained by the high rate of mergers of banking institutions during this same period leading to mutual fund mergers.

The third column shows the average of the quarterly total net asset for each year. The highest average quarterly total net asset is in 2007 followed the next year by a sharp decrease of more than 50%. The high mean turnover ratio in 2007 could be a consequence of the financial crisis that started that same year. It is worth mentioning that the highest turnover ratio fund in this study is considerably smaller than that of studies on US equity mutual fund.

Puetz and Ruenzi (2011), for instance, found a mean turnover ratio of close to 100% in 2001. This suggests that in general equity mutual funds in Spain have a lower turnover ratio than US equity mutual funds.

The average total net asset slowly rises during the period 2010-2014. The fourth, the fifth and the sixth columns present the mean, the minimum and the maximum of quarterly turnover ratios respectively. The highest mean turnover ratio was in 2000 (12.46%) and the least mean turnover ratio in 2013 (7.40%). The maximum quarterly turnover ratio was attained in 2007 (72.64%).

3. Empirical Analysis and Results

In this study, we examine whether mutual fund managers display overconfidence after a good performance. Overconfidence is measured with the use of a proxy: turnover ratio. To estimate our models, the turnover ratio of a quarter *t* ($TR_{p,t}$) is related to the performance in the previous quarter *t-1* ($Perf_{t-1}$). We have decided to use quarterly data given that Spanish mutual funds have the obligation to release quarterly reports, thus we infer that fund managers will be influenced by their relative position each quarter and act accordingly.

Our study is based on the following model proposed by Puetz and Ruenzi (2011):

$$TR_{p,t} = f(Perf_{t-1}, Controls) \quad (4)$$

First, we test the following quadratic model using the pooled regression approach (Ordinary Least Squares):

$$TR_{p,t} = \alpha + \beta_{1\alpha} Perf_{p,t-1} + \beta_{1\beta} (Perf_{p,t-1})^2 + \beta_2 Flow_{p,t} + \beta_3 lnTNA_{p,t-1} + \varepsilon_{p,t} \quad (5)$$

For the quadratic equation (5), we expect a negative slope for past performance ($Perf_{p,t-1}$) and a positive slope for squared past performance $(Perf_{p,t-1})^2$. In the estimation of this model, we conjecture negative coefficients for flows and total net assets. Table 3 presents the results of the regression analysis of this model (Equation 5).

Table 2

Quadratic Regression Estimation

Independent Variables	*Coefficients*
$Perf_{p,t-1}$	-0.017
	(-0.71)
$(Perf_{p,t-1})^2$	0.013
	(0.57)
$Flow_{p,t}$	0.007
	(0.87)
$lnTNA_{p,t-1}$	-0.023***
	(-10.94)
Constant	0.270***
	(15.82)
R^2	2.5%

Notes:
This table presents the results of the estimation of our quadratic model (Equation 5). The dependent variable is the fund's turnover ratio. The independent variables are past performance (raw quarterly returns): $Perf_{p,t-1}$ and $(Perf_{p,t-1})^2$. Two control variables were added to control for the indirect effect of flows: $Flow_{p,t}$ and $lnTNA_{p,t-1}$. The second column shows the regression coefficient of each independent variable and beneath it, in parentheses, the *t* statistics. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

We find a negative impact for the linear expression of past performance on turnover ratio and a positive relationship between the quadratic expression of past performance and turnover ratio. However, none of these two coefficients are significantly different from zero. Again, we find a significant negative impact of total net assets on the same dependent variable but the positive impact of flows does not appear to be statistically different from zero.

To further the analysis of our data, we have decided to separate performance into quintiles. A fund's past performance refers to the rank of the quarterly position of its raw returns in relation to other funds' returns. Equation (6), (7) and (8) show the ranking process of the funds. The best (worst) fund is assigned a one (zero) and the rest of the fund are distributed within this range with respect to their returns. We then distribute the funds' performance into three groups, the bottom quintile is LOW, the top quintile is TOP, the middle quintiles are classified under MID. As indicated below, the fund with the highest performance of the quarter obtains 0.2 in LOW, 0.6 in MID and 0.2 in TOP, thus summing 1. Similarly, a fund with a relative performance of 0.7 is allocated 0.2 in LOW, 0.5 in MID and 0 in TOP.

$$LOW_{p,t-1} = \min(Perf_{p,t-1}, 0.2) \quad (6)$$

$$MID_{p,t-1} = \min(Perf_{p,t-1} - LOW_{p,t-1}, 0.6) \quad (7)$$

$$TOP_{p,t-1} = Perf_{p,t-1} - LOW_{p,t-1} - MID_{p,t-1} \quad (8)$$

Our control variables are flow and total net assets. Puetz and Ruenzi (2011) predict that although the turnover ratio has been adjusted for flows, there might still be some indirect impact on turnover ratio. We calculate flows following the method suggested by Sirri and Tufano (1998). We first compute monthly flows and then convert them into quarterly flows, using the following formulas:

$$Flow_{p,m} = \frac{TNA_{p,m} - TNA_{p,m-1}(1 + r_{p,m})}{TNA_{p,m-1}} \quad (9)$$

$$Flow_{p,t=} \prod_{m=1}^{3}\left(1 + Flow_{p,m}\right) - 1 \quad (10)$$

where: $Flow_{p,m}$ is fund p's monthly flow

$TNA_{p,m}$ is the total net asset of fund p at the end of the month m

$r_{p,m}$ is the net return generated by fund p during month m

$Flow_{p,t}$ is fund p's quarterly flow

The following model is estimated using the pooled regression approach (OLS):

$$TR_{p,t} = \alpha + \beta_1^L LOW_{p,t-1} + \beta_1^M MID_{p,t-1} + \beta_1^T TOP_{p,t-1} + \beta_2 Flow_{p,t} + \beta_3 lnTNA_{p,t-1} + \varepsilon_{p,t} \quad (11)$$

Consistent with Puetz and Ruenzi (2011), we conjecture that fund managers with excellent past performance will feel overconfident about their skills and abilities and thus increase their turnover ratio. However, we do not expect managers of poor performance funds to decrease their turnover ratio. They will likely decide to change their strategy, thus engage in more trade. Consequently we expect a positive slope for funds in the top quintile and a negative slope for funds in the bottom quintile. We have no specific prediction for the sign of the coefficient of funds in the middle quintiles. However, we expect this coefficient to be smaller in absolute terms than the previous two.

Following Pollet and Wilson (2008), we expect fund managers to use new money inflows to increase their existing investment. An increase in the total net asset results in a decrease of the turnover ratio. Thus we expect negative coefficients for both flows and the natural logarithm of total net assets. We used an ordinary-least-squares approach to test our model. The results of the regression model (Equation 11) are presented in Table 2.

Table 3

Linear Regression Estimation

Independent Variables	*Coefficients*
$LOW_{p,t-1}$	-0.130** (-2.23)
$MID_{p,t-1}$	0.001 (0.16)
$TOP_{p,t-1}$	0.007 (0.16)
$Flow_{p,t}$	0.007 (0.84)
$lnTNA_{p,t-1}$	-0.023*** (-10.88)
Constant	0.289*** (15.29)
R^2	2.60%

Notes:
This table reports the results of the estimation of our linear regression model (Equation11). The dependent variable is the fund's turnover ratio and the independent variables are contained in the first column. The first three variables are ranks of past performance: $LOW_{p,t-1}$ for the bottom quintile, $MID_{p,t-1}$ for the three middle quintiles and $TOP_{p,t-1}$ for the upper quintile. The other two variables are control variables: $Flow_{p,t}$ and $lnTNA_{p,t-1}$. The second column shows the regression coefficient of each variable and beneath it, in parentheses, the *t* statistics. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

First, we find a positive impact of past performance on turnover ratio for the upper quintile. However, the coefficient β^T_1 is not statistically significant. Nevertheless, we find a significant negative relationship between performance and subsequent turnover ratio for the bottom quintile. In this case, the coefficient β^L_1 is significantly different from zero at the 5%-level. The coefficient of the three middle quintiles (β^M_1) is lesser, in absolute terms, than the coefficients of the extreme quintiles. Nonetheless, this latter coefficient is not statistically significant. Furthermore, we observe that the control variable $lnTNA_{p,t-1}$ has a significant negative impact on turnover ratio. The coefficient β_3 is statistically significant at the 1%-level. This result confirms the indirect effect of total net assets on turnover ratio. Finally, the other control variable ($Flow_{p,t}$) has a positive but non-significant impact on turnover ratio.

Overall, the results of the regression analysis of the second model align with the results of the first model. Both the linear and the quadratic models do not confirm a statistically significant relationship between past performance and turnover ratio. However when dividing performance in quintiles, we find significant evidence that funds with the lowest performance subsequently increase their turnover ratio. This happening can be explained by a change of strategy after poor performance and is not an evidence of overconfidence.

4. Conclusions

In this paper, we examine the overconfidence of managers of Spanish equity mutual funds between December 1999 and June 2014. While studies on retail investors' biases are abundant, few studies have focused on assessing the overconfidence of professional investors.

We gauge overconfidence with the use of turnover ratio. Contrary to the prediction of theories (Barber & Odean, 2000; Barber, 2001; Gervais & Odean, 2001; Glaser & Weber, 2007; Moore & Healy, 2008; Odean, 1998a; Odean, 1998b) and the result of previous investigations (Puetz and Ruenzi, 2011; Statman, Thorley, and Vorkink, 2006), we do not find strong evidence for overconfidence after good past performance in managers of domestic equity mutual funds in Spain. Nonetheless, we find that, though not statistically significant the relationship between past performance and turnover ratio is U-shaped. This is consistent with other studies such as that of Puetz and Ruenzi (2011).

It is worth mentioning that we find strong evidence of increase in trading activity in the period subsequent to poor performance. This phenomenon can be explained by the fact that managers decide to change their strategy. This result could be indicative of a possible risk-changes behavior after poor past performance.

Finally, a few concerns about the methodology employed in this study can be raised. Again, alternative methods other than raw returns to measure performance can provide more robustness to this study. These methods include but are not limited to Jensen's Alpha, Fama and French three-factor model and Carhart four-factor model. Finally, there are other methods to measure the relationship between two or more variables (Random effect and Fund Fixed Effect, for instance).

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