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Mutual fund performance attribution and market timing using portfolio holdings

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April, 2017

Abstract

We propose a novel performance attribution model for equity fund portfolios. The model analyses investment decisions based on portfolio holdings and measures the value added from different sources of performance such as past return strategies, security selection, market timing and passive timing. The model was tested for a sample of mutual funds. Empirical results show that security selection is the main contributor to fund performance regardless of the sample period considered or the asset pricing model used. The evidence of timing ability is mixed with low significance. Nevertheless there are noticeable differences between the timing ability of the best and worst performing funds, especially in crisis periods. Analysing the relationship between mutual fund performance (and its different components) and fund characteristics, we find that top funds are significantly smaller and more concentrated than other funds. Finally, we also examine the persistence in the performance and in its components finding evidence of positive persistence in past return strategies and picking skills although this persistence is not shown in the overall performance.

Keywords: performance attribution; mutual fund; market timing; security selection; passive timing

JEL Code: G23, G11

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1. Introduction

The development of mutual fund industries has generated interest by practitioners and academics. A large body of financial literature has analysed the management of mutual funds. In this field, the analysis of mutual fund performance is a relevant issue for both investors and managers because of its significant impact on wealth. Therefore, it is interesting to analyse whether fund managers are able to provide added value to investors. With this aim, the financial literature has typically identified two basic tools of active management for managers. The first tool is security selection, i.e., the manager's ability to invest (disinvest) in undervalued (overvalued) assets. The second tool is market timing, i.e., the ability to anticipate market behaviour and increase the portfolio beta in upward markets and/or decrease the beta in downward markets. Within this context, our work aims to analyse the performance attribution of mutual funds, paying particular attention to market timing ability.

One way to assess mutual fund performance is to compare its returns to those achieved with a passive portfolio that reply the portfolio's risk factors or style. Because data on returns are normally accessible, a large body of mutual fund performance literature is based on asset pricing models as Jensen's (1968) initial proposal, the multifactor models of Sharpe (1992) and Carhart (1997) and the conditional approach from Ferson and Schadt (1996). In recent mutual fund literature, multifactor models have been widely used by Gil-Bazo and Ruiz-Verdú, (2009), Busse et al. (2010), Fama and French (2010), Kacperczyk et al., (2014), Klein et al. (2015) and Ferson and Mo (2016), among others. Detailed portfolio holdings are another source of data for the assessment of mutual fund performance. Due to the lower availability of this type of data, fewer studies have been conducted using portfolio holdings. Some early studies include research by Cornell (1979) and Grinblatt and Titman (1989a and 1989b). One of the most commonly used approaches has been proposed by Grinblatt and Titman (1993), in which the fund performance is measured by analysing changes in the weights of portfolio holdings. One main advantage of this methodology is that performance is calculated directly and does not depend on the selection of benchmark or risk factors. Measures using portfolios holdings have evolved over time proposing different performance decomposition (e.g. Daniel et al. 1997; Jiang et al. 2007; Elton et al. 2012; Fulkerson 2013 and Ferson and Mo 2016). Studies by Ferson (2010), Elton and Gruber (2013) and Ferreira (2013) offer compelling reviews of different methodologies and empirical findings on mutual fund performance. In general, the evidence in the literature indicates that, after expenses, mutual fund performance is negative.[1]

Regarding market timing ability, the empirical evidence is less uniform and differs mainly depending on the methodology used. Early measures used to assess timing were

[1] This is also the most common finding in the Spanish market. See, e.g. Martínez (2003), Matallín-Sáez (2006) and Álvarez et al. (2014).

proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981). Both are return-based measures that capture changes in the relationship between systematic risk and the stock market return in a regression model. The evidence shown by these measures is that mutual funds do not reflect a significant timing ability or show negative results in some cases.

These measures have drawn some criticism in the literature. One of the most important criticisms is that the timing ability will be biased because the beta is time-varying. Grinblatt and Titman (1989b) indicate that structural changes in the beta can generate a biased estimation of performance. Bangassa et al. (2012) also find that generalized autoregressive conditional heteroskedasticity models with time-varying characteristics of factor loadings obtain more reliable results for timing ability. On the other hand, Rodríguez (2008) shows how multi-factor extensions of return-based measures perform better than conventional models. Additionally, Jagannathan and Korajczyk (1986), Bollen and Busse (2001) and Matallín-Sáez et al. (2015), among others, have noted that asymmetric behaviour in the stocks' beta in relation to market returns can generate artificial evidence of timing, which is referred to as *passive timing*. Empirical results usually show that this bias negatively impacts the timing evidence. Furthermore, Goetzmann et al. (2000), Bollen and Busse (2001) and Chance and Hemler (2001) found that timing evidence may differ due to the frequency of the return data. Additionally, some studies also provide evidence that cash inflows previous to an upward market may reduce portfolio betas and therefore, may bias market timing measurement (e.g. Edelen, 1999; and Muñoz et al. 2014). Another criticism for timing return-based measures is the spurious negative correlation between selection and timing abilities when these measures are applied, as noted by Jagannathan and Korajczyk (1986), Grinblatt and Titman (1989b) and Bollen and Busse (2001), among others.

Some of the above problems can be solved using timing measures that are based on portfolio holdings data, as proposed by Daniel et al. (1997), Jiang et al. (2007), Elton et al. (2012), Fulkerson (2013) and Ferson and Mo (2016). In these studies, the evidence of negative market timing that is typically found with return-based measures disappears when holdings-based measures are used. However, Daniel et al. (1997) note that, on average, mutual funds cannot effectively time the market. Only Jiang et al. (2007) found evidence of positive timing. Elton et al. (2012) did not provide evidence of successful timing when using a multifactor model. Fulkerson (2013) find that timing evidence depends on the sample period; concretely positive timing values vanished in last decades.

Within the context of holdings-based measures, we propose a new model that assesses the active management of mutual funds. In line with Daniel et al. (1997) and Kacperczyk et al. (2014), investment managers' decisions are observed through an analysis of changes in the portfolio holdings. Performance is then measured as the contribution of these changes to mutual fund returns. However, we contribute to previous literature by defining an attribution performance model that consists of four components linked to security selection and market timing measurement that allow us to isolate the effect of passive timing.

In the empirical section, the paper initially shows the results that are obtained through the traditional return-based measures of market timing ability. The analysis provides evidence of funds with positive and negative timing, although the number of negative cases is notably higher. In line with previous studies that use these measures (see, e.g., Henriksson, 1984; Ferson and Schadt, 1996; Jiang et al., 2007; Klein et al., 2015 and Ferson and Mo, 2016), the average timing of the funds is negative or insignificant. Next, we apply holdings-based measures in a similar manner to Daniel et al. (1997), Jiang et al. (2007) and Elton et al. (2012). In line with these studies and compared to return-based measures, the evidence of timing improves.

We then apply our performance attribution model using portfolio holding data, which enables us to measure the contribution of the selection and timing skills in mutual fund performance in an integrated manner. Relative to security selection, two components are considered. The first component measures the value added by the managers through past return strategies that consist of overweight/underweight securities with high (low) idiosyncratic returns in the past. Our results show that this component generates negative values on average. The second component is the value added by managers to anticipate the unexpected performance of securities. Although funds with positive and negative values exist, the contribution of this component is generally positive, being the largest contributor on average to the performance of mutual funds.

Regarding the timing ability, we consider two components. The first is related to the managers' ability to anticipate market returns. Our results show that there is little significance and that the mean, although negative, is close to zero. The component of passive timing follows a similar pattern; it is close to zero and not statistically significant.

Unlike previous studies that analyse portfolio holdings that focus on the aggregated results of the mutual fund sample, as seen in Daniel et al. (1997), Jiang et al. (2007) and Elton et al. (2012), we analyse the performance attribution in relation to the level of the fund performance. Thus, when mutual funds are ordered into deciles from the lowest to the highest performance, we find evidence that selection and timing abilities are the components with the highest contribution to the fund performance. It is also interesting to note that the best funds in terms of performance show a positive ability to both picking stocks and timing the market. This result seems more reasonable than the evidence of a negative correlation between selection and timing found with the return-based measures (see, e.g., Henriksson, 1984 and Bollen and Busse, 2001 among others), which is implicitly explained by the specifications of these measures (Jagannathan and Korajczyk, 1986 and Grinblatt and Titman, 1989b). On the other hand, the bad results of bottom performers are mainly explained by their poor timing abilities.

Next, we examine the robustness of the above results with two additional analyses. First, we divide the sample period into two sub-periods, depending on the financial market conditions, growth and crisis. The results show that the mutual fund performance responds better in crisis periods, which is in line with the recent literature, as seen in Kosowski (2011) and Glode (2011). Regarding contribution to performance, the most important components in both periods of growth and crisis are the past return strategies, the stock-picking and timing abilities. However, these abilities have different patterns in growth and crisis periods. The stock picking remains positive in both sub-periods but it is higher in the growth period. However, past return strategies and timing ability are negative in the growth period but positive in the crisis period. Similarly to the evidence of Kaczperczyk et al. (2014), managers seem to pick stocks better in booms and time the market in recessions. Additionally, the stock-picking ability also seems to have a different pattern in the worst performing funds depending on the financial context. The worst funds are able to have positive skills in picking stocks in growth periods while their picking skills are negative in recessions. Second, we analyse the robustness of our performance attribution model by using the Carhart (1997) four-factor model instead of the one-factor model.[2] The results remain qualitatively the same.

In short, our results show that stock picking is the most important component of performance and is positive on average, regardless of the sample period considered and asset pricing model used. The contribution of market timing to the performance is close to zero and takes different signs depending on the sample period analysed. These results are in line with those found by Daniel et al. (1997) and Elton et al. (2012) that also use portfolio holdings data. Therefore, on average, the mutual funds cannot effectively time the market, although we note that there are important differences between the timing abilities of the best- and worst-performing mutual funds, especially in crisis periods. The contribution of past return strategies to mutual fund performance is quite important although it also takes different signs depending on the sample period examined while passive timing has a residual importance in all the analyses carried out. Finally, we also analyse the characteristics of mutual funds in the first quintile of the performance measure or its components. The results provide evidence that the top funds are significantly smaller, are more concentrated than the other mutual funds and have a higher turnover in their portfolios.

The proposed performance attribution model contributes to the related literature in several ways. First, in relation to security selection, the model differentiates the mutual fund performance that is caused by investment strategies based on past return and the amount that is caused by the managers' ability to anticipate the idiosyncratic performance of assets. This allows the direct measurement of the relationship between active management and past returns

[2] Note that Kacperczyk et al. (2014) only examine stock picking and timing abilities through the CAPM model.

rather than an indirect measurement generated by adding a momentum factor in the regression model of a return-based performance measure (Carhart 1997). Additionally, the proposed model enables us to directly measure the economic relevance of investment strategies based on past return, in the value added by managers.

Second, the model considers time-varying parameters, which are extremely useful for both selection and market timing skills. Time-varying is useful in assessing the managers' ability to select assets as well as assessing the passive timing effect discussed above. Using a return-based measure, Bollen and Busse (2001) propose a procedure that compares mutual funds with synthetic funds to control for spurious timing. Similarly, Jiang et al. (2007) using portfolio holdings data also use passive portfolios to control for the passive timing effect. However, we propose a direct evaluation of this effect because we integrate it into our performance attribution model, which also allows us to directly measure its economic relevance. Consequently, we can clearly differentiate the variation of the beta portfolio that is caused by investment decisions of mutual fund managers and the variation that is caused by the asymmetric behaviour of the stocks as described by Jagannathan and Korajczyk (1986), Bollen and Busse (2001) and Matallín-Sáez et al. (2015) among others.

Third, the proposed performance attribution model allows the direct measurement of the economic value of market timing. Thus, previous studies assessing the timing ability with portfolio holdings data, such as Jiang et al. (2007), performed only an indirect estimate of the economic value of the market timing ability using simulations.

Fourth, we study persistence in the fund performance and the performance components. With this analysis, we attempt to determine whether management skills persist over time or occur randomly. For this purpose, we will apply a recursive portfolio approach in line with Carhart's (1997). Our study contributes in two ways. First, we apply a portfolio recursive approach to a portfolio-holdings context instead of return-based measures. Second, we measure persistence separately for each performance component finding evidence of positive persistence in past return strategies and picking skills although this persistence is not shown in the overall performance.

The remainder of the paper is organized as follows: Section 2 describes the mutual fund and asset data. In Section 3, the methodological framework is proposed. Section 4 contains the empirical results, Section 5 contains the robustness and additional analyses, and Section 6 concludes.

2. Data

The performance attribution model proposed is tested in a European mutual fund industry in order to provide evidence of management skills in a market outside the US market. Specifically, the empirical tests are applied in a sample of Spanish mutual funds due to its importance in the Euro Zone. By the end of 2014, the Spanish fund industry was ranked eighth in the Euro Zone fund industry in terms of assets (European Fund and Asset Management Association, 2014). Additionally, the Spanish fund industry deserves attention due to some particularities.[3] On one hand, the market is highly concentrated. The top 10 of the existing 79 Spanish fund companies control more than 75% of the total fund assets (Inverco, 2014). If we compare these figures with the US mutual fund industry, we find that competition in Spain is much more concentrated than that in the largest fund market in the world, where the top 10 companies manage approximately 53% of the total assets in 2013 (Investment Company Institute, 2014). On the other hand, the median fund size in Spain is much smaller than in the US market (as of December 2014; $88.9 million per fund in Spain as opposed to $2,001 million in US). Finally, the Spanish market was used to test the model due to ability of monthly portfolio holdings as opposed to the usual quarterly portfolio holdings available for other markets.

To carry out the study we combine two mutual fund data sets in our analysis. The first is the CNMV mutual fund dataset provided by the Spanish regulator, the Spanish Securities Exchange Commission (CNMV). This database has information on daily returns and monthly fund characteristics such as total net assets and the number of investors in all Spanish mutual funds. The database also contains quarterly portfolio holdings information for all Spanish mutual funds. Therefore, this database is free of survivorship bias. In addition to this information, CNMV provided us monthly portfolio holdings from December 1999 to December 2006[4] for research purposes, which overcomes any problem of reporting selection bias that may be present in the previous literature when using data based on high-frequency portfolios where mutual funds' management companies voluntarily supply reports to private data providers (Elton et al. 2010). The second data source is Morningstar Direct, which allows us to complete the CNMV quarterly portfolio holdings database from January 2007 onwards with the monthly holdings when available. As stated by Elton et al. (2012), Morningstar and CNMV holdings data include both the holdings of traded equity and the holdings of bonds, preferred stocks, other mutual funds, nontraded equity, derivatives and cash. Both databases were matched by fund names and fund ISIN (International Securities Identification Numbering) codes. The matching process of both datasets allowed us to analyse 81.5% of the monthly portfolio holdings of the funds in the sample period.[5]

We focus on actively managed Spanish domestic equity funds. The initial sample includes 194 funds that reported at least one year of daily returns and 11 portfolio holdings.

[3] Golez and Marin (2015) provide some insights about the particularities of the Spanish mutual fund industry.

[4] Monthly portfolio holdings provided by CNMV contain disclosed and undisclosed portfolios because management companies in Spain must report to investors on a quarterly basis, which is more frequent than the European Union's requirement of semi-annual portfolio reports. Because the fiscal year of Spanish management companies is the natural year, reports are mandatory at the end of each calendar quarter.

[5] Previous studies analysing market timing through portfolio holdings rely on quarterly or semi-annual holdings (Jiang et al., 2007) or on mutual funds that report in monthly terms (Elton et al., 2012) as opposed to our analyses, in which the majority of the funds in the sample report in monthly terms without imposing this as a requirement to be included in the sample. Therefore, our database is more complete.

From this sample, we eliminate funds that do not fulfil the official investment requirement for domestic equity funds that ensure the correct classification of the analysed portfolios as Spanish domestic equity funds. The removal of these misclassified funds does not imply any bias in the sample. The final sample consists of 160 Spanish domestic equity funds and 13,287 portfolio holdings.

Panel A of Table 1 reports some descriptive statistics for the 160 funds in our sample of Spanish domestic equity funds during the period 2000-2014. By averaging the time series for each fund over the year and across the funds to obtain the average of the portfolios that report in each year, we obtain the following characteristics: the average total net assets (TNA) of the funds in our sample are €56.21 million, and the average number of investors is 2,448. The funds invest 78.88% of their assets in common stocks, and the average number of stocks held in a fund is 35. Additionally, Panel B of Table 1 also reports the share of the fund portfolios classified in the main types of securities across the years of the time period analysed. As expected, the main investment is in domestic stocks. Table 1 also shows that the percentage invested in fixed-income and other mutual fund units is relatively small. The low percentage of non-controlled securities (less than 1% of the portfolios) reinforces the quality of our database.

(Insert Table 1 around here)

Finally, in relation to the security returns, our study mainly relies on DataStream, which provides daily information about the returns of domestic and foreign stocks and accounts for capital operations such as stock splits, the payment of dividends and seasoned equity offerings. Hence, we have information about the daily returns of all stocks across the entire time period of the sample. The ISIN code of each stock is used to link portfolio holdings with the stock returns. Additionally, the returns of Treasury Bills and other fixed-income securities are calculated using indices published by *Analistas Financieros Internacionales* (AFI). Finally, a low percentage of fund total assets (see Table 1) are non-controlled securities, which, together with cash and cash equivalents, receive a zero return. The Ibex-35 index return is used as a proxy for the stock market return, and the one-day Spanish T-bill Repos yield is the proxy for the risk-free rate. The 4-factor model of Carhart (1997) is also used in the robustness section. These factors have been calculated for the Spanish stock market with Compustat data.[6] The availability of the daily information to calculate the factors leads to the consideration of a shorter sample period when this model is applied, specifically the sample period is from March 2001 to June 2014.

[6] The factors of size, book to market and momentum have been calculated following the same procedure detailed on the website of Kenneth French considering the stocks traded in the Spanish stock market (see, e.g., http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

3. Methodology

3.1. Return-based timing measures

Fund managers can make timing decisions by changing the sensitivity of the portfolio to a set of factors that affect fund returns. The return-based timing measures are useful when fund betas are not directly observed. For that reason, traditional timing models regress the excess return on a fund against the excess return on a set of factors over time using a time series regression as follows:

$$r_{p,t} = \alpha_p + \beta_p r_{m,t} + \gamma_p r_{m,t}^2 + \varepsilon_{p,t} \tag{1}$$

$$r_{p,t} = \alpha_p + \beta_p r_{m,t} + \gamma_p \, max\ \left(r_{m,t}, 0\right) + \varepsilon_{p,t} \tag{2}$$

where $r_{p,t}$ and $r_{m,t}$ denote the excess fund and market returns over holding period t. Specifically, Equation (1) is known as the Treynor and Mazuy (1966) model, whereas Equation (2) is referred as the Henriksson and Merton (1981) model.

Most studies document negative but insignificant timing performance by mutual funds. However, these models suffer from different problems documented in the literature, such as the passive timing effect (see, e.g., Jagannathan and Korajczyk 1986, Bollen and Busse 2001 and Matallín-Sáez et al. 2015). Part of this effect is linked to some characteristics of the stocks in which the fund invest, the most relevant characteristic is that related to size (see, e.g., Matallín-Sáez, 2006). Therefore, considering previous literature (see, e.g., Comer 2006 and Klein et al. 2015, among others), we extend models (1) and (2) considering the additional risk factors proposed by Carhart (1997) as follows:

$$r_{p,t} = \alpha_p + \beta_{p,m} r_{m,t} + \gamma_p r_{m,t}^2 + \beta_{p,smb,t} r_{smb,t} + \beta_{p,hml,t} r_{hml,t} + \beta_{p,wml,t} r_{wml,t} + \varepsilon_{p,t} \tag{3}$$

$$r_{p,t} = \alpha_p + \beta_{p,m} r_{m,t} + \gamma_p \, max\ \left(r_{m,t}, 0\right) + \beta_{p,smb,t} r_{smb,t} + \beta_{p,hml,t} r_{hml,t} + \beta_{p,wml,t} r_{wml,t} + \varepsilon_{p,t} \tag{4}$$

where $r_{smb,t}$ is the risk factor defined as the return difference between small stocks and large stocks, $r_{hml,t}$ is the risk factor defined as the return difference between high and low book-to-market ratio stocks, and $r_{wml,t}$ refers to the momentum factor and captures the return difference of past winner stocks and past loser stocks.[7]

Various forms and different frequencies of data have been used in the literature to test mutual fund timing abilities. For that reason, in this paper, we first calculate the traditional

[7] The availability of the daily information to calculate the 4-factors leads to the consideration of a shorter sample period when using the Carhart (1997) model. Specifically, the sample period is from March 2001 to June 2014.

timing models (TM and HM models hereafter) and their respective extended models (3) and (4) using both monthly and daily returns.

3.2. Holdings-based timing measures

However, when the portfolio holdings of a fund are observed, we can estimate the fund beta at a point in time $\beta_{p,t}$ directly as the weighted average of the beta estimates for each security held by the fund, as shown in the following expression:

$$\beta_{p,t} = \sum_{i=1}^{N} w_{i,t} \beta_{i,t} \tag{5}$$

where w_{it} is the portfolio weight for stock i at the beginning of holding period $t+1$, and $\beta_{i,t}$ is the beta for stock i that is estimated using data prior to period $t+1$. The betas of individual stocks are estimated using the one-factor model with one year daily returns prior to the portfolio reporting date. We require that the security has at least 60 daily observations during the estimation period. Similarly to Jiang et al. (2007), non-stock securities are assumed to have a beta of zero.[8]

Following Jiang et al. (2007), we measure market timing by estimating the coefficient γ_p from the regressions:

$$\beta_{p,t} = c_p + \gamma_p r_{m,t+1} + \varepsilon_{p,t+1} \tag{6}$$

$$\beta_{p,t} = c_p + \gamma_p I_{m,t+1} + \varepsilon_{p,t+1} \tag{7}$$

where $\beta_{p,t}$ is the fund beta that is estimated at the beginning of period $t+1$, $I_{m,t+1}$ is an indicator that takes the value of one when $r_{m,t}>0$ and zero otherwise, and the estimated γ_p coefficients are referred to as the holdings-based Treynor and Mazuy measure (6) and the holdings-based Henriksson-Merton measure (7), respectively. A positive and significant γ_p indicates timing ability.

3.3. Holdings-based timing tests using active changes in portfolio weights

The holdings-based tests essentially measure the covariance between the fund beta levels at a given moment t and the market return of the subsequent holding period. However, as stated by Jiang et al. (2007), time variation in fund betas can be driven by both the active trading

[8] As stated in Elton et al. (2012), an estimation error in the betas of individual securities exists. However, this estimation error tends to cancel out and becomes very small when we move to the portfolio level and examine measures over time.

activities of fund managers and the passive portfolio weight changes due to non-proportional changes in stock prices.

As opposed to Jiang et al. (2007), which examines the changes in fund betas to evaluate the effect of active trading on market timing, we follow Grinblatt and Titman (1993), Daniel et al. (1997) and Fulkerson (2013) and analyse the changes in the portfolio weights; portfolio weights are observable, and therefore, they are more direct metrics than the betas. Specifically, the security portfolio weight change due to the active trading from period *t-1* to period *t* is calculated as follows:

$$\Delta w_{i,t} = w_{i,t} - w_{i,t}^{t-1} \tag{8}$$

where $w_{i,t}$ is the fund portfolio weight of security *i* at moment *t*, and w_{it}^{t-1} is the passive portfolio weight of security *i* at moment *t* that is inferred from fund portfolio holdings in the previous moment *t-1*. In other words, w_{it}^{t-1} is the hypothetical weight of security *i* at moment *t* if the fund follows a passive buy-and-hold strategy during period *t*. Given that w_{it}^{t-1} captures the portfolio weight change due to the non-proportional changes in security prices, Δw_{it} represents the portfolio weight change due to active trading by fund managers.

Next, similarly to Grinblatt and Titman (1993) and other related studies (see, e.g., Zheng, 1999 and Ferson and Khang 2002, among others), in (9), we define the abnormal performance $\Delta r_{p,t+1}$ as the return of mutual fund *p* in the next period, *t+1*, due to portfolio weight changes based on the active trading in period *t*.

$$\Delta r_{p,t+1} = \sum_{i=1}^{N} \Delta w_{i,t} r_{i,t+1} \tag{9}$$

where $r_{i,t+1}$ is the return of security *i* in period *t+1* and Δw_{it} is the portfolio weight change due to the active trading from period *t-1* to period *t* as defined in (6). Here, it is important to highlight that $\Delta r_{p,t+1}$ is not calculated from the real return of funds ($r_{p,t+1}$) because this measure can be affected by non-observable fund manager trading decisions during period *t+1*. This effect is known in the literature as "interim trading" (see, e.g., Goetzmann et al., 2000; Jiang et al., 2007; and Fulkerson, 2013). Hence, $\Delta r_{p,t+1}$ compares the expected returns of mutual fund *p* in period *t+1* according to the real portfolio holdings ($w_{i,t}$) in period *t* with respect to the hypothetical portfolio holdings from passive management (w_{it}^{t-1}) in period *t*.

As market timing shifts the portfolio systematic risk level and in line with the previous literature such as Jiang et al. (2007) and Elton et al. (2012) that used portfolio holdings, it is necessary to introduce an asset pricing model to frame the systematic risk of securities. Following Jiang et al. (2007) and Kacperczyk et al. (2014) we analyze timing ability in the context of the Capital Asset Pricing Model (1-factor model). Similarly to Grinblatt and Titman (1989b) and Kacperczyk et al. (2014) among others, we define the idiosyncratic component of the stock return, $r_{i,t+1}^{idiosync}$ as follows:

$$r_{i,t+1}^{idiosync} = r_{i,t+1} - \beta_{i,t+1} r_{m,t+1} \tag{10}$$

Note that this expression can be easily generalized to a multifactor model, as we will consider later, where the idiosyncratic component is the part of the return that is not priced by the model.

Replacing this expression in equation (9), we obtain the following expression that allows us to split the abnormal performance of mutual fund *p* into different terms.

$$\Delta r_{p,t+1} = \sum_{i=1}^{N} \Delta w_{i,t} \left(r_{i,t+1}^{idiosync} + \beta_{i,t+1} r_{m,t+1} \right) \tag{11}$$

We consider that $r_{i,t+1}^{idiosync}$ and $\beta_{i,t+1}$ could be time-varying. Therefore, we compute their changes from period *t* to period *t+1* as follows:

$$\Delta r_{i,t+1}^{idiosync} = r_{i,t+1}^{idiosync} - r_{i,t}^{idiosync} \tag{12}$$

$$\Delta \beta_{i,t+1} = \beta_{i,t+1} - \beta_{i,t} \tag{13}$$

Hence, equation (9) can also be rewritten as follows:

$$\Delta r_{p,t+1} = \underbrace{\sum_{i=1}^{N} \Delta w_{i,t} r_{i,t}^{idiosync}}_{\text{(i)}} + \underbrace{\sum_{i=1}^{N} \Delta w_{i,t} \Delta r_{i,t+1}^{idiosync}}_{\text{(ii)}} + \underbrace{\sum_{i=1}^{N} \Delta w_{i,t} \beta_{i,t} r_{m,t+1}}_{\text{(iii)}} + \underbrace{\sum_{i=1}^{N} \Delta w_{i,t} \Delta \beta_{i,t+1} r_{m,t+1}}_{\text{(iv)}} \tag{14}$$

The right side of equation (14) can be split into four terms, from (i) to (iv). Mutual fund literature has usually recognized two sources of performance: security selection and market timing. The first is related to manager's ability to invest (divest) in undervalued (overvalued) securities, while the second refers to the managers' ability to time the sign of the stock market return. Terms (i) and (ii) will be linked to security selection, and terms (iii) and (iv) are linked to market timing. We will now comment on each of these terms.

Term (i) captures the part of the performance of the given fund *p* that corresponds to a strategy such that the fund manager has changed the portfolio weight of security *i* based on its previous idiosyncratic return.

Term (ii) captures the part of the performance linked to the managers' stock-picking ability. Its value will be positive if the manager has overweighted (underweighted) securities *i* in moment *t* with increases (decreases) in their idiosyncratic returns in the following period. Thus, this term measures the value added by managers to anticipate the unexpected performance of securities. Previous literature has also measured performance using idiosyncratic terms. Using return-based measures, Grinblatt and Titman (1989b) split the Jensen (1968) measure into three components, defining selection ability as a nonzero idiosyncratic term. In the same vein but in a multifactor frame, Sharpe (1992) defines performance as the difference between the fund's return and the return of a passive portfolio that replicates the fund`s style. In relation to holding-based measures, Grinblatt and Titman (1989b) showed how Cornell's (1979) performance approach measures the selection by means of the idiosyncratic term. In general, in the holding-based measures (see, e.g., Grinblatt and Titman 1993 and Kacperczyk et al. 2014), the idiosyncratic return is implicitly included in the abnormal performance.

Term (iii) captures the value added by the manager due to his/her timing ability. As equation (15) shows, mutual fund managers can change the weight of the given security *i* in moment *t* with the aim of varying the beta of the mutual fund *p* in period *t*, and therefore attempt to anticipate the excess market return in the following period *t+1*.

$$\sum_{i=1}^{N} \Delta w_{i,t} \beta_{i,t} r_{m,t+1} = \Delta \beta_{p,t} r_{m,t+1} \tag{15}$$

In their analysis of holdings-based tests, Jiang et al. (2007) also use $\Delta\beta_{p,t}$ instead of $\beta_{p,t}$ in expressions (6) and (7). Then, when regressing these values with respect to the stock market returns, they estimated timing coefficients (γ_p). In contrast, our proposal does not estimate timing in a second stage as in Jiang et al. (2007), the timing is calculated directly as indicated by expression (15). In addition, our proposal allows us to measure the economic contribution of the timing ability in the overall performance of the fund. Similarly to equation (15), Elton et al. (2012) also analyse the variation in the fund beta, not between time periods but with respect a target beta to capture timing abilities. However, we use beta changes because they directly assess manager investment decisions without establishing any theoretical assumption on the portfolio beta over time. Moreover, using changes in beta enables us to assess the market timing ability into (14), a frame that integrates the different sources of the mutual fund performance.

Term (iv) measures the "*passive timing effect*" previously discussed in the literature. It captures the fact that the betas of the securities are not constant over time; instead, they tend to vary over time, showing asymmetries depending on the market status (option-like features). As a result, the returns on a passive portfolio investing in these securities may have an asymmetric relationship with market returns even when the funds are not market timers. This effect has been analysed by Jagannathan and Korajczyk (1986), Jiang et al. (2007) and Matallín-Sáez et al. (2015). Using portfolio holdings data, Jiang et al. (2007) control for the passive timing effect by means of passive portfolios. We contribute to the literature by proposing a more direct way to control for the effect of passive timing. Indeed, in (14), we include a term that directly measures the real effect of passive timing without using an estimation procedure.

4. Results

4.1. Return-based timing measures

First, we use return-based measures (1) to (4) to assess the market timing ability of Spanish equity mutual funds. Table 2 shows the results when the daily or monthly return data are used. The left side of the table shows the percentage of funds with a positive or negative timing coefficient (γ_p) and their significance. In line with Bollen and Busse (2001), the bootstrapping *p-values* are calculated. The right side of the table shows some statistics for the cross-sectional distribution of the market timing parameter.

Relating models (1) and (2) (i.e. traditional TM and HM models) Table 2 shows that the number of funds with negative timing abilities is higher than the number of funds with positive timing skills. This evidence is strengthened when using daily data and when applying the HM model. Furthermore, the negative sign of the mean and the median timing coefficient notes an overall evidence of perverse market timing. Previous studies with return-based measures, such as Henriksson (1984), Ferson and Schadt (1996), Jiang (2003) and Jiang et al. (2007), among others, have found similar evidence: on average, mutual funds exhibit negative market timing skills. The number of funds with negative (positive) timing decreases (increases) when using models (3) and (4) in Panel B. Although the mean remains negative, both the mean and the median increases. Therefore, the evidence of timing ability improves when applying models which consider additional risk factors. Finally, the most noticeable finding when using the 4-factor models is the important decline in the number of funds in which the timing parameter is significant.

(Insert Table 2 around here)

4.2. *Holdings-based timing measures*

According to holdings-based measures (6) and (7), the market timing ability is measured, respectively, as the slope between the beta of the fund and the stock market return or its sign in the next period. Similarly to Jiang et al. (2007), we consider different time periods to anticipate stock market returns, concretely over one, three, six and 12 months after the portfolio reporting date. Table 3 shows the results obtained. Specifically, the left side of the table reports the percentage of funds with positive or negative timing coefficient (γ_p) and their significance, while the right side of the table reports some statistics of the cross-sectional distribution of the market timing parameter.

For the TM measure expressed in (6), the proportion of positive and negative timing values is, on average, approximately 41% to 59%. The significance is low when considering a 1-month forecasting period of market returns, but the significance increases when longer time periods are examined. Concretely, only 4.38% (10.63%) of the funds in the sample show a negative (positive) timing parameter when the one-month forecasting period is examined, while this percentage increases to 18.13% (25.63%) when a one-year forecasting period is considered.

For the HM measure expressed in (7), the proportion of positive and negative timing is, on average, approximately 42% to 57%. Here, we also observe an increase in the significance related to the amplitude of the forecasting period examined. Table 3 also reports that the mean and median are positive for both models, regardless of the time horizon considered, and the number of cases with positive and statistically significant timing is notably higher than the number of cases with negative timing coefficients. These results are consistent with the findings of Daniel et al. (1997), Jiang et al. (2007) and Elton et al. (2012) because previous research illustrates that the negative timing ability documented by return-based measures disappears when analysing portfolio holdings.

(Insert Table 3 around here)

4.3. *Holdings-based timing test using active changes of portfolio weights*

Using the portfolio holdings information, we estimate the monthly performance of Spanish equity mutual funds through equation (9) as well as its breakdown into the four components explained in equation (14). Specifically, equations (9) and (14) are calculated for each mutual fund *p* and each month *t*, and these values are averaged for each mutual fund *p* across their sample period.

Table 4 shows the average values of mutual fund performance and the breakdown. The left side of the table shows the percentage of funds with positive or negative averages and their significance, while the right side of the table shows some statistics of the cross-sectional distribution of these averages.

The first row of the table reports the statistics on the mutual funds' performance. We can observe that 45% (55%) of the Spanish equity mutual funds report a negative (positive) performance, although these values are only statistically significant for 0.63% (1.88%). Additionally, Table 4 shows that fund performance attributable to investment decisions that lead to changes in the portfolio weights is, on average, 0.099% per year. Considering that this value is a pre-expenses number, this evidence is in line with previous literature that, analysing fund net returns, usually obtains an average negative or insignificant performance. In this sense, Ferreira et al. (2013) provide extensive international evidence on how mutual funds underperform the market.

Next, Table 4 shows the results for the different components of performance as explained in equation (14). We can see that the first component (i) that captures the performance attributable to an investment strategy based on past idiosyncratic return, reaches a negative (positive) value in 55.63% (44.38%) of the mutual funds analysed, being significant for the 23.13% (13.75%) of the cases. On the right-hand side of the table we can observe that, on average, this term contributes negatively to Spanish mutual fund performance. This finding means that, in general, the decision to invest (divest) in securities that performed well (poorly) in the recent past does not add any value to the mutual fund, as suggested by the contrarian investment strategy of Jegadeesh and Titman (1993), Griffin et al. (2003) and Wang and Wu (2011).

However, the second component (ii) of the performance attribution provides evidence of a higher number of managers with positive and statistically significant stock-picking abilities. Additionally, its contribution to the overall performance has an average value of 0.574% per year. Therefore, we provide evidence of significant stock-picking abilities among fund managers for Spanish equity mutual funds.

Finally, Table 4 reports the results for the managers' timing skills. We can see that 54.38% (45.63%) of mutual funds show negative (positive) timing skills, although these figures decrease to 1.88% (1.25%) when the statistical significance is examined. Hence, we can see that the number of managers with timing skills is quite similar to those who do not have this ability. In addition, the right side of the table shows that the contribution of market timing skills to the overall performance is negative and not significant. Our analysis fails in finding statistical significant market timing abilities, similarly to Elton et al. (2012) using the one-factor model and Daniel et al. (1997) using portfolio holdings.

Regarding the passive timing effect gathered in component (iv), we can see that the number of mutual funds with positive and negative values is almost the same, although the mean contribution of passive timing to the overall performance is negative (-0.008% per year) but not significant.

(Insert Table 4 around here)

In spite of the cross-sectional distribution of the performance components shown in Table 4, it is interesting to examine possible patterns of the performance attribution, depending on the value added by mutual fund managers. For that reason, we rank each mutual fund *p* according to their average performance ($\Delta r_{p,t+1}$) into deciles. The average values of the performance and its components in each decile are shown in Table 5.

Table 5 shows that the abnormal performance between deciles 1 and 10 varies from -1.96% to 2.46%. The negative abnormal performance of the bottom funds is caused especially by negative past return strategies and timing skills (-1.228%, and -0.803%, respectively). However, the positive abnormal performance of 2.46% for the top funds is explained by both the stock-picking and timing results. Table 5 also shows that the overall performance difference of 4.42% between bottom and top performers is explained by the significant difference in the timing skills shown by these portfolios (1.80%).

(Insert Table 5 around here)

Therefore, the paper provides evidence of mutual funds with positive and negative performance, although the number of funds with positive performance is slightly superior. Furthermore, the fund performance is mainly explained by two components of the proposed performance attribution model: past return strategies and stock-picking skill. However, the comparison of mutual funds with the best and the worst performance allows us to detect that past return strategies and timing have negative impact for the worst funds, while the positive contribution of the stock-picking and timing is higher for the best-managed funds.

5. Robustness and additional analyses

5.1. Robustness analysis related to the sample period

The previous section has reported the performance attribution of Spanish equity mutual funds for the entire time period analysed (2000-2014). However, this sample period includes time periods with different financial contexts. For that reason, we split the time period into two sub-periods. The period from 2000 to September 2008 can be referred as “before the global financial crisis” or “economic growth period” and the period from October 2008 to June 2014 can be referred as “during the global financial crisis” or “crisis period.” The split is made in September 2008 because the bankruptcy of Lehman Brothers can be considered the beginning of the global financial crisis.[9]

The aim of the robustness analysis is twofold. First, it allows us to examine whether the findings are robust or not in terms of the time period studied. Second, it allows us to analyse the management behaviour of mutual funds in two different financial contexts.

In the aftermath of the recent financial crisis, this issue has attracted great interest among analysts of mutual fund performance. Kosowski (2011) and Glode (2011) find that mutual funds perform better in poor economic periods than in good periods. Kacperczyk et al. (2014) also show that managers' skills are related to economic cycles.

Table 6 shows the results of equation (9) and its decomposition in (14) for the two subsamples considered. Panel A reports the findings for the time period before the global financial crisis, while Panel B gathers the results for during the global financial crisis.

Consistent with the recent financial literature (see, e.g., Kosowski, 2011 and Glode, 2011), we find that the performance of Spanish mutual funds was better during the financial crisis period (1.189%) than in periods of economic growth (-0.006%). Similarly, Table 6 also shows that the different components of the performance attribution are higher during the global financial crisis, except the stock-picking.

(Insert Table 6 around here)

Finally, Table 6 also provides robustness to the importance of the different components to explain the mutual fund performance. The stock-picking skill tends to be positive in both sub-periods although it is only statistically significant in the growth period. The timing ability is positive during the global financial crisis but negative in the years prior to October 2008, in accordance with the poor performance of mutual funds during that period.[10] This finding of positive and significant stock-picking abilities during growth periods is consistent with the results of Kacperczyk et al. (2014).

Next, Table 7 displays the performance and the performance attribution to the different components by ranking funds into deciles according to their average abnormal performance in the two subsamples examined. The first item that attracts attention in Table 7 is the similar findings obtained for the first subsample in comparison to the analysis of the entire time period. In particular, Table 7 shows some symmetry in the performance outcomes of the best- and

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[9] Although the bankruptcy of Lehman Brothers took place in the US market, it is also a relevant date for the remaining financial markets due to the globalization of the economy. The split made in 2008 makes perfect sense in the Spanish mutual fund industry since this year the industry suffered a reduction of 30% in the assets under managed.

[10] Note that previous papers using portfolio holdings information (see, e.g., Daniel et al., 1997) also provide evidence of changes in the sign of the timing ability, depending on the sample period analysed.

worst-managed funds (2.348% vs -2.304%). Similarly to previous analyses, the good performance of mutual funds is primarily driven by stock-picking and timing skills. The comparison of the best- and worst-managed funds (the last columns of Panel A) indicates that the performance difference is 4.652% per year. This difference is mainly explained by past return strategies (1.355%), the stock-picking ability (1.101%) and timing skills (2.288%). However, consistent with Table 5, only the difference in the timing ability between the best and worst funds is statistically significant.

Second, Panel B in Table 7 shows a higher dispersion level in the results obtained during the global financial crisis. As a consequence, the abnormal performance of both the best and worst funds in absolute terms is higher (10.119% vs -5.006%, respectively); this effect is especially important for the best funds. Finally, in relation with the performance attribution, stock-picking and timing skills are the most relevant. The last columns of Panel B in Table 7 highlight the relevant gap between the mutual funds. The best mutual funds significantly outperform the worst funds by 15.125% per year, showing that, again, the stock-picking and timing abilities are the most important components for explaining the abnormal performance.

(Insert Table 7 around here)

Table 7 highlights that in a complicated financial context for portfolio management, such as the global financial crisis, the value added by mutual fund managers plays an important role. As suggested by the results, complex contexts emphasize the differences in the abnormal returns achieved by the best and worst mutual funds, in which the stock-picking and timing abilities are the most important skills.

5.2. Robustness analysis related to the asset pricing model

We also carry out a robustness analysis to verify whether our findings can be influenced by the asset pricing model used. Hence, this section proposes the use of the 4-factor model proposed by Carhart (1997) instead of the 1-factor model used in equation (10). The 4-factor model is defined as follows:

$$r_{i,t+1} = \alpha_{i,t+1} + \beta_{i,t+1} r_{m,t+1} + \beta_{i,smb,t+1} r_{smb,t+1} + \beta_{i,hml,t+1} r_{hml,t+1} + \beta_{i,wml,t+1} r_{wml,t+1} + \varepsilon_{i,t+1} \quad (16)$$

where $r_{smb,t+1}$ defines the return difference between small stocks and large stocks in period t+1, $r_{hml,t+1}$ defines the return difference between high and low book-to-market ratio stocks, and $r_{wml,t+1}$ refers to the momentum factor and captures the return difference of past winner stocks and past loser stocks. The availability of the daily information to calculate the factors leads to the consideration of a shorter sample period in this robustness section than before. Specifically, the sample period is from March 2001 to June 2014. For that reason, to compare the results obtained when using the 1-factor model and the 4-factor model for the same time period, we re-estimate equation (14) for the new sample period. These results are shown in Panel A of Table 8, while Panel B reports the findings that use the 4-factor model.

Table 8 shows that the results are qualitatively the same regardless of the asset pricing model used. Both panels again provide evidence that the most important component of the performance attribution is related to the positive stock-picking ability. On the other hand, the timing ability, on average, shows a small negative value in both panels, although it is not significantly different from zero. Note that Elton et al. (2012) show an average positive timing coefficient when using the 1-factor model but a negative coefficient when a multifactor model is considered. Additionally, Table 8 also shows that the number of funds with positive (negative) timing is almost the same, being the statistical significance of these figures quite modest.

(Insert Table 8 around here)

Finally, Table 9 shows the performance attribution results with the ranking of funds into deciles according to their average performance. Here, we can observe that the major differences between the best- and worst-managed mutual funds are explained in terms of stock-picking and market timing abilities in both panels. Note that the passive timing has residual importance and the past return strategies show a contrarian behaviour. Therefore, the conclusions drawn from Table 9 allow us to conclude that our empirical findings are robust regardless of the asset pricing model used.

(Insert Table 9 around here)

5.3. Performance attribution and the characteristics of mutual funds

We compare the characteristics of the Spanish mutual funds allocated in the first quintile of the performance and the four performance components to the funds not included in this portfolio. The results obtained are reported in Table 10.

Table 10 shows several statistically significant differences between the top funds and the remaining funds. First, the funds in the first quintile (Q1) are smaller than the remaining funds in terms of both the money under management and the number of investors putting their money in the portfolios. Second, they exhibit higher portfolio turnover, which is consistent with a more active management style. Finally, these funds also tend to have less diversified portfolios. These findings are similar to those previously obtained in the literature (see, e.g., Kacperczyk et al. 2014).

(Insert Table 10 around here)

5.4. Persistence in performance attribution

After analysing the performance attribution of the mutual funds, it is interesting to explore the existence of persistence in performance and its components. Whether there is persistence in the mutual fund's performance component, a portfolio with investments based on a lower (higher) past value of the component will show a lower (higher) value in the component. To measure persistence, we apply a portfolio recursive approach with the following algorithm:

1- We calculate the value of the performance and its components of the mutual funds with model (14) and rank mutual funds in increasing order, according to the value they achieved in the ranking period to form deciles.

2- At the beginning of the next period, we form ten equally weighted portfolios, according to the decile's past performance or component. The first portfolio (D1) invests in the past worst-performing funds, and conversely, the last portfolio (D10) invests in the previous period's best funds. The same investment strategy is followed for the other deciles. On the whole, we formed 50 different decile portfolios, ten for five items, the performance and its four components.

3- This procedure is repeated at the beginning of each period. Therefore, each portfolio represents a dynamic investment strategy that rebalances the selected funds in accordance with their previous performance or component.

4- We calculate the value of the performance attribution according to model (14) for each of the 50 decile portfolios.

The algorithm is applied considering quarterly ranking and holding periods. We analyse whether investing in the worst (best) mutual funds in the previous quarter provide poor (good) results in the following quarter. Thus, the existence of persistence will be confirmed as to whether the performance achieved by a fund in a quarter shows continuity in the next quarter.

Table 11 shows the results of persistence. The columns display the value of the performance and its components across the decile portfolios form to each measure analysed. If there is performance persistence, we should observe that funds ranked in the worst (best) decile according to their past performance remain in the worst (best) performance decile during the holding period. Similarly, if there is persistence in the stock-picking abilities, we should observe that funds ranked in the worst (best) deciles according to their past picking skills remain in the worst (best) deciles of picking skills in the next period and so on with the other performance components. Figure 1 shows the values of Panel A of Table 11 for the whole sample period. If there is persistence, the lines present a positive slope.

Table 11 and Figure 1 show that mutual fund performance has not been achieved persistently over time. In spite of the lack of overall performance persistence, Table 11 shows positive and statistically significant persistence in two of its components; past return strategies and stock-picking. This finding indicates that those mutual fund managers that follow successful past return strategies continue being successful over time. Similarly, those fund managers with stock-picking abilities maintain this skill over time. However, since the deciles have been built independently for each performance component, we cannot conclude that the same manager has both abilities at the same time and this explains the lack of overall performance persistence. Besides, in some cases the timing ability reports a negative persistence.

(Insert Table 11 around here)

(Insert Figures 1, 2a and 2b around here)

The results for the expansion period are reported in Panel B while Panel C reports the results for the crisis period. The results of both panels are quite similar to those in Panel A. Thus, the findings are robust regardless of the time period analysed (whole sample, growth period and crisis period). Figures 2a and 2b show the value of the performance and its components across deciles in the sub-periods examined.

In summary, certain mutual fund managers present persistence in their abilities to select the securities that must be overweighted/underweighted over time according to their idiosyncratic returns. However, they do not have abilities in the other performance components which lead to a lack of overall performance persistence.

6. Conclusions

The main objective of the study has been to analyse the investment abilities of Spanish equity mutual fund managers through portfolio holding measures that quantify the contribution of portfolio weight changes in mutual fund returns. To perform this study, we propose a performance attribution model consisting of four components that are linked to security selection and market timing abilities. Specifically, the model considers two sources of security selection (past return strategies and the managers' ability to anticipate the unexpected performance of securities). The other two components of the performance attribution model are related to timing skills. The first measures the value added by managers due to market timing ability, and the second captures the variation in the portfolio's beta due to the passive timing effect because the stocks' beta can be asymmetrical with respect to the market returns.

The model contributes to the literature in several ways. First, the model proposes an original split of the performance attribution, which enables us to directly measure the selection and timing abilities of managers without using an estimation procedure, as was done in previous studies. Second, the model considers time-varying parameters, which is useful for splitting selection and timing and for separating the manager's ability to identify past return strategies and passive timing effects. In fact, unlike previous studies, passive timing is not assessed through an estimation procedure but is integrated and isolated within the model itself. Third, the model also directly calculates the actual economic value added by each component of the performance.

In the empirical part of the study, the timing ability is first measured by traditional return-based measures. Consistent with previous literature, the average timing parameter is negative. The study then applies holdings-based timing measures that were previously used in financial literature. The results provide evidence of an improvement in the timing skills of mutual fund managers, a finding that is consistent with previous studies.

Finally, our model of performance attribution is applied. We find that the abnormal performance of mutual funds has positive and negative values, although statistical significance is scarce. On average, the pre-expense performance average is positive but economically irrelevant. Regarding the two selection components, we provide evidence that the value added by managers due to past return strategies is negative while the value added by managers to anticipate the unexpected performance of securities, is positive on average and is the main contributor to the abnormal performance of mutual funds.

In relation to market timing skills, the evidence is mixed and has low significance. On average, the contribution of the timing to the performance is close to zero, taking different signs depending on the sample period analysed. Nevertheless, there are noticeable differences between the timing abilities of the worst and best mutual funds, especially during crisis periods. Moreover, the passive timing component also shows little significance among the mutual funds sample, taking a negative value close to zero.

In summary, the study does not provide evidence of economically significant performance for the Spanish mutual fund sample analysed. However, the performance attribution analysis notes that the stock-picking ability is more relevant than the market timing skill, although mutual fund performance improves during crisis periods, especially with the market timing ability. Additionally, the study shows that mutual funds with the best results in terms of performance and its components (past return strategies, stock-picking, timing and passive timing) are statistically smaller and more concentrated than the other funds. Finally, persistence in performance and its components were analysed. The results provide evidence of positive and significant persistence in past return strategies and stock-picking skills while there is negative persistence in the timing skills (for the whole and the growth period) which turns into a lack of persistence in the overall performance.

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Table 1. Summary statistics of Spanish domestic equity fund characteristics and portfolio holdings

The table is split into Panel A and Panel B. Panel A reports characteristics of mutual funds, such as the number of funds analysed, the size of the portfolios, the number of investors and the average number of stocks held by the portfolios with a breakdown according to the years of the sample period. Panel B reports the portfolio share of fund portfolios in the main types of securities across the years. The assets invested by funds are classified as follows: stocks (Spanish, European and others), fixed-income, other mutual fund units, cash and cash equivalents, and non-controlled securities. The data corresponds to the average of the portfolios that report in each year.

Panel A:	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Number of Funds	105	108	107	110	112	120	118	119	113	104	78	72	68	61	54
Total Net Assets (thousand €)	74,871	61,858	50,248	44,556	64,333	77,939	86,411	87,495	45,826	32,113	32,640	31,110	27,922	44,725	81,126
Number of Investors	2,869	2,822	2,759	2,632	2,917	2,977	3,166	3,415	1,998	1,522	1,573	1,559	1,575	1,969	2,964
Average No. of Stocks Held	41	38	36	34	37	38	39	39	35	32	33	32	30	30	33
Panel B:															
Stocks	80.65%	77.64%	77.81%	76.42%	76.78%	79.39%	81.78%	81.99%	76.70%	72.47%	77.82%	79.08%	81.78%	81.44%	81.46%
Spanish	70.69%	69.19%	70.70%	70.98%	71.60%	74.93%	77.88%	78.63%	74.28%	67.96%	72.18%	73.95%	76.00%	74.54%	74.04%
European	8.47%	7.65%	6.61%	5.23%	5.04%	4.33%	3.83%	3.25%	2.38%	4.49%	5.61%	4.96%	5.55%	6.69%	7.29%
Others	1.49%	0.80%	0.49%	0.22%	0.14%	0.13%	0.07%	0.10%	0.04%	0.02%	0.04%	0.17%	0.23%	0.21%	0.13%
Fixed-Income	5.27%	5.56%	4.49%	3.10%	3.15%	3.83%	2.04%	1.62%	4.31%	4.49%	2.53%	2.32%	1.99%	1.60%	1.40%
Other Mutual Fund Units	0.37%	0.19%	0.12%	0.14%	0.08%	0.05%	0.33%	0.98%	1.29%	0.83%	1.05%	0.73%	0.70%	0.31%	0.16%
Cash and Cash Equivalents	12.77%	15.58%	17.04%	19.84%	19.53%	16.21%	15.40%	14.93%	16.99%	21.53%	18.13%	17.31%	14.92%	15.48%	13.81%
Non-controlled Securities	0.93%	1.03%	0.55%	0.49%	0.47%	0.52%	0.45%	0.48%	0.71%	0.69%	0.46%	0.56%	0.60%	1.17%	3.17%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 2-Mutual fund market timing using return-based measures

This table reports statistics about the timing skills of Spanish equity mutual funds using monthly return data and daily return data. Panel A reports the results of the traditional Treynor-Mazuy (TM) and Henriksson-Merton (HM) models for the entire sample period (December 1999-June 2014) while Panel B reports the results for both the traditional models and the Treynor-Mazuy extended with Carhart (1997) additional factors (TM4F) and Henriksson-Merton extended with Carhart (1997) additional factors (HM4F) for the period March 2001-June 2014. The table is split into two parts. The left-hand side of the table provides statistics about the percentage of mutual funds that show a given sign of the timing coefficient as well as their statistical significance with the consideration of bootstrapped p-values while the right-hand side provides information about the cross-section distribution of the market timing parameters.

Measure – Frequency	Number of funds	γ_p <0	p-value <=0.05	γ_p >0	p-value <=0.05	Mean (p-value)	Median	5th percentile	95th percentile
Panel A: December 1999 to June 2014									
TM - Monthly data	160	75.63%	35.63%	24.38%	3.13%	-0.35 (0.000)	-0.17	-1.33	0.38
TM - Daily data	160	73.75%	53.13%	26.25%	10.00%	-0.43 (0.000)	-0.20	-1.68	0.27
HM - Monthly data	160	70.63%	25.63%	29.38%	3.13%	-0.07 (0.000)	-0.04	-0.31	0.12
HM - Daily data	160	82.50%	63.75%	17.50%	3.75%	-0.04 (0.000)	-0.03	-0.15	0.01
Panel B: March 2001 to June 2014									
TM - Monthly data	147	71.43%	34.01%	28.57%	6.12%	-0.35 (0.000)	-0.16	-1.41	0.35
TM - Daily data	147	68.71%	50.34%	31.29%	11.56%	-0.36 (0.000)	-0.15	-1.52	0.23
HM - Monthly data	147	71.43%	27.21%	28.57%	4.76%	-0.08 (0.000)	-0.04	-0.32	0.09
HM - Daily data	147	76.87%	57.82%	23.13%	5.44%	-0.04 (0.000)	-0.02	-0.15	0.01
TM4F - Monthly data	147	57.14%	0.68%	42.86%	1.36%	-0.09 (0.120)	-0.05	-0.69	0.49
TM4F - Daily data	147	62.59%	8.84%	37.41%	0.68%	-0.20 (0.001)	-0.07	-0.97	0.30
HM4F - Monthly data	147	58.50%	0.68%	41.50%	0.68%	-0.02 (0.043)	-0.01	-0.19	0.13
HM4F - Daily data	147	68.03%	10.88%	31.97%	0.00%	-0.02 (0.000)	-0.01	-0.09	0.02

Table 3-Mutual fund market timing using holdings-based measures

This table reports descriptive statistics about the timing skills of Spanish equity mutual funds based on the holdings-based Treynor-Mazuy (TM) and the Henriksson-Merton (HM) timing measures for the one, three, six, and 12 months horizons. The table is split into two parts. The left-hand side of the table provides statistics about the percentage of mutual funds that show a given sign of the timing coefficient as well as about their statistical significance with the consideration of bootstrapped p-values. The right-hand side provides information about the cross-section distribution of the market timing parameters.

Measure – Horizon	Number of funds	γ_p <0	p-value <=0.05	γ_p >0	p-value <=0.05	Mean (p-value)	Median	5th percentile	95th percentile
TM - 1 month	160	42.50%	4.38%	57.50%	10.63%	0.071 (0.003)	0.066	-0.391	0.512
TM - 3 months	160	40.00%	9.38%	60.00%	20.00%	0.061 (0.008)	0.052	-0.388	0.473
TM - 6 months	160	40.00%	13.13%	60.00%	19.38%	0.046 (0.027)	0.036	-0.316	0.450
TM - 12 months	160	41.25%	18.13%	58.75%	25.63%	0.014 (0.496)	0.027	-0.403	0.346
HM - 1 month	160	49.38%	7.50%	50.63%	5.63%	0.008 (0.837)	0.007	-0.669	0.765
HM - 3 months	160	39.38%	5.00%	60.63%	18.75%	0.132 (0.008)	0.096	-0.447	0.905
HM - 6 months	158	40.00%	6.33%	58.75%	26.58%	0.171 (0.001)	0.106	-0.360	1.017
HM - 12 months	142	39.58%	14.79%	59.03%	27.46%	0.069 (0.015)	0.051	-0.509	0.615

Table 4-Mutual fund performance attribution using active changes of portfolio weights

This table reports descriptive statistics about the performance obtained by Spanish equity mutual funds as well as their attribution to the different management skills based on equation (14). The table is split into two parts. The left-hand side of the table provides statistics about the percentage of mutual funds that show a given sign in the different components as well as their statistical significance with the consideration of bootstrapped p-values. The right-hand side of the table provides information about the cross-section distribution of the performance attribution parameters.

Performance attribution	Number of funds	<0	p-value <=0.05	>0	p-value <=0.05	Mean (p-value)	Median	5th percentile	95th percentile
Performance	160	45.00%	0.63%	55.00%	1.88%	0.099% (0.332)	0.103%	-1.650%	1.812%
(i) Past return strategy	160	55.63%	23.13%	44.38%	13.75%	-0.458% (0.022)	-0.067%	-4.620%	2.484%
(ii) Stock-picking	160	45.63%	11.25%	54.38%	21.88%	0.574% (0.006)	0.090%	-2.692%	5.224%
(iii) Timing	160	54.38%	1.88%	45.63%	1.25%	-0.009% (0.876)	-0.019%	-0.915%	1.031%
(iv) Passive timing	160	48.75%	1.25%	51.25%	1.88%	-0.008% (0.124)	0.000%	-0.102%	0.080%

Table 5- Performance attribution analysis ordering funds by performance

This table shows the performance attribution results splitting funds into deciles according to their average performance. Last column of the table reports the differences between the best and worst performing funds. Tests for significance were run by bootstrapped one-sided p-values.

Performance and attribution	1 (Worst)	2	3	4	5	6	7	8	9	10 (Best)	10 minus 1	p-value
Performance	-1.960%	-0.792%	-0.446%	-0.246%	-0.031%	0.172%	0.322%	0.545%	1.036%	2.460%	4.420%	(0.000)
(i) Past return strategy	-1.228%	-0.181%	-0.985%	0.118%	0.414%	0.386%	-1.328%	-0.740%	-0.735%	-0.235%	0.993%	(0.223)
(ii) Stock-picking	0.154%	-0.191%	0.804%	-0.315%	-0.397%	-0.230%	1.806%	0.895%	1.477%	1.710%	1.556%	(0.125)
(iii) Timing	-0.803%	-0.403%	-0.277%	-0.050%	-0.058%	-0.005%	-0.154%	0.393%	0.293%	1.000%	1.803%	(0.000)
(iv) Passive timing	-0.083%	-0.016%	0.011%	0.000%	0.009%	0.021%	-0.001%	-0.004%	0.001%	-0.015%	0.068%	(0.036)

Table 6- Robustness analysis of the performance attribution by using different time periods

This table reports descriptive statistics about the performance obtained by Spanish equity mutual funds as well as their attribution to the different management skills based on equation (14). The table is split into two panels. Panel A reports the statistics for the time period February 2000-September 2008 which can be referred to as “before the global financial crisis,” while Panel B reports the statistics for the time period October 2008-June 2014, which can be referred as “during the global financial crisis”. Furthermore, each panel is split into two parts. The left-hand side of the panels provides statistics about the percentage of mutual funds that show a given sign in the different components as well as about their statistical significance with the consideration of bootstrapped p-values. The right-hand side of the panels provides information about the cross-section distribution of the performance attribution parameters.

Performance and attribution	Number of funds	<0	p-value <=0.05	>0	p-value <=0.05	Mean (p-value)	Median	5th percentile	95th percentile
Panel A: February 2000 to September 2008									
Performance	160	53.13%	0.63%	46.88%	1.88%	-0.006% (0.955)	-0.046%	-1.650%	1.920%
(i) Past return strategy	160	58.13%	25.63%	41.88%	11.25%	-0.627% (0.002)	-0.163%	-4.822%	2.523%
(ii) Stock-picking	160	43.13%	8.13%	56.88%	20.63%	0.694% (0.001)	0.119%	-2.322%	5.645%
(iii) Timing	160	51.25%	1.25%	48.75%	1.25%	-0.065% (0.425)	-0.004%	-0.989%	1.108%
(iv) Passive timing	160	48.75%	1.25%	51.25%	1.25%	-0.009% (0.376)	0.000%	-0.116%	0.102%
Panel B: October 2008 to June 2014									
Performance	107	29.91%	0.93%	70.09%	1.87%	1.189% (0.002)	0.535%	-3.923%	10.507%
(i) Past return strategy	107	44.86%	11.21%	55.14%	19.63%	0.498% (0.114)	0.135%	-4.271%	5.620%
(ii) Stock-picking	107	44.86%	13.08%	55.14%	9.35%	0.318% (0.467)	0.193%	-6.321%	8.435%
(iii) Timing	107	48.60%	2.80%	51.40%	0.93%	0.376% (0.223)	0.057%	-4.105%	7.000%
(iv) Passive timing	107	42.99%	1.87%	57.01%	4.67%	-0.003% (0.736)	0.004%	-0.145%	0.130%

Table 7-Performance attribution analysis ordering funds by performance in subperiods

This table shows the performance attribution results splitting funds into deciles according to their average performance. The table is split into two panels. Panel A reports the statistics for the time period February 2000-September 2008 which can be referred to as "before the global financial crisis," while Panel B reports the statistics for the time period October 2008-June 2014, which can be referred as "during the global financial crisis". The last column of both panels reports the differences between the best and worst performing funds. Tests for significance were run by bootstrapped one-sided p-values.

Performance and attribution	1 (Worst)	2	3	4	5	6	7	8	9	10 (Best)	10 minus 1	p-value
Panel A: February 2000 to September 2008												
Performance	-2.304%	-0.798%	-0.517%	-0.368%	-0.145%	0.023%	0.243%	0.531%	1.019%	2.348%	4.652%	(0.000)
(i) Past return strategy	-1.797%	0.430%	-0.184%	-0.685%	-0.828%	-0.282%	-0.656%	-0.685%	-0.998%	-0.442%	1.355%	(0.165)
(ii) Stock-picking	0.826%	-0.846%	-0.055%	0.537%	0.686%	0.364%	0.781%	0.958%	1.656%	1.928%	1.101%	(0.220)
(iii) Timing	-1.321%	-0.377%	-0.290%	-0.232%	0.008%	-0.080%	0.109%	0.257%	0.367%	0.967%	2.288%	(0.000)
(iv) Passive timing	-0.011%	-0.006%	0.011%	0.011%	-0.011%	0.021%	0.009%	0.000%	-0.006%	-0.104%	-0.093%	(0.169)
Panel B: October 2008 to June 2014												
Performance	-5.006%	-1.174%	-0.205%	0.208%	0.460%	0.661%	1.146%	1.960%	3.612%	10.119%	15.125%	(0.000)
(i) Past return strategy	0.493%	1.501%	-0.291%	0.734%	0.145%	0.729%	0.126%	-1.274%	3.036%	-0.430%	-0.923%	(0.272)
(ii) Stock-picking	-1.758%	-1.372%	0.616%	-0.811%	0.558%	-0.229%	0.627%	2.967%	-1.397%	4.200%	5.959%	(0.026)
(iii) Timing	-3.642%	-1.281%	-0.542%	0.288%	-0.241%	0.138%	0.387%	0.267%	1.898%	6.369%	10.011%	(0.000)
(iv) Passive timing	-0.099%	-0.022%	0.012%	-0.002%	-0.003%	0.023%	0.006%	-0.001%	0.075%	-0.019%	0.080%	(0.157)

Table 8- Robustness analysis of the performance attribution by using different asset pricing models

This table reports descriptive statistics about the performance obtained by Spanish equity mutual funds as well as their attribution to the different management skills. The table is split into two panels. Panel A reports the statistics obtained when using 1-factor model while Panel B reports the statistics obtained when using a 4-factor model for the period March 2001-June 2014. Furthermore, each panel is split into two parts. The left-hand side of the panels provides statistics about the percentage of mutual funds that show a given sign in the different components as well as about their statistical significance with the consideration of bootstrapped p-values. The right-hand side of the panels provides information about the cross-section distribution of the performance attribution parameters.

Performance and attribution	Number of funds	<0	p-value <=0.05	>0	p-value <=0.05	Mean (p-value)	Median	5th percentile	95th percentile
Panel A: One-factor model in (10)									
Performance	159	39.62%	0.63%	60.38%	2.52%	0.166% (0.162)	0.159%	-1.238%	1.892%
(i) Past return strategy	159	57.86%	22.01%	42.14%	12.58%	-0.343% (0.076)	-0.130%	-4.190%	2.652%
(ii) Stock- picking	159	37.11%	9.43%	62.89%	21.38%	0.580% (0.006)	0.296%	-3.136%	5.345%
(iii) Timing	159	55.35%	3.77%	44.65%	0.63%	-0.068% (0.313)	-0.034%	-1.164%	1.027%
(iv) Passive timing	159	42.14%	2.52%	57.86%	1.26%	-0.003% (0.615)	0.004%	-0.068%	0.069%
Panel B: Four-factor model in (16)									
Performance	159	39.62%	0.63%	60.38%	2.52%	0.166% (0.162)	0.159%	-1.238%	1.892%
(i) Past return strategy	159	56.60%	21.38%	43.40%	11.95%	-0.314% (0.078)	-0.056%	-3.953%	2.341%
(ii) Stock-picking	159	35.85%	8.81%	64.15%	18.24%	0.545% (0.006)	0.198%	-3.318%	5.094%
(iii) Timing	159	51.57%	1.89%	48.43%	0.63%	-0.070% (0.313)	-0.022%	-1.109%	1.074%
(iv) Passive timing	159	37.74%	0.63%	62.26%	3.77%	0.005% (0.530)	0.012%	-0.134%	0.138%

Table 9-Robustness analysis of the performance attribution ordering funds by performance and using different asset pricing models.

This table shows the performance attribution results splitting funds into deciles according to their average performance. The table is split into two panels. Panel A reports the statistics when using 1-factor model while Panel B reports the statistics when using a 4-factor model. The last column of both panels reports the differences between the best and worst performing funds. Tests for significance were run by bootstrapped one-sided p-values.

Performance and attribution	1 (Worst)	2	3	4	5	6	7	8	9	10 (Best)	10 minus 1	p-value
Panel A: One-factor model in (10)												
Performance	-2.295%	-0.608%	-0.368%	-0.081%	0.090%	0.204%	0.359%	0.619%	1.069%	2.671%	4.966%	(0.000)
(i) Past return strategy	-0.202%	-0.744%	-0.357%	0.721%	-0.358%	-0.113%	-0.068%	-0.277%	-0.619%	-1.398%	-1.197%	(0.170)
(ii) Stock-picking	-0.766%	0.663%	0.008%	-0.613%	0.514%	0.349%	0.309%	0.672%	1.408%	3.241%	4.007%	(0.001)
(iii) Timing	-1.285%	-0.518%	0.010%	-0.199%	-0.070%	-0.050%	0.110%	0.217%	0.266%	0.837%	2.122%	(0.000)
(iv) Passive timing	-0.043%	-0.008%	-0.029%	0.010%	0.004%	0.019%	0.008%	0.008%	0.014%	-0.010%	0.034%	(0.180)
Panel B: Four-factor model in (16)												
Performance	-2.295%	-0.608%	-0.368%	-0.081%	0.090%	0.204%	0.359%	0.619%	1.069%	2.671%	4.966%	(0.000)
(i) Past return strategy	-0.053%	-0.709%	-0.313%	0.702%	-0.276%	-0.051%	-0.029%	-0.304%	-0.553%	-1.541%	-1.488%	(0.098)
(ii) Stock-picking	-0.953%	0.656%	-0.006%	-0.633%	0.365%	0.261%	0.224%	0.760%	1.377%	3.384%	4.337%	(0.000)
(iii) Timing	-1.270%	-0.518%	-0.053%	-0.171%	-0.017%	-0.022%	0.132%	0.148%	0.231%	0.840%	2.110%	(0.000)
(iv) Passive timing	-0.019%	-0.038%	0.004%	0.020%	0.017%	0.016%	0.033%	0.016%	0.014%	-0.012%	0.007%	(0.432)

Table 10- Performance attribution and mutual funds characteristics

This table shows the characteristics of mutual funds splitting funds into those in Quintile 1 (Q1) and the others quintiles according to their performance and its four components depending on the analysis. The funds characteristics are Age measured as the fund age in years. Log(TNA) is the logarithm of the fund total net assets in each month. Number of Investors is the number of people investing their money in the fund each month. Expenses are the fund management and custodial fee expressed in annual terms. Turnover is the annual fund turnover ratio. Flow is the absolute monthly flow into a fund and finally, the number of holdings gathers the number of different securities hold by the mutual fund. The p-values measure the statistical significance of the difference between the first quintile and the other portfolios.

	Quintile 1			Others				
Performance	Mean	Stdev.	Median	Mean	Stdev.	Median	Difference	p-value
Age	8.16	5.33	7.31	8.60	5.07	8.07	-0.44	(0.000)
Log(TNA)	48,503	68,935	22,083	66,084	96,605	31,894	-17,581	(0.000)
# Investors	2,240	3,735	791	2,894	5,017	972	-654.43	(0.000)
Expenses	1.85%	0.56%	2.00%	1.87%	0.64%	2.00%	-0.01%	(0.733)
Turnover	52.71%	33.29%	45.92%	36.94%	27.74%	31.21%	15.77%	(0.000)
Flow	-216.51	7102.09	-24.30	-102.49	5881.93	-49.08	-114.02	(0.436)
# Holdings	36.11	11.05	35.00	38.62	12.43	36.00	-2.51	(0.000)
Past return strategy	Mean	Stdev.	Median	Mean	Stdev.	Median	Difference	p-value
Age	8.73	5.30	8.46	8.45	5.08	7.79	0.29	(0.021)
Log(TNA)	57,592	78,988	27,632	63,760	94,908	30,119	-6,167	(0.002)
# Investors	2,655	4,288	834	2,788	4,911	938	-133.62	(0.241)
Expenses	1.87%	0.55%	2.00%	1.87%	0.65%	2.00%	0.00%	(0.481)
Turnover	53.44%	31.64%	47.90%	36.73%	28.10%	30.98%	16.70%	(0.000)
Flow	-140.19	7047.43	-72.46	-122.00	5899.22	-35.26	-18.18	(0.901)
# Holdings	36.55	12.26	35.00	38.51	12.16	36.00	-1.96	(0.000)
Stock Picking	Mean	Stdev.	Median	Mean	Stdev.	Median	Difference	p-value
Age	8.34	5.21	7.44	8.55	5.10	8.04	-0.20	(0.095)
Log(TNA)	52,395	99,685	20,638	65,088	89,650	32,722	-12,693	(0.000)
# Investors	2,067	3,702	814	2,939	5,017	977	-871.83	(0.000)
Expenses	1.87%	0.57%	2.00%	1.87%	0.64%	2.00%	0.00%	(0.086)
Turnover	54.70%	31.17%	47.19%	36.34%	28.00%	30.62%	18.36%	(0.000)
Flow	-10.52	5752.14	-5.58	-155.16	6247.56	-56.82	144.64	(0.323)
# Holdings	37.20	12.20	35.00	38.35	12.19	36.00	-1.15	(0.000)
Timing	Mean	Stdev.	Median	Mean	Stdev.	Median	Difference	p-value
Age	8.13	5.27	7.38	8.60	5.09	8.07	-0.47	(0.000)
Log(TNA)	55,377	86,651	24,188	64,326	93,137	31,382	-8,950	(0.000)
# Investors	2,516	4,423	812	2,824	4,879	971	-307.70	(0.004)
Expenses	1.85%	0.56%	2.00%	1.87%	0.65%	2.00%	-0.01%	(0.334)
Turnover	46.84%	32.35%	40.16%	38.37%	28.63%	31.79%	8.47%	(0.000)
Flow	-322.19	6561.77	-32.89	-75.48	6039.42	-45.56	-246.71	(0.109)
# Holdings	36.41	11.16	36.00	38.55	12.42	36.00	-2.13	(0.000)
Passive Timing	Mean	Stdev.	Median	Mean	Stdev.	Median	Difference	p-value
Age	8.50	5.20	7.85	8.51	5.11	7.92	-0.01	(0.960)
Log(TNA)	55,645	91,729	22,303	64,258	91,892	31,691	-8,612	(0.000)
# Investors	2,587	4,745	820	2,805	4,802	955	-218.11	(0.056)
Expenses	1.88%	0.66%	2.00%	1.86%	0.62%	2.00%	0.02%	(0.453)
Turnover	52.19%	30.62%	45.03%	36.99%	28.53%	30.91%	15.21%	(0.000)
Flow	-40.65	6408.28	-35.52	-147.38	6082.43	-44.23	106.74	(0.466)
# Holdings	37.53	12.26	36.00	38.26	12.18	36.00	-0.73	(0.012)

Table 11- Quarterly persistence of performance attribution

This table shows the persistence results for the performance and its components. Mutual funds are ranked and assigned to portfolio-deciles every quarter according to the past performance or the past value of the other components. This investment strategy is held during the following three months. Decile 1 portfolio invests in the past worst performing funds according to the performance metric used and, conversely decile 10 invests in the previous period's best funds. The table is split into three panels. Panel A reports the statistics for the entire sample period (February 2000-June 2014). Panel B reports the statistics for the period February 2000-September 2008 which can be referred to as "before the global financial crisis," while Panel C reports the statistics for the time period October 2008-June 2014, which can be referred as "during the global financial crisis". The last columns of both panels reports the differences between the best and worst performing funds as well as the p-values associated to these differences.

Performance and components	1 (Worst)	2	3	4	5	6	7	8	9	10 (Best)	10 minus 1	p-value
Panel A: All sample												
Performance	-0.070%	0.716%	-0.200%	1.126%	0.497%	-0.012%	-0.613%	-0.143%	1.421%	-0.113%	-0.043%	(0.957)
(i) Past return strategy	-10.055%	-5.437%	-1.902%	-1.561%	-0.462%	0.147%	0.575%	1.694%	2.974%	4.673%	14.728%	(0.000)
(ii) Stock picking	-3.137%	-2.022%	-0.790%	-0.043%	0.079%	0.750%	1.609%	2.762%	4.519%	8.677%	11.814%	(0.000)
(iii) Timing ability	-0.080%	-0.406%	0.036%	0.482%	-0.005%	-0.419%	-0.213%	-0.573%	-0.361%	-0.803%	-0.722%	(0.197)
(iv) Passive timing	0.007%	0.008%	0.015%	0.012%	0.042%	-0.011%	0.018%	-0.021%	-0.007%	0.012%	0.005%	(0.876)
Panel B: February 2000 to September 2008												
Performance	0.769%	1.076%	-0.038%	-0.024%	0.474%	0.268%	-0.418%	-0.292%	1.833%	0.396%	-0.373%	(0.559)
(i) Past return strategy	-7.430%	-5.382%	-2.532%	-1.719%	-0.942%	-0.293%	-0.078%	1.608%	2.212%	5.314%	12.744%	(0.000)
(ii) Stock picking	-3.508%	-1.719%	-0.364%	-0.499%	-0.435%	0.208%	1.074%	2.909%	4.686%	7.467%	10.975%	(0.000)
(iii) Timing ability	0.868%	0.187%	0.564%	0.298%	-0.002%	0.092%	0.209%	-0.474%	0.125%	-0.235%	-1.102%	(0.030)
(iv) Passive timing	0.012%	-0.012%	0.029%	0.016%	0.041%	0.004%	0.027%	-0.011%	-0.005%	-0.013%	-0.024%	(0.443)
Panel C: October 2008 to June 2014												
Performance	-1.084%	0.324%	-0.525%	2.047%	0.649%	-0.302%	-0.837%	0.007%	0.716%	-0.489%	0.595%	(0.700)
(i) Past return strategy	-13.941%	-5.518%	-0.973%	-1.288%	0.300%	0.789%	1.645%	1.524%	4.187%	3.591%	17.532%	(0.000)
(ii) Stock picking	-2.492%	-2.339%	-1.615%	0.785%	0.498%	1.461%	2.530%	2.513%	4.335%	10.688%	13.180%	(0.000)
(iii) Timing ability	-1.385%	-1.320%	-0.868%	0.771%	0.002%	-1.459%	-0.723%	-0.665%	-0.854%	-1.335%	0.050%	(0.969)
(iv) Passive timing	0.025%	0.046%	0.007%	0.012%	0.042%	-0.036%	0.007%	-0.021%	-0.008%	0.057%	0.032%	(0.584)

Figure 1- Quarterly persistence of performance attribution

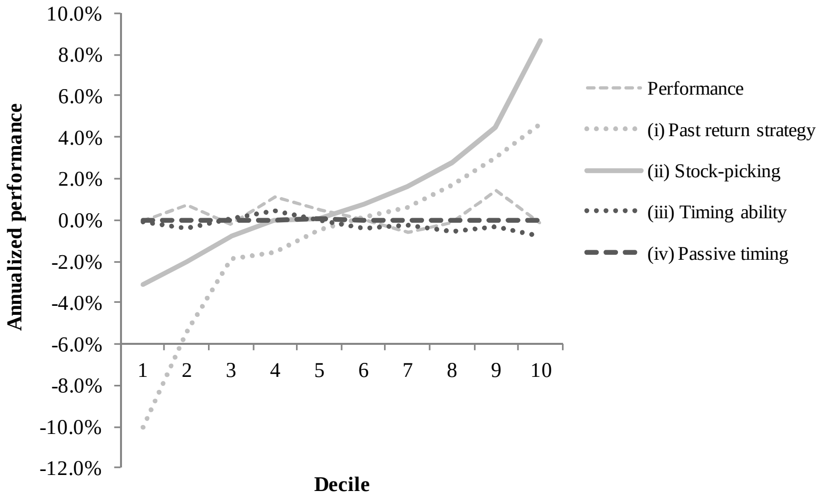
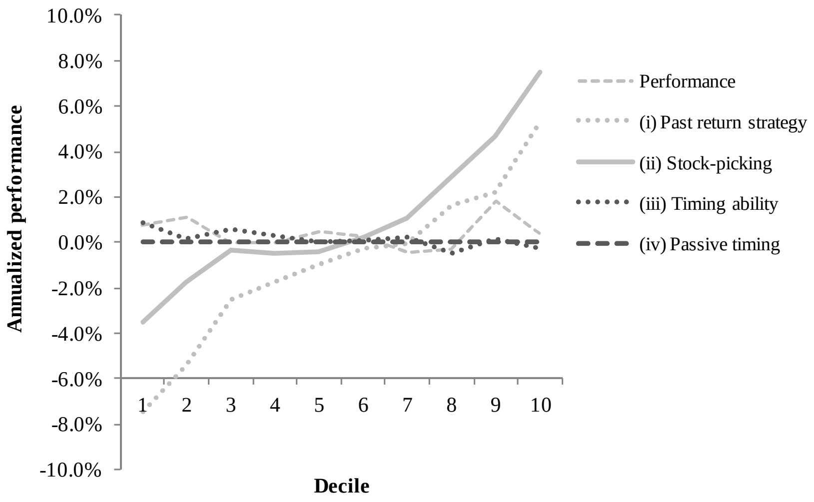


Figure 2- Quarterly persistence of performance attribution according market states

2a February 2000 to September 2008



2b October 2008 to June 2014