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Abstract

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Keywords: F15, F21, F36, Z13

JEL Classification: Procedural mutual funds, performance, quantile regression

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1. Introduction

Performance evaluation of mutual funds has attracted the interest of researchers and industry participants alike for some decades now. Although in its early stages this literature was mainly focused in the design and empirical applications of methodologies to analyze performance (or efficiency), today the study of those factors related to the decision making process and their consequences on funds' efficiency are gaining importance.

In this context, the literature on portfolio evaluation has experienced a dramatic evolution since the late eighties. This has partly paralleled the evolution of the asset pricing models, considering different methodological approaches and different sources of risk and other variables to adjust returns. In this scenario, since most investments are handled by professional managers, it is important to consider the role they are playing and, if possible, to measure how they can affect performance. The manager or, where appropriate, the team made up of multiple managers, has the ultimate power to design a portfolio consistent with their objectives and policy set.

The manager's (or team of managers') role is gaining prominence from the point of view of the analysis of funds' efficiency. She/he has always enjoyed the limelight because her/his decisions are directly related to the investors' profits. From a managers' point of view, the reward scheme primarily consists of economic incentives (fees), although other motivations such as reputation, contracts, or job loss might also underlie their expectations (Brown et al., 1996; Goetzmann et al., 2003; Alexander et al., 2007; Kempf et al., 2009). These and other related priorities may be affected by those decisions made by each manager or team of managers.

Traditionally, funds have been managed by individual specialists. However, even in those cases where an auxiliary management team is considered instead, the final decision usually rests upon the principal manager. Nowadays, for a significant share of total managed funds, prior to executing an order, a consensus tends to be reached within the team. From the point of view of the investor it could seem that the risk of error is more diversified (or more indirect), since the decision does not rely on one person only. From an academic viewpoint, this type of actions is attracting the attention of several research initiatives on mutual funds' management, Academics are starting to become aware of measurable managers' characteristics whose influence is closely related to the performance and/or efficiency achieved by the fund.

It is generally accepted that mutual funds, considered jointly, underperform the market or benchmarks. However, other approaches argue that managers display some skills which enable the funds they manage to beat the market. Our study explores this possibility, attempting to understand the influence of the manager(s) as a source of differences in mutual funds' efficiencies. Specifically, in relation to the structure of management, there is no consensus as to whether individual or team management can generate efficiency differentials. Therefore, in this study, apart from estimating each fund's degree of efficiency, we will also analyze, in a second stage, the determinants of mutual funds' performance/efficiency, with an explicit focus on the role of managers, in order to identify which factors may be considered influential for obtaining better performance. However, although the analysis will focus more tightly on the role of managers, we will split the analysis of determinants into three main sources of variation, or types of information that may influence funds' efficiencies, namely: (i) the structure and features of the fund; (ii) some characteristics of the manager, or team of managers; and (iii) other factors related to the environment.

In order to perform the study, we consider frontier techniques to measure efficiency. Specifically, as indicated recently by Glawischnig and Sommersguter-Reichmann (2010), there has been a growing interest in the application of the deterministic Data Envelopment Analysis (DEA) method (without losing sight of more standard methodologies) for measuring the performance of financial investments, particularly of mutual funds. In this study, we propose going beyond the DEA and related approaches (such as Free Disposal Hull, FDH, its non-convex counterpart) considered so far in the literature for measuring each fund's degree of efficiency since, despite their virtues for measuring mutual fund performance, these methods have also some caveats. Specifically, they suffer from a lack of robustness given that, since they are envelopment estimators, are very sensitive to extremes and/or outliers in the output direction. This ultimately results in poor estimation of the corresponding efficiencies. However, the literature has evolved and, in more recent years, has proposed two new estimators, namely, the order-m estimator (Cazals et al., 2002) and the order-α estimator (Aragon et al., 2005). We will be using both estimators, which are qualitatively robust and bias-robust as shown in Daouia and Ruiz-Gazen (2006).

Yet we are particularly interested in providing some answers to the puzzling question as to whether active fund managers are able to add value. On this particular issue, our second-stage strategy will take into account the fact that the distributions of mutual funds' performances can have peculiar shapes, or be heavy-tailed. Under such circumstances, it may be misleading to use regression techniques that focus on the "average effect for the average fund". Alternatively, we will use a quantile regression approach (Koenker, 2001) which allows investigating the relationship between the variety of managers' characteristics we consider (along with other likely determinants) at a range of points of the conditional mutual funds' performance distribution. This approach is more informative than, for instance, conducting an OLS regression since it might be the case that the managerial abilities were more relevant for some particular funds—for instance, the highest-performance ones—than for the *average* fund. In addition to this, whilst the optimal properties of standard regression estimators are not robust to modest departures from normality, quantile regression results are characteristically robust to outliers and heavy-tailed distributions (Coad and Rao, 2008). This is particularly important given how problematic it can be to conduct a second-stage regression when the first stage yielded efficiency scores obtained either via DEA or FDH (and, to a lesser extent, order-m and order-α), as pointed out by Xue and Harker (1999), Simar and Wilson (2007), Balaguer-Coll et al. (2007), or Banker and Natarajan (2008).

The remainder of this paper is organized as follows. In Section 2 we perform a brief review of the literature analyzing the question as to whether active fund managers are able to add value. Section 3 presents the methods selected both to measure performance as well as analyzing its determinants. Section 4 describes the data as well as the funds attributes and the set of determinants. Results are presented and discussed in Section 5. Finally, Section 6 presents some concluding remarks.

2. A sketch of the literature

The fundamental tenet that advocates in favor of maximizing risk-adjusted returns requires a more accurate perception when a deeper managerial analysis is considered. Thus, performance is mainly derived from the activity of the manager. Yet occasionally management does not necessarily respond to investors' expectations but can be related to other variables as well. In such a case, performance might diverge from investors' expectations. Previous research initiatives have sought to explore the role of mutual fund's managers and their contribution to the performance achieved since manager attributes have been labeled as determinants of funds underperformance. For instance, Bär et al. (2011), among others, assess whether manager characteristics have any impact on investment style and performance by focusing on the management structure (i.e. either a single manager or a managers' team); they found that those funds handled by a team of managers had the worst performance.

This literature dates back to Golec (1996), who documented that mutual fund manager' characteristics determine the fund's performance in relation to the risk and costs incurred. Since then, an additional literature has emerged to explore the role of managers as a source of efficiency, i.e. the sources of a positive impact on performance from superior stock-picking and timing skills. For instance, in a recent contribution, De Roon et al. (2010) extend the previous analysis including as determining variables: team management, gender, CFA[1] holder and experience for a sample of funds of funds. Their results indicate that ownership experience and factors involved in CFA have an impact on efficiency. Other authors such as Atkinson et al. (2003) have also sought to explain the differences in outcome based on gender differences. However, results were not always conclusive since, as indicated by Niessen and Ruenzi (2007), under the assumption of equality in educational attainment and experience they found no significant differences between funds managed by men or women.

Studies that analyze some particular features such as tenure, age and educational level (see, among others Hambrick and Mason, 1984; Malhotra et al., 2007) suggest the importance of considering their contribution to performance. Thus, according to Shukla and Singh (1994), and Chevalier and Ellison (1999a) the higher performance would correspond to managers who attended the most selective undergraduate institutions. Golec (1996) and Chevalier and Ellison (1999a,b) also stress the importance of holding an MBA certificate and to extend the analysis to an assessment of the experience factor. Similar arguments are put forward by Porter and Trifts (1998), Wermers (2003), or Ding and Wermers (2009). Gottesman and Morey (2006) go deeper, extending the analysis to managers trained in centers with high GMAT and MBA endorsed by the ranking of the top 30 by Business Week. Finally, a recent study by Takahashi (2010) suggests that managers benefit from the effect of academic interactions.

In this context which analyzes the determinants of mutual funds' performance, two other additional perspectives are considered as a source of relevant information for the analysis. On the one hand, it is broadly extended the study of funds' own characteristics (age, expenses, size, family belonging, popularity,

[1]CFA means Chartered Financial Analyst, it is the award received when the program offered by CFA Institute is completed. For more information visit: http://www.cfainstitute.org/about/membership/process/Pages/index.aspx.

asset allocation, investment objectives, fund ratings, etc.)[2] regarding either funds' performance or the determinants of funds flows.[3] On the other hand, there is controversy about the impact of costs. Related to this, Ippolito (1989) finds evidence that mutual funds' managers outperform passive portfolios; however, Elton et al. (1993) argued that such a result was driven by non-benchmark stocks, finding that mutual fund managers underperformed passive portfolios—in the sense that the higher the fees, the lower the performance.

Wermers (2003) found that actively managed mutual funds underperform passive benchmarks after fees strengthened the funds' underperformance, which has been strongly discussed in recent literature. Therefore, earlier studies have documented a negative relation between funds' operating expense ratio and performance. These studies, among others, would include Gruber (1996), Carhart (1997), Sirri and Tufano (1998), and the more recent approach by Gil-Bazo and Ruiz-Verdú (2009), who found evidence of a higher charge of fees for the underperforming funds case. Conversely, Barber et al. (2005) use fund flows' data from 1970 to 1999 and cross-sectional regressions, documenting that there is no relation between fund flows' and operating expenses. Otten and Bams (2007b) find no evidence of costs' influence on performance after controlling for tax treatment, fund objectives, investment style and time-variation in betas.

On the other hand, as cited above, there is a third element which, although less treated, is not less important and deserves being mentioned as well. It refers to the environmental factors that can also affect the immediate surroundings of the funds and, ultimately, impact on their efficiency. Among these factors one may consider market conditions (Shrider, 2009), or the volatility of the market (Cao et al., 2008), a social factor marked by new investment trends, for example, ethical funds (Bauer et al., 2005), the investor "sentiments" (Indro, 2010; Beaumont et al., 2008), or the managerial replacements (Khorana and Servaes, 1999). Prather et al. (2004) presents a literature review listing those specific factors which have a direct influence on funds' performance. They suggest considering popularity, growth, cost and management after taking into consideration general market conditions and the fund's investment objective. They conclude that, "contrary to popular belief, the management variables are not related to excess returns" except for managers who deal with several funds, in which case it reduces the likelihood of success. However, other authors reach different conclusions. Li et al. (2011) consider the impact of managers' characteristics (education and career concern) on the risk taken, and also on the overall performance for a sample of hedge funds; they found evidence that managers from higher-SAT undergraduate institutes tend to take less risk and, again, there is some empirical evidence of this conservative pattern for the most settled managers. Menkhoff et al. (2006) study the impact of qualitative characteristics: experience on risk taken, overconfidence and herding of fund managers; they found evidence that inexperienced managers take higher risks and, according to major findings in the literature, they achieve significantly higher returns compared to their more experienced counterparts.

[2] See, for instance, Prather et al. (2004), Galagedera and Silvapulle (2002), Barber et al. (2005), Otten and Bams (2007a) and Ferreira et al. (2012), among others. Annaert et al. (2003) link fund size with performance, but they fail to find evidence of any relation between fund age and performance.

[3] See Sirri and Tufano (1998), or Jain and Wu (2000).

3. Methods

3.1. Mutual fund evaluation using frontier techniques: recent developments

Among the *classic* or *standard* alternatives to evaluate the performance of mutual funds, we find not only the most popular ones, namely, Sharpe's, Treynor's or Jensen's and multifactor alpha measures, but also some others which are not so popular such as Omega, the Sortino ratio, Kappa 3, the upside potential ration, the Calmar ratio, the Sterling ratio, the Burke ratio, the excess return on value at risk, the conditional Sharpe ratio, and the modified Sharpe ratio (see Eling and Schuhmacher, 2007, for a detailed review of these measures). However, there is still no universally accepted assessment approach.

In relatively recent times, some investigators and practitioners have been considering the application of the so-called frontier estimation methodologies from production theory to the analysis of financial problems. As indicated by Brandouy et al. (2012), since the pioneering study by Sengupta (1989), who was probably the first to introduce an explicit efficiency measure into a Mean-Variance (MV) portfolio model, a number of contributions in this particular field has increasingly been found in the specialized literature.

Compared with most of the *classic* measures, nonparametric frontier alternatives such as Data Envelopment Analysis (DEA), introduced by Charnes et al. (1978), as a multidimensional tool, offers a way to extend the traditional mean-variance framework to incorporate additional dimensions such as, for instance, alternative risk measures, or costs. When evaluating a portfolio, the things that the investors want to minimize (such as risk) will be considered the inputs, and the things to be maximized (such as return) the outputs. With this information, it will be capable of yielding a single number (*efficiency scores*) which summarizes the performance of the fund. This is particularly appealing, especially when considering that alternative investments' returns often have skewed distributions (possibly with non-zero excess kurtosis), so that mean and variance, and possibly any performance index relying on these two moments, will be not enough to evaluating the performance of mutual fund.

Based on these advantages, the number of contributions in this particular field has grown considerably. Among the contributions, some of the most important ones have been recently reviewed by Brandouy et al. (2012), and they would include Basso and Funari (2003), Choi and Murthi (2001), Galagedera and Silvapulle (2002), Glawischnig and Sommersguter-Reichmann (2010), Murthi et al. (1997), or Wilkens and Zhu (2001), to which one may add the new proposals by Kerstens et al. (2011) and Lamb and Tee (2012). These, and related studies, can be classified in some categories such as those referred to by Brandouy et al. (2012), which would include: (i) models directly transposed from production theory; (ii) models combining traditional performance measures such as those referred to above with additional dimensions; (iii) models directly transposed from portfolio theory; (iv) hedonic price models.

Among these studies, the survey by Glawischnig and Sommersguter-Reichmann (2010) indicates that there have also been published some papers using parametric frontier approaches such as, for instance, Annaert et al. (2003), who consider Bayesian methods. However, the nonparametric applications clearly outnumbers the parametric ones. Among them, we find not only DEA and its sibling, Free Disposable

Hull (FDH), which drops the convexity assumption imposed by DEA, but also some contributions such as those by Daraio and Simar (2006) who consider partial frontier methods following the initial ideas developed by Cazals et al. (2002).

The partial frontier methods, among which we can highlight not only the contributions of Cazals et al. (2002), known as order-m estimators, but also the order-α estimators proposed by Daouia and Simar (2007). Both order-m and order-α offer several advantages over DEA and FDH. Specifically, as indicated by Wheelock and Wilson (2009), DEA and FDH are highly sensitive to extreme values and noise in the data, but order-m or order-α are not. In addition, they do not impose the convexity assumption (as it is the case under DEA), and they have several desirable properties that make it useful for drawing inferences about efficiency. The asymptotic properties of both DEA and FDH[4] also show that they have slow rates of convergence, reflecting the curse of dimensionality (see Simar and Wilson, 2008, p.441) which is common with nonparametric estimators.

3.1.1. Order-m estimators

As indicated by Simar and Wilson (2008), the economic theory underlying efficiency analysis dates to the work of Koopmans (1951), Debreu (1951), and Farrell (1957), who made the first attempt at empirical estimation of efficiency scores for a set of observed production units—in our case, mutual funds (p.421 Simar and Wilson, 2008). This requires first to define the set of attainable combinations of inputs ($\mathbf{x}$) and outputs ($\mathbf{y}$), i.e. the production set, $\boldsymbol{\Psi}$, which is:

$$\boldsymbol{\Psi} = \{(\mathbf{x}, \mathbf{y}) \in \mathbb{R}_+^{p+q} | (\mathbf{x}, \mathbf{y}) \text{ are attainable}\} \tag{1}$$

where $\mathbf{x} \in \mathbb{R}_+^p$ is the vector of inputs and $\mathbf{y} \in \mathbb{R}_+^q$ is the vector of outputs. For all possible output values we may define the section of possible values of $\mathbf{x}$ as

$$X(\mathbf{y}) = \{\mathbf{x} \in \mathbb{R}_+^p | (\mathbf{x}, \mathbf{y}) \in \boldsymbol{\Psi}\} \tag{2}$$

In this particular setting the Farrell (1957) measure of input-oriented efficiency of a given mutual fund $(\mathbf{x}, \mathbf{y})$ is defined as

$$\widetilde{\theta}(\mathbf{x}, \mathbf{y}) = \inf\{\theta : (\theta\mathbf{x}, \mathbf{y}) \in \boldsymbol{\Psi}\} = \min\{\theta : \theta\mathbf{x} \in X(\mathbf{y})\}, \tag{3}$$

where $\theta(\mathbf{x}, \mathbf{y})$ is the proportionate reduction of inputs required for a mutual fund with the input-output mix $(\mathbf{x}, \mathbf{y})$ to become efficient, i.e., to achieve the value of 1, since the efficient frontier corresponds to those funds whose $\widetilde{\theta}(\mathbf{x}, \mathbf{y}) = 1$.

In the case of output efficiency scores, the production set $\boldsymbol{\Psi}$ is characterized by output feasibility sets defined for all $\mathbf{x} \in \mathbb{R}_+^p$. In this case, we will define, for all possible input values the set of possible values of $\mathbf{y}$ as

$$Y(\mathbf{x}) = \{\mathbf{y} \in \mathbb{R}_+^q | (\mathbf{x}, \mathbf{y}) \in \boldsymbol{\Psi}\} \tag{4}$$

[4]Which are discussed in, for instance, Gijbels et al. (1999), Park et al. (2000), or Simar and Wilson (2000).

In this output-oriented setting the Farrell (1957) measure of output-oriented efficiency of a given mutual fund $(\mathbf{x}, \mathbf{y})$ will be defined as

$$\widetilde{\theta}(\mathbf{x}, \mathbf{y}) = \sup\{\theta : (\mathbf{x}, \theta\mathbf{y}) \in \mathbf{\Psi}\} = \max\{\theta : \theta\mathbf{y} \in Y(\mathbf{x})\}, \tag{5}$$

According to either DEA or FDH, the efficiency measure is obtained by comparison to the full frontier of all observations, defining the maximum output that is technically feasible with a given level of inputs. Alternatively, according to the order-m estimators, what will actually be used as a benchmark is the *expected* maximum output achieved by any m funds chosen randomly from the population, which employs at most input level $\mathbf{x}$ (Pilyavsky and Staat, 2008).

Therefore, for any $\mathbf{y}$, the *expected* maximum level will be defined as:

$$\mathbf{y}^{\partial} = \widetilde{\theta}\mathbf{y}. \tag{6}$$

When we choose a high value for m ($m \to \infty$), the order-m estimator results in the same benchmark as FDH, yielding the same results. Therefore, the most interesting cases will be those for which we define a finite value for m. In these cases the order-m does not envelop *all* the data, being more robust to outliers in data.

Note that the order-m efficiency scores are not bounded by 1 as it is the case under DEA or FDH. In these cases, values equal to unity correspond to *efficient* funds, whereas values higher than unity correspond to inefficient funds. According to order-m one may find values for θ lower than one, indicating that the fund operating at the level $(\mathbf{x}, \mathbf{y})$ is more efficient than the average of m peers randomly drawn from the population of units using less inputs than $\mathbf{x}$.

Formally, the proposed algorithm (Cazals et al., 2002) to compute the order-m estimator has the following steps, for n funds, $i = 1, \ldots, n$:

1. For a given level of $\mathbf{x}_0$, draw a random sample of size m with replacement among those $\mathbf{x}_i$, such that $\mathbf{x}_i \leq \mathbf{x}_0$.

2. Obtain the efficiency measures, $\widetilde{\theta}_i$.

3. Repeat steps 1 and 2 B times and obtain B efficiency coefficients $\widetilde{\theta}_i^b (b = 1, 2, \ldots, B)$. The quality of the approximation can be tuned by increasing B, but in most applications $B = 200$ seems to be a reasonable choice.

4. Compute the empirical mean of B samples as:

$$\bar{\theta}_i^m = \frac{1}{B} \sum_{b=1}^{B} \widetilde{\theta}_i^b \tag{7}$$

3.1.2. Order-α estimators

There is a similar estimator to order-m which shares some of its underpinnings, namely, the order-α quantile-type frontiers. Compared with order-m, the idea of order-α is the opposite: whereas the m parameter of order-$Malmquist$ serves as a trimming parameter which allows to tune the percentage of points that will lie above the frontier, in the case of order-α the frontier is determined by fixing first the probability $(1-\alpha)$ of observing points above the order-α frontier. Therefore, with order-α we reverse the causation and choose the proportion of the data lying above the frontier directly.

The order-α partial frontiers were originally proposed by Aragon et al. (2005) in the univariate case and were extended to the multivariate case by Daouia and Simar (2007). Similarly to the order-$Malmquist$ estimators, order-α estimators also have better properties than the usual nonparametric frontier estimators (either DEA or FDH). They are $\sqrt{n}$-consistent estimators of the full frontier, since the order of the frontier is allowed to grow with sample size, they are asymptotically unbiased and normally distributed with a known expression for the variance (see Aragon et al., 2005). In addition, it can be shown (Daouia and Simar, 2007, see) that the order-α frontiers are more robust to extremes than the order-m frontiers (see Daraio and Simar, 2007, p.74).

Yet the main virtue of order-α estimators is the same as that of order-m, i.e. the fact that in finite samples, order-α estimators do not envelop all the data, and they are therefore more robust to outliers than FDH or DEA. These outliers which, In the particular output-oriented case we are dealing with will have an efficiency scores of 1, will be considered as super-efficient with respect to the order-α frontier level.

Therefore, analogously to order-m partial frontiers, where a mutual fund operating at $(\mathbf{x},\mathbf{y})$ is benchmarked against the expected maximum output (recall we are in the output-oriented case) among m peers drawn randomly from the population of funds with output levels of at least $\mathbf{y}$. In the case of order-α quantile frontiers the benchmark is the output level not exceeded by $(1-\alpha)\times 100\%$ of funds among the population of funds providing input levels of at least $\mathbf{x}$.

Following Simar and Wilson (2008), for $\alpha \in (0,1]$, the α-quantile output efficiency score for the mutual fund operating at $(\mathbf{x},\mathbf{y}) \in \boldsymbol{\Psi}$ can be defined as

$$\theta_{\alpha}(\mathbf{x},\mathbf{y}) = \sup\{\theta | F_{\mathbf{y}|\mathbf{x}}(\theta\mathbf{y}|\boldsymbol{x}) > 1-\alpha\} \tag{8}$$

We will have that $\theta_{\alpha}(\mathbf{x},\mathbf{y})$ converges to the FDH estimator $\theta(\mathbf{x},\mathbf{y})$ when $\alpha \to 1$. As indicated in Daraio and Simar (2007), in cases where $\theta_{\alpha}(\boldsymbol{x},\boldsymbol{y}) = 1$, the fund is "efficient" at the level $\alpha \times 100\%$, since it is dominated by mutual funds providing less input than $\boldsymbol{x}$ with probability $1-\alpha$. In those cases where $\theta_{\alpha}(\boldsymbol{x},\boldsymbol{y}) > 1$ then the unit $(\mathbf{x},\mathbf{y})$ has to increase its output to the level $\theta_{\alpha}(\mathbf{y},\mathbf{y})\mathbf{x}$ to achieve the output efficient frontier of level $\alpha \times 100\%$. We can also apply the plug-in principle to obtain an intuitive nonparametric estimator of $\theta_{\alpha}(\mathbf{x},\mathbf{y}) = 1$ by replacing $F_{\mathbf{y}|\mathbf{x}}(\cdot|\cdot)$ with its empirical counterpart to obtain:

$$\widehat{\theta}_{\alpha,n}(\mathbf{x},\mathbf{y}) = \sup\{\theta | \widehat{F}_{\mathbf{y}|\mathbf{x},n}(\theta\mathbf{y}|\mathbf{x}) > 1-\alpha\} \tag{9}$$

3.2. Analying the determinants of mutual fund performance using regression quantiles

Typical linear models such as ordinary least squares (OLS) or logistic regression models (e.g. Tobit) have been for years the workhorse of the applied economics and finance researchers. They provide the analyst with information that, albeit extremely valuable, is confined to the analysis of *average* impacts of the covariates on the variable of interest—in our case, mutual funds' performance. Unfortunately, this implies missing relevant information, since the impact over the entire conditional distribution of efficiencies could vary depending on different parts of the distribution such as the upper and lower tails or, more generally, on each particular quantile (Coad and Hölzl, 2009).

The analysis of the differential impact on each quantile is actually possible using quantile regression (see, for instance, the survey by Buchinsky, 1998), whose main advantage is to being able to estimate the conditional quantiles of a response variable distribution—which in our case would be the performance of mutual funds—in a linear model providing a fuller view of the likely causal relationships between the variables considered in the analysis. Quantile regression has additional advantages which suit particularly well the application we are dealing with, since social phenomena are usually plagued with non-standard conditions such as non-normality or heteroskedasticity. These conditions represent difficulties for the assumptions on which OLS models are based to be met. For instance, managerial finance data such as the dispersion of the annual compensation of chief executive officers is usually expected to increase with firm size, suggesting heteroskedasticity might exist. Taking into account the nice features of quantile regression, applications have flourished over the last few years, a compendium of which is provided by Fitzenberger et al. (2002).

Therefore, in this particular setting we will be dealing with, quantile regression makes it possible to consider the entire distribution of mutual funds' performances when analyzing how the different covariates impact on performance, providing us with a more complete view of the relationship among variables. Accordingly, it will be possible to examine if for low-performance mutual funds (i.e. those corresponding to the lower quantiles), the sign and significance of the determinants is the same as for high-performance funds (i.e. those corresponding to the highest quantiles). It will then be possible to disentangle with more precision those factors which make the performance of mutual funds to differ. These arguments would imply that we will consider both high- and low-performance funds to be of interest *per se*, as well as those corresponding to other quantiles of the conditional distribution.

In the particular field of finance and mutual fund evaluation, the number of studies using quantile regression methods is relatively modest, although it has been growing in the last few years. For instance, Bassett Jr and Chen (2001) uses regression quantiles to extract additional information from the time series of returns by identifying the way style affects returns at places other than the average. In Meligkotsidou et al. (2009), the authors introduce the idea of modeling the conditional quantiles of hedge fund returns using a set of risk factors, whereas Luo and Li (2008) investigate whether and how futures market sentiment and stock market returns heterogeneously affect the trading activities of institutional investors in the spot market in Taiwan. The aims of our paper are relatively closer to those by Füss et al. (2009), who analyze the impact of experience and size of hedge funds on performance, or Chen and Huang (2011), who study the relation between mutual fund performance and Morningstar's fiduciary grades, using in both cases quantile regression. However, none of these contributions have considered partial frontiers' methods to evaluate performance in the first stage of the analysis, nor have they considered an explicit approach to analyze how those covariates which reflect more closely managers' characteristics influence the performance of mutual funds.

Yet considering a two-stage method in which efficiencies are obtained in the first stage, and the analysis of determinants is undertaken in the second one may be troublesome. Simar and Wilson (2007) proposed a bootstrap method which overcame many of the difficulties found in previous literature—which were mostly related to the fact of *nonparametric* methods such as DEA in the first stage with *parametric* methods in the second stage such as OLS or Tobit regressions.[5] Other approaches to deal with this issue include Balaguer-Coll et al. (2007), Banker and Natarajan (2008), McDonald (2009), Illueca et al. (2009), Ramalho et al. (2010). In the particular case of mutual fund performance evaluation, Daraio and Simar (2006, 2005) have proposed alternative nonparametric methods to overcome the problems derived from estimating regressions where the dependent variable is obtained by solving linear programming problems. An updated summary of this literature is provided by Simar and Wilson (2011).

In this scenario, an additional advantage of using quantile regression in the context of evaluating the determinants of mutual funds' performance is the fact that the standard least-squares assumption of normally distributed errors does not hold for our data because the location patterns follow a fat-tailed distribution (Coad and Hölzl, 2009). However, although standard regression estimators are not robust to departures from normality, the quantile regression estimator is characteristically robust to outliers on the dependent variable (Buchinsky, 1998). Furthermore, quantile regression also relaxes the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Avoiding this assumption facilitates to analyzing discrepancies in the relationship between the endogenous and exogenous variables at different points of the conditional distribution of the dependent variable, i.e. mutual funds' efficiencies.

The regression quantiles specify the τ^{th} quantile of the conditional distribution of y_i, where y_i is the variable containing the performance of mutual funds which, in our case, will be either $\bar{\theta}_i^m$ or $\widehat{\theta}_{\alpha,n}$, given $\boldsymbol{x}$ as a linear function of the covariates. As described by Koenker and Bassett (1978), estimation is performed by minimizing the following equation:

$$\underset{\boldsymbol{\beta}\in\mathbb{R}^k}{\text{Min}} \sum_{i\in\{i:y_i\geq \boldsymbol{x}'\boldsymbol{\beta}\}} \tau|y_i-\boldsymbol{x}'\boldsymbol{\beta}| + \sum_{i\in\{i:y_i< \boldsymbol{x}'\boldsymbol{\beta}\}} (1-\tau)|y_i-\boldsymbol{x}'\boldsymbol{\beta}| \tag{10}$$

where k is the number of explanatory variables, and τ represents the vector containing each quantile, and the vector of coefficients to be estimated, $\boldsymbol{\beta}$, will differ depending on the particular quantile.

[5]For instance, the efficiency scores obtained using linear programming techniques are dependent by construction.

4. Data and performance measurement

4.1. Data sources

We obtained data of equity funds from Morningstar. Our data correspond to Spanish mutual funds only. This is the European fifth most important market in terms of assets managed. The sample period runs from July 1st, 2001 to June 30th, 2011. The sample comprises the universe of open-end funds categorized as Equity Funds (EF) and Balanced equity-bonds funds (BF). A total of 274 Spanish mutual funds are classified under these categories. For each mutual fund, Morningstar provides historical information of fund characteristics and managerial attributes in addition to those variables that will be labeled as inputs or outputs. The evolution of mutual fund assets in Spain from 1990 to 2012 (which includes the analyzed period) is shown in Figure 1.

4.2. Input and output selection

As indicated in previous sections, one of the main benefits of using frontier techniques to evaluate the performance of mutual funds is the ability for handling multiple inputs and outputs in the model. According to Basso and Funari (2001), "DEA approach allows defining mutual fund performance indexes that can take into account several inputs and thus consider different risk measures (standard deviation, standard-semi deviation and beta) and redemption cost." Although including an excessive number of inputs and outputs may derive into the emergence of the "curse of dimensionality", this problem is much less severe when order-m and order-α estimators are used, as indicated previously (Simar and Wilson, 2008). Some authors, including Prather et al. (2004), have argued that the lack of consensus in establishing "fund-specific organizational and managerial factors that impact performance" (Prather et al., 2004) might make possible to choose variables arbitrarily. Following these lines of reasoning, Eling (2006) set out an opened selection of both classical and newer measures as possible inputs and outputs applying DEA. As the variables presented merely reflect an opened list of possible risk, return and cost measures, the right selection of inputs and outputs becomes an ongoing concern because non-standard procedure is present. Despite these threats, although there is not a widely accepted most recent literature has aimed to follow a reasonable and widely accepted criterion.

Within this particular literature, Murthi et al. (1997) considered for computing their portfolio efficiency index the standard deviation of returns, expense ratio, loads and turnover as inputs, and mean gross return as output. Choi and Murthi (2001) applied the same inputs and outputs as Murthi et al. (1997) although adopting a different DEA formulation. Wilkens and Zhu (2001) developed their study with standard deviation and percentage of periods with negative returns as inputs, and mean return, minimum return and skewness as outputs. In Joro and Na (2002) there is an extension of the traditional mean-variance framework using DEA, and their methodology includes the risk and cost associated with the transaction as inputs, and return and skewness are included as outputs. Chang (2004) proposed a new non-standard DEA formulation based on minimum convex input requirement set: the standard deviation, β, total assets and loads, while the output was the traditional mean return. When defining the set of inputs and outputs it is also important to consider that, as indicated by Nguyen-Thi-Thanh (2006), some investors might be more concerned with central tendencies (mean, standard deviation), while others may care more about extreme values (skewness, kurtosis). In this line, Lozano and Gutiérrez (2008) proposed a quadratic-constrained DEA models consistent with second-order stochastic dominance in order to get an optimal portfolio benchmark for any rational risk-averse investor. See also Briec and Kerstens (2009), who present a quadratic program that extends the multi-horizon analysis by Morey and Morey (1999) in several ways, or Joro and Na (2006), who suggested a cubic-constrained a mean-variance-skewness framework similarly to Briec et al. (2007)—who consider both skewness and mean return as outputs.

To apply our methodological approach we must thereby define some variables as inputs and outputs. As a main output we consider the daily mean return over the sample period (y_1), assuming reinvestment of all income and capital gain distributions. The other output (skewness, measuring the asymmetry of the distribution, y_2) has also been computed from the daily returns distribution. As inputs, the risk of the fund is measured by the standard deviation of the daily returns (x_1), as well as kurtosis (x_2),[6] also computed from the daily returns. In some of the proposed models the degree of active management and costs of the fund are also considered as input. In order to include them, we consider two variables, namely, the expense ratio, representing the percentage paid as management fees including managers' compensation and operating expenses (x_3), and the annualized turnover ratio, as a measure of trading activity or the manager propensity to trade (x_4). We also consider the beta as an input, x_5, since it measures the systematic risk, also known as "un-diversifiable risk" or "market risk". Finally, we consider size as a possible source of economies of scale in mutual fund management. We measured size as the average of the amount of the managed assets over the sample period. Our sample is free of survivorship bias, since the Morningstar data set provides information on all mutual funds operating during the entire period considered. The descriptive statistics for input and outputs are presented in Table 1.

4.3. Determinants of mutual fund performance

In our study, in order to more closely match the literature on the determinants of mutual fund performance, we define a set of variables related to fund, in addition to considering the aforementioned classification of fund—equity funds (EF) and balanced funds (BF), which are reflected in the FC variable (fund category). Specifically, we will also consider two sets of likely determinants of fund performance, some of which will be characteristics of the funds, whereas others will be managers' attributes. Among the former, we will consider: (i) age of the fund (in years), which we can assume to be a reasonable proxy for the competitiveness of the fund; and (ii) fund size (in logs), which we will consider as an indicator of economies of scale. Among the latter, i.e. characteristics of the managers or group of managers, we will consider: (i) banking vs. independent managers, which is a dummy variable taking value of 1 in the case of a banking manager and 0 for independent managers; (ii) manager structure, which is also a dummy variable taking the value of 1 for multiple managers and 0 in the case of a single manager; (iii) number

[6] In the case of non-normal distributions, Glawischnig and Sommersguter-Reichmann (2010) consider taking non-central measures by using information about skewness and kurtosis.

of funds under the same management (i.e. funds managed per manager or group of managers); and (iv) tenure of active management, which is related with the manager experience and should be an indicator of managers' investing abilities.

According to the studies by Chen et al. (2004) and Babalos et al. (2012), the expected impact of the FS (fund size) is that small funds outperform large funds. Ferreira et al. (2012) also find that small US mutual funds perform better than large funds, but this negative size effect is not consistent when non-US funds are considered. However, according to other views such as Carhart (1997) and Wermers (1997), among others (Holmes and Faff, 2007; Hu and Chang, 2008), a positive relationship between fund size and performance may arise by considering the benefits from economies of scale. Choi and Murthi (2001) find no significant links. Therefore, the literature is not conclusive when assessing the impact of size on performance. Some of these disparate results are reviewed in Bertin and Prather (2009), Ivkovic and Weisbenner (2009), Barber et al. (2005), or Frazzini (2006). Our methodologies might fit this context particularly well, since an *inconclusive* link could be related to varying coefficients for the different quantiles of the conditional distribution of performance.

According to the studies by Hu and Chang (2008) and Hu et al. (2011) the expected impact of fund age (FA) is that performance *worsens* with the age of the fund. However, according to other views such as Chen et al. (2004), or Ferreira et al. (2012), among others, there is no evidence of relation between fund age and performance. Again, the evidence is *mixed*.

The manager's professional profile (banking vs. independent), reflected in the manager classification variable (MC) has received relatively limited attention in the literature. The related literature would include, among others, Chen et al. (2007), who focused on analyzing the funds managed by insurance companies, and Matallín-Sáez et al. (2012), who explicitly analyzes the differences arising between funds handled by banking managers vs. their independent counterparts. Both studies found that performance worsens when non-independent managers are implementing active management. Some of the reasons explaining these findings relate to the fact that non-independent managers (i.e. banking and insurance agents) are exposed to the proliferation of competitive products, not only diversified funds and, in addition, the management strategies they usually applied were less aggressive than those applied by independent managers. In contrast, according to Frye (2001), who considered mostly bond mutual funds, the evidence was the opposite, and banking managers outperform their non-banking counterparts.

According to the studies by Prather et al. (2004) the expected impact on performance of the number of mutual funds under the same management, MF, is lower when managers manage more than two funds. This would occur because effectiveness is reduced due to the dispersion of effort, time and consciousness. This result is supported by Hu and Chang (2008), whose findings indicate that fund's performance lowers when the number of managed funds increases. However, according to other views such as Huij and Derwall (2011), the more concentrated the portfolios, the better performance is achieved due to some pernicious effects derived from diversification, which would contribute to erode performance.

As for the role of multiple (team) or single managers (MM), according to the studies by Chen et al. (2004), Bär et al. (2011) and De Roon et al. (2010) there is a negative impact in performance of teams in comparison with the single managers. In contrast, Han et al. (2012) find a positive impact between mutual fund performance and team management. In the middle of these conflicting views, both Prather and Middleton (2002) and Karagiannidis (2010) find no differences in the performance between those funds handled either by a single manager or a team of managers.

The literature has also been considering if the managers' tenure, or their years of experience (TEN), might also have an impact on fund performance. According to Hambrick and Mason (1984), Switzer and Huang (2007), and Malhotra et al. (2007), there is no empirical evidence supporting this effect. However, according to Golec (1996), and Hu and Chang (2008), there is a positive relation between tenure and performance. In the same vein, Khorana et al.'s (2007) results indicate that the best performance is related to longer managerial tenure, similarly to Agarwal et al. (2009), whose findings enable them to assert that experienced managers outperform the inexperienced counterparts. Although the studies supporting the positive link dominate, there are differing views such as those by Boyson (2010), who found that the link is actually negative—performance deteriorates with managerial experience.

Although these are the most relevant variables considered by the literature, the effects of some other relevant covariates on funds' performance have also been examined. Unfortunately, our database did not include information enough to extend the analysis in the directions contemplated by more specific studies analyzing some particular managers' characteristics. Among the questions examined by these studies we find the impact of gender (Atkinson et al., 2003; Niessen and Ruenzi, 2007; De Roon et al., 2010), CFA certificate or studies in SAT centers (Shukla and Singh, 1994; Chevalier and Ellison, 1999a; Golec, 1996), MBA Certificate (Porter and Trifts, 1998; Ding and Wermers, 2009), the quality of the MBA the manager has attended (Gottesman and Morey, 2006), academic interactions (Takahashi, 2010), expectations (Brown et al., 1996; Goetzmann et al., 2003; Alexander et al., 2007), or overconfidence, herding and risk (Menkhoff et al., 2006).

In sum, these are some of the variables that the most relevant literature has been considering when analyzing how managers' and other related characteristics affect funds' performance. However, although many of the reviewed literature has found some strong links between the variables under analysis, in some cases the findings are conflicting. We consider that the methodologies employed in this paper, both in the first and second stage of the analysis, can partly explain some of these conflicting views on how the different covariates might impact on funds' performance.

5. Results

5.1. Expected order-m and order-α efficiency estimates

Tables 2 and 3 report summary statistics (mean, 1st quartile, median, 3rd quartile and standard deviation) for mutual fund efficiencies obtained using order-m and order-α. In both cases results are reported for different choices of the tunning parameters. Specifically, we report results for $m = 75$ and $m = 150$, in the case of order-m, and for $\alpha = 0.95$ and $\alpha = 0.99$, in the case of order-α. Recall that, for both order-m and order-α, the higher the values of the tunning parameters, the higher the similarities with the results obtained for FDH.

The joint evaluation, for all 205 mutual funds, is reported in the last row of each panel in both Tables 2 and 3. Results are also reported for different classifications of mutual funds. Specifically, we provide results using the fund classification (equity funds vs. balanced funds, FC), manager classification (banking vs. independent, MC) and multiple vs. single manager classification (MM).

A mere cursory look at summary statistics indicate performance varies remarkably across categories of funds (balanced funds vs. equity funds, funds managed by banks vs. funds managed by independent managers, and funds managed by single managers vs. funds managed by multiple managers), across efficiency measures (order-m vs. order-α), as well as different *trimming* parameters (different values of m and different values of α). Some stylized facts, though, are robust to these sources of variation. For instance, balance funds (BF) are more efficient, on average, than equity funds (EF) throughout. This result holds regardless of the summary statistic considered—not only the mean but also the 25^{th}, 50^{th} (the median) and 75^{th} quantile. This robustness is also present for funds managed by a single manager, whose efficiency is consistently worse than that of funds managed by multiple managers, regardless of the summary statistic, efficiency measure or trimming parameter chosen.

However, when comparing funds managed by banks vs. independent managers, patterns are not robust across any of the dimensions considered. Under such circumstances, one could *a priori* be inclined to conclude that the differences in performance between these two types of funds will *probably* not be significant. Yet this conclusion would require conducting a specific test. We will examine this issue with some more detail in the next few paragraphs.

Using several summary statistics apart from the mean helps when describing the distributions of efficiency scores. However, it is even more informative to consider the graphical representation of the entire distributions of efficiencies—obtained either using order-m or order-α. There are several methods to do so, including univariate density functions estimated via kernel smoothing (Silverman, 1986), box plots, or their combination, namely, violin plots (Hintze and Nelson, 1998).

Therefore, because of this convenient combination of densities and box plots, we consider it reasonable to use violin plots. In this case, the density trace is plotted symmetrically to the left and right of the (vertical) box plot (i.e. there is no difference in the density traces apart from the direction in which they extend). By adding these two densities and the box plot enables comparing distributions more easily (our purpose) than using density traces only.

Figure 2 represents the violin plots for mutual funds' efficiencies. It contains three subfigures corresponding not only to order-m and order-α, but also to the non-robust DEA and FDH methodologies, in order to see more clearly how results vary according to different methods to measure performance. Thus, Figure 2a provides violin plots for efficiencies obtained using DEA and FDH. Since we are maximizing in the Farrell's sense, the minimum value is one. Efficiencies above such threshold indicate that the analyzed fund could increase its output using the same amount of inputs as those funds on the efficient frontier. As expected, the dropping the convexity assumption leads naturally to obtain a much higher number of efficient funds, a result that we can observe in the *violin* corresponding to FDH.

The violin plots for order-m are not entirely coincidental. As shown in Figure 2b, results are quite robust to the specification of the trimming parameter (m)—in this case, we have considered an additional parameter ($m = 100$) to see more clearly how results evolve depending on its value. Recall that this parameter allows to *adjust* the number of outliers. However, because of allowing for the existence of outliers, we have a remarkable amount of probability mass below unity, which causes the shape of the violins to differ strongly from that obtained for DEA and FDH—actually, we have *proper* violins for order-m.

Finally, Figure 2c displays the violin plots for efficiencies obtained using order-α. In this case we corroborate how large it is the impact of modifying the α parameter, which sets the percentage of outliers—likewise the order-m case, we have also considered an additional parameter ($\alpha = .90$) to see more clearly how results evolve depending on the trimming parameter. We can also corroborate how close order-α results are to FDH when setting an α parameter high enough, as shown by the third violin plot ($\alpha = .99$).

Therefore, considering the plots in Figure 2, we have a graphical illustration of some features corresponding to each of the techniques considered to measure mutual funds' efficiency. Whereas Figure 2a clearly indicates DEA and FDH do not allow for outliers, Figure 2b and Figure 2c clearly indicate the same does not hold for both order-m or order-α. However, in the case of order-α the trimming parameter has an impact which can be very strong, as shown by the violin plots corresponding to $\alpha = .90$ and $\alpha = .95$, for which the number of outliers (efficiencies below unity) is quite substantial.

However, although we focus on the entire distributions, we do not know whether the observed *differences* are significant or not. There are some tests such as the Li (1996) test which enables ascertaining whether the differences between two given distributions, say $f(\Delta)$ and $g(\Delta)$, estimated via kernel smoothing, are significant or not. More recently, Simar and Zelenyuk (2006) have adapted the Li (1996) test to the case of efficiency scores obtained using linear programming techniques. Although some modifications of Simar and Zelenyuk's test would permit adapting it to the particular case of efficiency scores obtained using either order-m or order-α, we consider it more informative to use a comprehensive approach. Specifically, we use quantile regression as indicated in section 3.2 which allows including other sets of covariates for analyzing the determinants of mutual fund performance. This will be the main objective of the following section.

5.2. On the determinants of mutual fund performance: the role of managers

Results on the *determinants* of mutual fund performance, considering all different methods to measure performance, are provided in table 4 (order-m, $m = 75$), table 5 (order-m, $m = 150$) and table 6 (order-α, $\alpha = 0.99$). We select a high value of α because it provides close results to those yielded by FDH. Reporting results for other values of the trimming parameter and for other efficiency measurement methods allows granting some extra robustness to the analysis.

These tables provide coefficients and standard errors for selected quantiles ($\tau = \{.10, .25, .50, .75, .90\}$). Note that the quantile $\tau = .50$ refers to the *median* of the conditional distribution. Whilst OLS regressions report estimates based on the *mean*, quantile regression based on $\tau = .50$ provides an analogous result for a different moment of the distribution—i.e. the median. Therefore, this *median*-regression model can be used to achieve the same goal as conditional mean-regression modeling, namely, to represent the relationship between the central location of the response and a set of covariates. However, as indicated by Hao and Naiman (2007), when the distribution is highly skewed, which is the case of efficiency scores (many efficiency scores are located in the vicinity of one), the mean can be difficult to interpret, whereas the median remains highly informative (Hao and Naiman, 2007, p.3). The results in tables 4, 5 and 6 go further on this respect, reporting results not only for the median ($\tau = .5$) but also for other quantiles and, therefore, are much more informative.

In each of these tables (Tables 4–6) we provide quantile regression results for all selected covariates (FC, FS, FA, MC, MF, MM, TEN). For each table, the dependent variable is the efficiency of each fund yielded by order-m (with $m = 75$ and $m = 150$) and order-α ($\alpha = .99$). Recall that, since we are maximizing in the Farrell's sense, the higher the value of the score, the lower efficiency level. Therefore, efficiency scores closer to unity indicate that the fund is actually more efficient.

The results reported in these three tables clearly show that this type of analysis is relevant because some conclusions could not be reached using other regression techniques such as OLS, or censored regression. For instance, as indicated in table 4, taking into account the values obtained for the fund category (FC) variable, which is a dichotomous variable whose value is 1 for equity funds (EF) and 0 for balanced funds (BF), the impact on performance is <u>negative</u>—recall that we are maximizing in the Farrell's sense, so higher values indicate worse performance. However, the magnitude of the effect varies strongly across the different quantiles, being particularly strong for the highest one ($\tau = .90$). For the other selected quantiles, the effect is also negative and highly significant. Therefore, claiming that the differences in performance between these two types (equity, EF, or balanced, BF) are either significant or not, and to what extent, is in this particular case a claim that is subject to certain subtleties. Basing the conclusions on a conditional-mean model would only provide information about the *average* effect. In this case, the conditional-*median* effect (revealed by $\tau = .50$) would indicate that the *median* effect is also negative and significant.

The reasons explaining why balanced funds (BF) outperform equity funds can be multiple. There is no previous literature on this respect. The results show how balanced funds' performance is better than that attributable to equity funds, and this result holds throughout the entire distribution. Usually, EF funds take on more market risk than funds BF, since EF portfolios are composed almost entirely of equities, while BF funds also invest in debt securities that are less volatile than equities. In our efficiency analysis, risk was an input and return was an output. Therefore, the fact that BF funds achieve better performance than EF could be indicating that during the sample period analyzed the risk assumed by EF funds has not been rewarded in the stock market with greater return. Therefore, funds with higher risk, EF, appear to perform more poorly.

The funds' size variable, FS, shows also some of the advantages of applying quantile regression. It indicates that the size of the funds is relevant for those funds whose performance is relatively poor (highest efficiency scores), since results are only positive for the quantiles corresponding to the tails of the distribution $\tau = .10$, $\tau = .90$, in the case of order-m (Tables 4 and 5). Although this result is not entirely corroborated for order-α (Table 6), for which all quantiles show a negative impact (positive sign), the effect of this variable is never significant—neither for order-m nor for order-α. This would stand with previous literature such as Choi and Murthi (2001), who found no links between size and performance and, in general, with what was indicated in section 4.3, where we concluded that the evidence was inconclusive. This would suggest that economies of scale do not necessarily emerge when large funds' performance is compared with that obtained for small funds—which might be inefficient than their larger counterparts due to the costs associated.

The results obtained for the fund age variable (FA) indicate that the effect of the variable is mostly negative on performance (positive coefficient) and significant. In addition, the magnitude of the estimated coefficient is rather stable, with the exception of the median ($\tau = .50$), for which the magnitude is lower—albeit the negative impact (positive coefficient) still holds. This result is very robust, not only for the different quantiles but also for the different measurement methods (order-m and order-α) and even for the different trimming parameters considered ($m = 75$ and $m = 150$). This inverse relation between age and performance is also found in Hu and Chang (2008) and Hu et al. (2011). This would imply that performance decreases with the age of the fund or, in other words, not necessarily older funds would perform better than newer ones. However, it is also highly believed that survival funds (identified as the older ones) are also able to outperform the younger due to the accumulated experience.

We also provide results for the different variables related to the role of managers. The manager classification (MC), which can be either *bank* ($MC = 1$) or *independent manager* ($MC = 0$) has a generally positive impact (negative coefficient), but it is only significant for $\tau = .75$, in the case of order-m. In the case of order-α it is non-significant throughout. In the case of order-m, only the median ($\tau = .50$) shows a negative effect (positive coefficient), although the coefficient's value differs sharply for the different m values. Actually, the magnitude of the estimated coefficient varies remarkably across quantiles, being of higher magnitude for the highest quantiles, a result which is corroborated for both order-m (Tables 4 and 5) and order-α (Table 6). Although some of the previous literature holds conflicting views Matallín-Sáez et al. (2012); Frye (2001), it should be taken into account that the Spanish mutual fund industry, as well as some other European counterparts, present some kind of singularities not shared by other fund industries, such as the US case. In the US, managers are considered as external specialized professionals, whereas in the European context banking vs. professional managers coexist.

In contrast, the variable MF (number of funds under the same management) has a negative impact (positive coefficient) throughout and, in the case of order-m, and for both choices of trimming parameter, it is significant with the exception of the highest quantile ($\tau = .90$). This would imply that the larger the number of funds under the same management, the worse the performance of the fund, with the exception of the worst performing funds, for which this effect would be irrelevant. Unfortunately, this result is not as robust as it could get, since for order-α (Table 6) the sign of the impact is the same, although significance is lost for most quantiles—except for $\tau = .10$—implying that this effect would be relevant for the best performing funds only. The magnitude of the impact also varies depending on the selected quantile, being especially high for the upper and lower ones; this result is robust across methods and trimming parameters. Once more, these are results that are usually concealed by OLS regressions. The reasons for this inverse relationship between performance and the number of managed funds are explained, for instance, in Prather et al. (2004) and Hu and Chang (2008). According to these authors, the effectiveness is reduced when managers handle more than two funds. In addition, there might emerge problems related to diversification, as indicated by Huij and Derwall (2011).

The multiple managers (team) or single manager variable (MM) is a dicotomous variable taking a value of 1 (in case there is a team of managers) or 0 (in case there is a single manager). Therefore, the information it reports has some resemblances with that provided by MF. However, the correlation between them is very low. In the case of MM, the pattern is different, mostly positive (negative coefficients) for the vast majority of the quantiles (only with the exception of $\tau = .10$ in the case of order-m, see Tables 4 and 5). However, with the exception of the lowest quantiles ($\tau = .10$ and $\tau = .25$ for order-α, see Table 6), the effect is not significant. Therefore, given the lack of robustness of the results for the different methodologies, trimming parameters (α, m) and quantiles (τ), we may conclude there is no link between performance and the fact that there is a team of managers or a single manager. Prather and Middleton (2002), Prather and Middleton (2006) and Karagiannidis (2010) reach similar results, finding no differences in performance between a single manager or a group of managers.

The active manager tenure (TEN) variable is mostly significant, although only for the central quantiles. This finding holds strongly across methods (order-m and order-α) and trimming parameters. For the particular case of order-m (Tables 4 and 5), for the upper and lower quantiles ($\tau = .10$ and $\tau = .90$) the effect is not significant—in the case of order-α, this also occurs for the $\tau = .75$ quantile (Table 6). Regardless of significance, the effect is negative throughout (positive coefficient), indicating that being tenured is not positive for funds' performance. In addition, the magnitude of the effect is stronger (the coefficients are higher) for the worst funds, since the value of the estimated coefficients increase from $\tau = .10$ to $\tau = .75$, and this result is valid across methods and trimming parameters. Depending on the methodologies applied we find an inverse relation between tenure and performance. An overconfidence effect seems to appear for the more experienced managers and also some lack of motivation should justify this fact. Additionally, we find no impact between tenure and performance which is line of the evidence found in Hambrick and Mason (1984), Switzer and Huang (2007), and Malhotra et al. (2007).

6. Conclusions

The mutual fund industry has been one of the fastest growing sectors within the capital markets in many countries during the last decades, and its growth has been quite remarkable. Although the international financial crisis might has implied a slowdown in many countries, especially in those most affected by the crisis, the share of population now owning a mutual fund has increased dramatically in a relatively short period of time. In the particular case of Spain (the European fifth most important mutual fund industry in terms of assets managed) on which we focus, the mutual fund industry benefited from a combination of low interest rates, the increasing age of the population, an increasing awareness of mutual fund products, and a much more active participation of both savings banks and commercial banks, which in Spain are, by and large, the most important financial institutions in terms of intermediated funds. The literature on mutual fund performance evaluation has undergone a parallel expansion, and its magnitude is now quite remarkable. A specific field of this literature has been analyzing whether managers add value to the performance of mutual funds they handle. This is, precisely, what we have done in this study.

In contrast to the traditional methodologies for measuring mutual funds' performance, our approach is based on the use of nonparametric frontiers due to some key advantages such as the ability to simultaneously handle multiple factors while still providing the analyst with a single real number as a performance index—the so-called efficiency scores. Although DEA (Data Envelopment Analysis) has been, by and large, the most intensely used frontier technique (considering not only nonparametric but parametric approaches as well), in recent years this literature has evolved and some of the estimators used now are superior in several dimensions, especially in terms of robustness.

After measuring performance in this first stage of the analysis, the second stage was devoted to the analysis of the determinants of mutual funds' performance. This was not an easy task for two reasons, one substantive, the other methodological. The substantive reason relates with the difficulties encountered by the mutual fund literature in finding *conclusive* evidence on the impact of some particular variables on performance. The methodological one relates to the difficulties in conducting inference in the second stage of the analysis when efficiencies were yielded by linear programming methods in the first stage—as pointed out by Simar and Wilson (2007), Balaguer-Coll et al. (2007), or Banker and Natarajan (2008). The quantile regression methods we use represent an advantage on both regards. On the one hand, they provide information on whether the estimated coefficients might differ (in terms of sign, magnitude and significance) depending the quantile of the conditional distribution of performance, which would ultimately allow reconciling some of the conflicting views found in the literature. On the other hand, quantile regression methods are much more robust to either the existence of outliers or skewed distributions of the dependent variable (Buchinsky, 1998).

Our results are therefore robust on several dimensions. The first stage of the analysis was performed considering several partial frontier techniques, and several tuning parameters (m, in the case of order-m, and α, in the case of order-α), i.e. two levels of robustness. In the second stage of the analysis, a third level of robustness is added, since results are provided for five quantiles of the conditional distribution of performance. The findings suggest that, indeed, the links among the variables considered are intricate, and difficult to summarize in an *average* effect. Only in the case of the age of the fund we found an effect whose magnitude, sign, and significance is mostly robust across the three levels of robustness—the higher the age, the worse the performance. However, in the case of the variables reflecting managers' characteristics, the different methodologies and tuning parameters indicate that the findings cannot be boiled down to an average effect for the average fund.

While to a large extent research has analyzed the role the fund characteristics play, manager characteristics are also attracting the interest due the important role they play in this scenario. However, this is the first study that provides simultaneously detailed insights on this issue. Additionally the methodologies applied suggest a new path to continuing exploring in other funds industries as this is a pioneering Spanish approach. The results suggest that as important as the fund, the manager also is; thus, before to reach the decision to pick, the investors should need to be aware about which are the variables able to report an undeniable impact on their wealth.

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Table 1: Descriptive statistics for inputs and outputs, mutual funds (2001–2011)[a]

	Mean	1st quartile	Median	3rd quartile	Std. dev.	Min.	Max.
Class: Equity Funds (EF)							
INPUTS							
Std. dev. (x_1)	5.2990	4.5248	5.2436	6.0246	1.1258	2.8291	8.3400
Kurtosis (x_2)	0.0388	–0.2643	–0.0342	0.1031	0.6105	–1.4733	4.1045
Expense ratio (x_3)	1.9669	1.7033	2.0671	2.3517	0.5713	0.2475	3.9600
Turnover (x_4)	1.1105	0.0000	0.5500	1.5550	1.4599	0.0000	6.4400
Beta (x_5)	1.1626	1.0788	1.1946	1.2737	0.2146	0.3894	1.8458
OUTPUTS							
Return (y_1)	0.4236	0.1231	0.4754	0.6109	0.3798	–0.7044	2.2218
Skewness (y_2)	–0.3080	–0.3681	–0.3003	–0.2476	0.2002	–1.9251	0.3511
Fund size (in logs)	16.5159	15.6370	16.4007	17.3655	1.2474	12.6460	20.8435
Number of funds				170			
Class: Balanced Funds (BF)							
	Mean	1st quartile	Median	3rd quartile	Std. dev.	Min.	Max.
INPUTS							
Std. Dev. (x_1)	5.3839	4.7085	5.1872	5.8664	1.1365	3.0666	9.2116
Kurtosis (x_2)	0.0609	–0.2810	–0.0120	0.1210	0.5493	–0.8698	2.6782
Expense Ratio (x_3)	1.6683	1.3350	1.7133	2.1142	0.5838	0.1200	2.5967
Turnover (x_4)	1.2182	0.1775	0.5850	1.4150	1.9484	0.0000	13.8300
Beta (x_5)	0.7283	0.6205	0.7119	0.8263	0.1535	0.4101	1.2597
OUTPUTS							
Return (y_1)	0.2986	0.1816	0.2935	0.4130	0.1714	–0.5281	0.9230
Skewness (y_2)	–0.3219	–0.4217	–0.3481	–0.2508	0.2315	–1.0233	0.7401
Fund Size (in logs)	16.4667	15.8664	16.3382	17.1289	0.9240	14.8406	19.1150
Number of funds				104			

[a] The table presents some descriptive statistics of the mutual fund sample. The sample period runs from July 1st, 2001 to June 30st, 2011. The size is measured by the assets in millions of euros and management fees and loads costs are shown as percentages of the assets. EF represents equity funds and BF, balanced funds.

Table 2: Order-m efficiencies, mutual funds (2001–2011)

Type of fund		Mean	1st quartile	Median	3rd quartile	Std.dev.
$m = 75$						
Fund classification (FC)	EF	103.6343	99.4265	100.0000	108.9539	11.0137
	BF	97.2925	93.9269	99.2808	100.7499	8.9752
Manager classification (MC)	Banking	101.2477	97.8334	100.0000	104.2237	11.0899
	Independent	101.1722	96.9115	100.0000	105.8822	10.2018
Multiple/single managers (MM)	Multiple managers	100.2626	94.7261	100.0000	103.7666	8.5301
	Single manager	101.3722	97.8767	100.0000	104.9095	11.0431
All funds		101.2172	97.5455	100.0000	104.4850	10.7205
$m = 150$						
Type of fund		Mean	1st quartile	Median	3rd quartile	Std.dev.
Fund classification (FC)	EF	106.0551	99.9745	100.0000	110.0467	11.7789
	BF	100.9685	98.0472	100.0000	103.3547	6.9998
Manager classification (MC)	Banking	103.9261	99.8163	100.0000	105.3937	10.6056
	Independent	104.3975	99.4656	100.0000	106.9964	10.3971
Multiple/single managers (MM)	Multiple managers	102.8435	98.4991	100.0000	104.2735	7.6034
	Single manager	104.323	99.8093	100.0000	106.4074	10.9023
All funds		104.1164	99.6612	100.0000	105.7884	10.5047

Table 3: Order-α efficiencies, mutual funds (2001–2011)

$\alpha = .95$						
Type of fund		Mean	1st quartile	Median	3rd quartile	Std.dev.
Fund classification (FC)	EF	95.9150	94.0386	100.0000	101.3333	15.3800
	BF	83.5442	76.0920	89.6445	99.5733	18.2957
Manager classification (MC)	Banking	90.3240	82.6069	99.7293	100.0000	18.9298
	Independent	90.9643	85.7143	96.8334	100.0000	16.2035
Multiple/single managers (MM)	Multiple managers	91.6500	83.5978	95.2960	100.0000	14.8245
	Single manager	90.4191	82.8862	98.9846	100.0000	18.2481
All funds		90.6049	83.0417	98.7352	100.0000	17.7476
$\alpha = .99$						
Type of fund		Mean	1st quartile	Median	3rd quartile	Std.dev.
Fund classification (FC)	EF	106.8658	100.0000	101.4245	111.7202	12.0859
	BF	100.2095	100.0000	100.0000	102.1725	9.5082
Manager classification (MC)	Banking	104.3486	100.0000	100.0000	108.3292	12.9910
	Independent	103.5737	100.0000	100.0000	105.8853	9.3369
Multiple/single managers (MM)	Multiple managers	100.9515	100.0000	100.0000	103.5491	9.6064
	Single manager	104.5521	100.0000	100.0000	108.2906	11.7595
All funds		104.0086	100.0000	100.0000	106.9304	11.5126

Table 4: Regression quantiles for mutual fund performance, order-m ($m = 75$)

	Quantile (τ)				
Covariates	0.10 (best performance)	0.25	0.50	0.75	0.90 (worst performance)
(Intercept)	72.948 (55.179,86.415)	84.850 (77.875,97.333)	94.675 (75.226,106.117)	93.034 (74.320,122.587)	93.489 (58.907,126.803)
FC	8.073 (4.407,12.949)	5.048 (3.866,6.970)	3.269 (2.042,5.615)	6.495 (5.027,8.550)	13.732 (6.214,17.099)
FS	0.239 (−0.981,1.204)	−0.080 (−0.883,0.250)	−0.184 (−0.969,0.710)	−0.207 (−1.837,1.073)	0.267 (−2.044,1.620)
FA	0.652 (0.358,1.074)	0.508 (0.266,0.855)	0.264 (0.163,0.538)	0.596 (0.503,0.788)	0.502 (0.209,1.214)
MC	−1.754 (−5.080,3.402)	−0.149 (−1.905,1.083)	0.058 (−2.953,1.012)	−2.098 (−5.818,−0.123)	−2.303 (−6.195,3.662)
MF	0.402 (0.084,1.038)	0.346 (0.204,0.500)	0.198 (0.009,0.494)	0.467 (0.173,0.766)	0.100 (−0.416,0.675)
MM	0.477 (−7.114,5.262)	−1.216 (−3.043,1.072)	−0.730 (−2.846,0.848)	−2.086 (−4.464,3.556)	−0.950 (−9.371,6.937)
TEN	0.145 (−0.349,0.393)	0.240 (0.048,0.445)	0.374 (0.194,0.617)	0.513 (0.125,0.920)	0.262 (−0.090,1.607)

FC: fund category (dichotomous variable, 1: EF, equity funds; 0: BF, balanced funds); FS: fund size; FA: fund age; MC: manager classification (dichotomous variable, 1: bank; 0: independent manager); MF: number of funds under the same management; MM: multiple/team of managers (dichotomous variable, 1: team of managers; 0: otherwise); TEN: active manager tenure.

Table 5: Regression quantiles for mutual fund performance, order-m ($m = 150$)

Covariates	Quantile (τ) 0.10 (best performance)	0.25	0.50	0.75	0.90 (worst performance)
(Intercept)	88.494 (80.672,90.953)	94.994 (90.594,97.836)	97.899 (78.221,107.673)	106.350 (76.829,123.918)	103.615 (66.848,150.497)
FC	3.911 (2.283,7.094)	1.810 (1.023,2.943)	1.489 (0.436,3.851)	5.654 (3.931,7.949)	15.800 (8.207,21.018)
FS	0.022 (−0.532,0.604)	−0.034 (−0.294,0.197)	−0.167 (−0.873,0.664)	−0.922 (−1.984,1.080)	−0.514 (−3.437,1.505)
FA	0.325 (0.192,0.578)	0.168 (0.090,0.384)	0.187 (0.090,0.420)	0.688 (0.548,0.798)	0.739 (0.534,1.563)
MC	−1.281 (−3.874,0.879)	0.078 (−0.387,0.652)	0.430 (−1.871,1.048)	−2.731 (−5.828,−0.386)	−1.744 (−9.239,4.390)
MF	0.283 (0.020,0.530)	0.111 (0.056,0.210)	0.089 (−0.045,0.376)	0.448 (0.075,0.799)	0.425 (−0.500,1.127)
MM	0.108 (−3.785,1.826)	−0.298 (−1.838,0.921)	−0.701 (−1.773,2.103)	−0.141 (−4.255,3.172)	−2.792 (−11.565,9.859)
TEN	0.049 (−0.081,0.216)	0.147 (0.013,0.265)	0.338 (0.037,0.544)	0.534 (0.238,0.850)	0.504 (−0.092,1.651)

FC: fund category (dichotomous variable, 1: EF, equity funds; 0: BF, balanced funds); FS: fund size; FA: fund age; MC: manager classification (dichotomous variable, 1: bank; 0: independent manager); MF: number of funds under the same management; MM: multiple/team of managers (dichotomous variable, 1: team of managers; 0: otherwise); TEN: active manager tenure.

Table 6: Regression quantiles for mutual fund performance, order-α ($\alpha = .99$)

Covariates	Quantile (τ) 0.10 (best performance)	0.25	0.50	0.75	0.90 (worst performance)
(Intercept)	81.353 (71.130,88.617)	98.531 (80.393,99.986)	91.139 (71.131,103.921)	82.355 (56.482,112.427)	91.482 (21.803,129.818)
FC	5.541 (4.023,10.782)	0.500 (0.095,5.238)	3.568 (2.123,5.990)	5.491 (2.899,9.355)	9.641 (2.854,19.750)
FS	0.307 (−0.480,0.907)	0.000 (−0.222,0.088)	0.132 (−0.727,1.299)	0.660 (−1.472,2.345)	0.261 (−2.001,4.209)
FA	0.382 (0.070,0.724)	0.063 (0.009,0.543)	0.381 (0.210,0.619)	0.636 (0.250,0.908)	0.590 (0.426,1.250)
MC	−0.739 (−3.750,1.346)	−0.049 (−0.878,0.272)	0.181 (−1.123,1.849)	1.222 (−5.114,2.545)	−1.313 (−8.023,10.863)
MF	0.359 (0.163,0.613)	0.027 (−0.002,0.269)	0.124 (−0.032,0.354)	0.056 (−0.141,0.652)	0.578 (−0.494,1.237)
MM	−3.899 (−10.966,−0.392)	−0.431 (−8.275,−0.049)	−2.658 (−4.772,0.273)	−2.118 (−6.570,2.538)	−1.383 (−9.059,19.244)
TEN	0.136 (−0.116,0.440)	0.039 (0.006,0.346)	0.258 (0.010,0.465)	0.347 (−0.056,0.700)	0.398 (−0.443,1.601)

FC: fund category (dichotomous variable, 1: EF, equity funds; 0: BF, balanced funds); FS: fund size; FA: fund age; MC: manager classification (dichotomous variable, 1: bank; 0: independent manager); MF: number of funds under the same management; MM: multiple/team of managers (dichotomous variable, 1: team of managers; 0: otherwise); TEN: active manager tenure.

Figure 1: Evolution mutual fund assets in Spain, 1990–2012

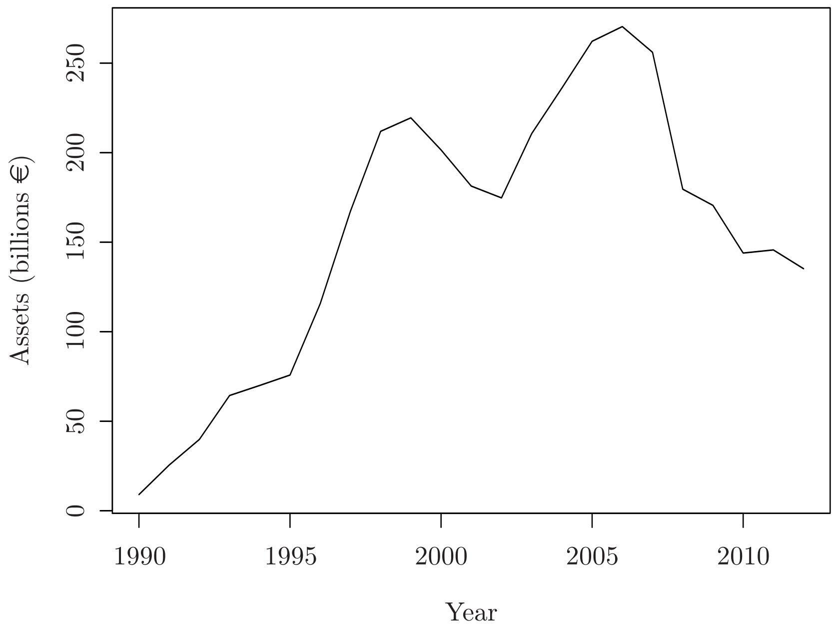
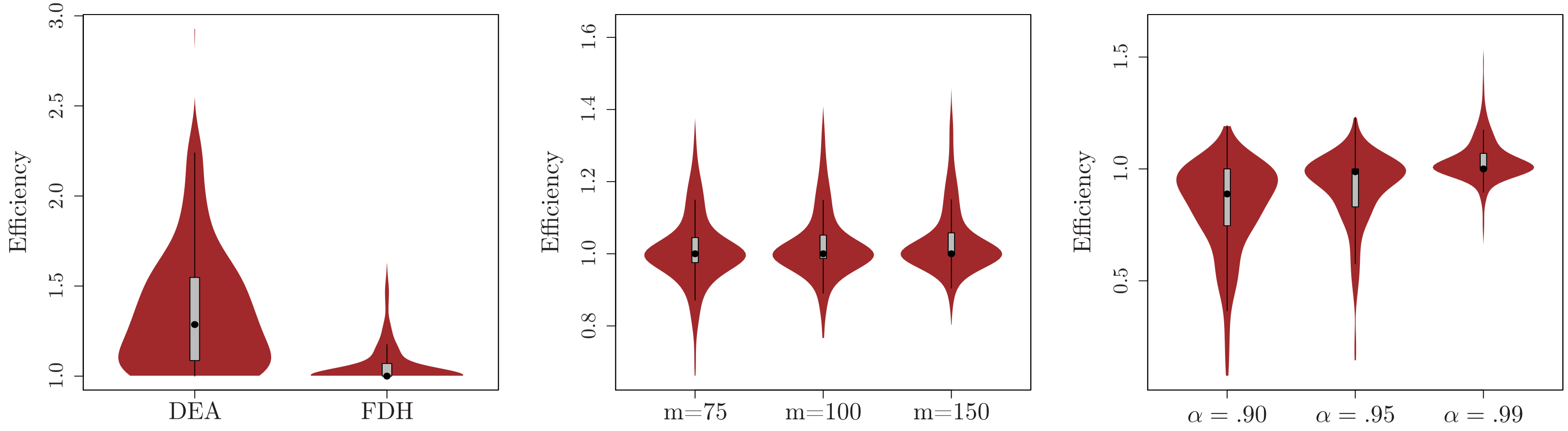


Figure 2: Violin plots, efficiencies of mutual funds (2001–2011)



(a) DEA vs. FDH

(b) Order-m

(c) Order-α

Note: higher efficiency values on the OY axis indicate worse performance.