The Performance of US Equity Mutual Funds

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Abstract

This paper examines the performance of US no-load equity mutual funds. Fund performance is derived using stochastic frontier analysis for a flexible functional form. This analysis allows us to derive parametric estimates of efficiency scores for each fund in our sample. Our results indicate that US no-load equity funds display varying levels of efficiency over time but also dependent on size and on investment style. As part of a sensitivity analysis we unveil the underlying dynamics of funds efficiency with respect to risk and operational characteristics such as flows, assets, and Morningstar star ratings. Panel VAR estimations reveal that the response of funds efficiency to a shock in risk is positive and substantial. Some evidence of reverse causality is also observed. Finally, we extend our analysis to investigate the relationship between funds performance and key covariates across subgroups defined by size.

Keywords: fund performance, stochastic frontier analysis, panel VAR, risk.

JEL Classification: G11, G12, G14, G23.

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1. Introduction

Mutual funds play within the financial markets an important role. Mutual funds are key financial intermediaries in the segment of institutional investors that aim to channel savings to profitable investments. Indicative of their importance to the financial markets investment companies held a substantial percentage of the outstanding shares of U.S.-issued stocks, bonds, and money market securities at year-end 2011. Although their mandate is to offer retail investors an access to investment services such as professional management, risk diversification and liquidity there exist costs that are linked with the ability of fund managers to achieve the optimal allocation of available capital, aiming at consistently superior risk-adjusted return compared to a passive benchmark or its peers. Thus, the analysis of whether active fund managers add value, from a performance point of view, to their portfolios entails important investment and policy implications for the fund management industry.

Mutual funds in the USA have gained considerable popularity as an investment vehicle for retail investors. According to Investment Company Institute (ICI) almost a quarter of US households' financial assets were managed by investment companies in 2011. In general, mutual funds are sold to consumers through either a direct or an indirect channel. In the former case investors do not pay any front-end or back-end loads but they are confronted with a 12b-1 fee for marketing and distribution of the fund. These funds are known as no-load funds. On the other hand, indirectly, investors have the option to buy their fund from a broker or an advisor who acts as an intermediate and receives fee for providing financial advice and other services to the investors. Funds sold through the indirect channel entail a complicated fee structure that varies according to fund's share class.

There are a number of reasons that constitute US no-load equity funds an interesting case to examine. No-load funds have received substantial popularity among retail and institutional investors during the last years. Their popularity has substantially contributed to the shrinkage of expenses and fees in the US mutual fund industry in general. According to the Investment Company Institute no load share classes have attracted significant inflows compared to their counterparts charging loads over the last years. In particular, total net assets of long-term funds in no-load share classes have reached in 2010 USD 5.16 trillion from 1.98 trillion in 2002, an astonishing growth of almost 160%.

In particular, total net assets of long-term funds in no-load share classes have reached in 2011 USD 5.23 trillion from 1.98 trillion in 2002, an astonishing growth of almost 160%. At the same period total net assets of long-term funds in load share classes have marked an increase of 57% reaching USD 2.44 trillion at year-end 2011.

Moreover, load funds provide a plethora of investment opportunities through multiple share classes, fulfilling an ever expanding investors' appetite and, thus, choices among broker-intermediated funds. A fund that is offered through a different share class scheme manages the same portfolio though the realized return is affected by the designated fee structure. The three most common share classes available for retail investors are A, B and C. Funds belonging to class A typically charge investors with a front-end load and an annual 12b-1 fee of 25 to 35 basis points that brokers receive. The B and C classes have no participation fees but may charge a contingent deferred sales load upon exit and usually charge higher annual 12b-1 fees of about 1 percent (Nanda et al. 2009).

Although there is anecdotal evidence against the existence of managerial ability, measuring the performance of fund managers remains a hot topic in the literature. Traditional performance measures compare the returns of the portfolio under consideration to the returns of a series of benchmark passive portfolios that mimic naïve investment strategies. Multi factor performance evaluation models generate the so-called alpha that is used to identify managerial quality. Positive (negative) alpha is indicative of a skilled (unskilled) manager. However, it has widely been recognized that this kind of performance measurement entails several inherent limitations such as failure to directly account for funds' transaction costs or/and the issue of proper benchmarking. Thus, a continuously thriving strand of empirical research tries to overcome the aforementioned obstacles by introducing performance measures that are based on the frontier analysis of Koopmans (1951) and Farrell (1957).

There are a number of important contributions to the literature. Departing from the standard non-parametric DEA analysis, the main question this paper aims to answer, thus addressing a missing link in the literature is: what is the no-load fund's efficiency across different classes and over time? In addition, we also raise the following question; does risk affect efficiency and how does this relationship evolve over time and across classes? By answering this particular question we shall reveal the underlying dynamics of a complex relationship without imposing any restrictions. The interaction between performance and risk has gained significance since the credit crunch. In particular, several shortcomings in the functioning of the financial markets in US and more specifically significant incentive misalignments have greatly contributed, at the micro level, to the crisis (Caprio et al. 2007). Moreover, observed misalignment in incentive structures of management of the funds (see Berk & Green, 2004) could have contributed to an understatement of true risk, generating mispricing of fund's net asset value. In light of this, our analysis permits to examine whether the underlying relationship between risk and performance is subject to variability, and in particular what is the response of performance to shocks in risk. This is an issue of particular importance as the recent crisis has demonstrated that shocks, due to risk, may hold the key for understanding the underlying reasons for the malfunctions in the industry.

A careful review of the performance evaluation studies reveals that non-parametric frontier-based methods have monopolized the relevant literature (for a thorough review the reader should refer to Matallín-Sáez et al. 2014). To the best of our knowledge, we estimate for the first time in the literature a SFA functional form for a sample of US open-end no-load funds accounting explicitly for random disturbances resulting from events beyond the control of management and potential inefficiencies. Compared to the non-parametric counterparts our specification offers greater flexibility whereas the inclusion of exogenous variables explicitly in the SFA functional form results in superior explanatory power. In this way, we attempt to broaden the findings of those studies that measure fund performance using frontier analysis. The presence of a stochastic term renders SFA-based efficiency scores less sensitive to the impact of outliers compared to non-parametric (DEA-based) models. Second, our model takes into account possible time variation in efficiency scores. Third, we introduce a novel methodology where issues related to endogeneity and dynamics are taken into account within a panel-Vector Autoregression (panel-VAR thereafter) model. Within this model all variables enter as endogenous, whilst due to the Vector Autoregression the dynamics of funds efficiency are considered. Next, we examine the direction of causality between US no-load funds performance as measured by efficiency and some key variables such as risk, flows and fund size. Finally, we believe that in the context of our panel VAR analysis we contribute to current research by shedding new light on the underlying dynamics of no-load funds in relation to performance and portfolio risk. Our findings clearly indicate that a decline in fund performance is associated with an upward shift to risk levels of the funds under consideration. Examining the reverse causality it is worth noting that the impact of a shift in risk on efficiency is positive and follows an upward path that persists throughout the period of analysis. In effect this finding indicates that the causal relationship runs from risk to funds' performance and carries a positive sign. Funds that take large bets are more likely to achieve a superior performance. This result is of some importance as it reveals the dynamic response of funds performance to risk. Focusing on a static framework could bias the results. The importance of this kind of empirical research is emphasized by extensive number of studies see, inter alia, Brown, Harlow and Starks (1996) - (BHS hereafter), Chevalier and Ellison (1997), Busse (2001), Huang et al. (2011), Schwarz (2012) and Cullen et al. (2012).

The rest of the paper is organized as follows: Section 2 reviews studies on the tackled issue and summarizes the main gap in contemporary research. Section 3 outlines the main hypotheses we test in our study.Section 4 describes the employed methodology and data while Section 5 discusses empirical results. Finally, Section 6 summarizes key findings and provides policy implications.

2. Literature review

2.1 Research on mutual funds performance and Frontier Analysis

This section describes the two strands of mutual fund literature that are related to our study. In particular, in the first subsection we present a brief review of the latest studies on fund performance evaluation with a special focus on the frontier-based performance evaluation studies. The main findings of the relation between funds' risk adjusted performance and their characteristics namely risk, assets and flows are summarized in the second subsection.

As discussed earlier, traditional performance measures compare the excess returns of the managed portfolio to the market excess returns and to a series of benchmark passive portfolios that reproduce naïve investment strategies. Turning to the most recent mutual fund performance studies, Carhart (1997) multi-factor performance evaluation model is seminal and highly cited. We refer inter alia to the studies of Agnesens (2013), Namvar et al. (2013) and Chen et al. (2013) in which fund performance is measured by means of Carhart four factor model. In this context, fund performance is derived as the intercept (alpha) of a regression of fund's excess returns on the market excess returns and those of well diversified benchmark portfolios that mimic naïve investment strategies such as the size effect, the growth and the momentum effect. Stated differently, this model allows for direct comparisons of active fund managers with comparable passive strategies. In a recent study, Hunter et al. (2014) expanded the standard multi factor performance evaluation models of equity and fixed income funds with a benchmark factor that accounts for funds' specific risk.

The past two decades have seen a dramatic growth of frontier techniques in the evaluation of traditional and alternative mutual funds. We can distinguish two main approaches of frontier-based methodologies that are commonly used in empirical research on efficiency of financial intermediaries: parametric approach and non-parametric approach. Berger and Humphrey (1997) show that the key difference between these two approaches rest on the implicit assumptions set on data with respect to (i) the functional form of the best practice frontier (ii) allowance / non-allowance of random error which may produce transitory positive or negative deviations in outputs, inputs, costs, or profits, and (iii) in cases where random error is allowed, the distributional assumptions imposed on it to distinguish the effect from the inefficiencies and the random disturbance.

Frontier-based mutual fund performance studies are clearly dominated by the non-parametric approach namely Data Envelopment Analysis (hereafter DEA). In the spirit of Markowitz's (1952) seminal paper the DEA approach yields an empirically derived frontier of the relatively best performing unit considering simultaneously multiple dimensions of the investment process such as costs, risk and return. As stated earlier, DEA-based techniques rely on mutual funds' cost and risk variables as inputs and a well-defined indicator of return as one of the outputs in order to compute the efficient frontier. The first attempt to measure mutual fund portfolio performance employing DEA belongs to Murthi et al. (1997) who developed the 'DEA portfolio efficiency index'. They employed data from the US market with standard deviation of returns, expense ratio, loads and turnover as inputs and mean gross return as output. In a related study, Murthi and Choi (2001) employing the same input-output mix as Murthi et al. (1997) they presented evidence that their new non-parametric efficiency index yielded comparable results fund rankings to the Sharpe index. Anderson et al. (2004) analyzed the efficiency of real estate funds employing a series of inputs such as loads, various costs and a standard measure of funds' risk (the standard deviation) and raw return as output. Daraio and Simar (2006) added to their model as a new input the fund size. They suggested a robust non-parametric performance measure based on the premise of order-m frontier. In addition Simar and Vanhems (2012) provide detailed probabilistic characterization of directional distances. As for markets outside US, measuring the performance of Italian funds by means of various DEA-based models attracted the interest of Basso and Funari (2001). They employed multiple risk measures and sales charges in place of inputs whereas fund mean return and the number of periods that the fund was not dominated served as outputs whilst Basso and Funari (2003, 2007) have also used the DEA models for analyzing the performance of ethical mutual funds. Galagadera and Silvapulle (2002) opt for DEA formulation to assess the relative performance of Australian mutual funds. Lozano and Gutierez (2008) conducted a relative efficiency analysis for a sample of Spanish funds using six different DEA-like linear programming models and certain return and risk variables whilst Garcia (2010) analyzed total productivity by means of a DEA model for a sample of Portuguese pension funds. Performance evaluation of hedge funds by means of DEA-based models has attracted the interest of Gregoriou (2003) and Gregoriou et al. (2005). Employing an extensive sample of US and European mutual funds together with a series of frontier estimators Kerstens et al. (2011) proposed the use of the shortage function as an efficiency measure consistent with general investor preferences. More recently, Premachandra et al. (2012) responding to the line of criticism faced by standard DEA-models appealed to the use of an innovative two-stage DEA model that decomposes the overall efficiency of a decision-making unit into two components, an operational management efficiency and portfolio management efficiency. For demonstration purposes, the authors assessed the relative performance of 66 large mutual fund families in the US over the period 1993–2008.

In view of the growing body of the literature (see Abdelsalam et al. 2014) that evaluates mutual fund performance employing frontier techniques factor models have been in the epicenter of heated debate. Most importantly, frontier techniques have become very popular in evaluating the performance of professional money managers combining simultaneously several dimensions of the investment process to a single performance measure the so-called efficiency score. However, frontier techniques are not free of criticism (Glawischnig and Reichmann, 2010, Matallín-Sáez et al. 2014). To this end, Abdelsalam et al. (2014) in their study of Islamic and Socially Responsible Funds relied on two robust variants of the DEA technique namely the partial frontier evaluation models. In particular the order-m and order-a approaches were implemented in order to gauge the performance of the examined mutual funds. Partial frontier models have drawn their popularity mainly from their ability to yield reliable results even in the presence of extreme values and noise that are often seen in data samples. Moreover, partial frontiers compared to other non-parametric commonly employed methods such as the DEA (Data Envelopment Analysis) and FDH (Free Disposal Hull) are free of the convexity assumption.

On the other hand, fund performance evaluation studies that rely on stochastic frontier analysis are extremely limited. Annaert et al. (2003) employed a European sample of equity mutual funds. They concluded that size and past performance are significant predictors of fund efficiency. Related empirical evidence can be found in the study of Santos et al. (2005) who evaluated the performance of 307 Brazilian stock mutual funds employing stochastic frontiers. They documented a positive relationship between fund’s efficiency and management skill to beat the market while portfolios with low volatility appeared to be more efficient.

2.2 Mutual fund performance and fund characteristics

Despite the dramatic growth of academic interest in the behavior of the mutual fund industry there are controversial topics that need to be addressed. For example, the risk-taking behavior of mutual fund managers, the reaction of funds’ performance to assets under management and the response of investors’ flows to fund performance are among the challenges that remain in the core of academic research. These issues belong to a broader field of research that explores how various fund characteristics relate to fund performance. The list of fund characteristics is long and it spans operational costs such as expenses, turnover and loads, past performance, fund’s age, fund’s assets under management, fund’s risk, fund family asset size, manager’s level of education, past performance, fund flows (for a brief literature review on the topic the reader can refer to Agnesens, 2013),

Risk remains a fundamental concept in our perception of fund management industry. As such it has caught the attention of researchers in the field emphasizing on the risk shifting strategies adopted by fund managers. In particular, it has been established that fund managers change their portfolio riskiness acting in response to explicit or implicit incentives present in the mutual fund industry. As for the latter the term tournament was coined by Brown, Harlow and Starks (1996) in order to suggest that fund managers that did not perform well in the first period are likely to increase fund volatility in the latter part of the evaluation period to a greater degree than winners. On the contrary, Chevalier and Ellison (1997) and Qui (2003) argue that winners rather than losers adopt the gambling strategy. A further related study by Huang et al. (2011), who applied a holdings-based measure of risk shifting, shows that highly risky funds underperform compared with those funds that have stable risk exposure. Berk and Green (2004) provide a different explanation by arguing that managers of successful funds are prepared to take greater risk in order to attract more cash inflows and increase their asset-based compensation. Funds are priced at the net asset value and thus the most skilled managers are expected to receive larger compensation through managing more assets.

There has been also extensive research that explores the relationship between fund’s asset size and performance. Chen et al. (1992) and Indro et al. (1999) among others examined the effect of economies of scale in fund management industry. The argument is based on the premise that larger funds have better skills in processing available information and can achieve substantially lower trading commissions due to the block of trades that characterizes their transactions. As a result, lower expenses lead to better performance. As already stated, liquidity constraints combined with organizational structure frictions encountered in the fund management industry could render larger funds with a handicap. To this aim, Chen et al. (2004) showed that it is easier for smaller funds to put their available funds into their best ideas finishing with superior risk-adjusted returns than larger funds.

Our study also relates to the literature that explores the relation between investor flows and fund performance. Mutual fund investors tend to chase past returns whereas they appear less reluctant to withdraw their money from funds that did not perform well in the past. Henceforth, studies have documented an asymmetric positive response of flows to past performance (Ippolito, 1992, Gruber, 1996, Chevalier and Ellison, 1997, and Sirri and Tufano, 1998). Goetzmann and Peles (1997) verify a significant effect of past returns on fund flows only for the top performing funds. Lynch and Musto (2003) show that the well-documented non-linear flow-performance relationship is consistent with fund incentives. Recently Rakowski and Wang (2009) examine the interaction between fund flows and performance and concluded that there is a negative relationship between past performance and fund flows.

The literature review unambiguously shows and confirms that there are gaps in contemporary research on mutual funds performance. In particular, we can identify four main areas that require a further investigation. First, we try to test the link between fund’s risk attitude and fund efficiency. This test is particular important in the light of the global financial crisis. One expects that fund managers are expected to shift the degree of risk in their portfolio to manipulate their performance and thus reap a greater portion of investors' flows. Second, an important and inconclusive argument is that an increase in fund's efficiency causes an increase in fund's risk level. The more efficient a fund becomes the more flexible is to engage in a riskier investment strategy. Finally, we explore the hypothesis that an increase in fund's asset size results in an increase in fund's efficiency a finding that might confirm the presence of economies of scale.

3. Hypotheses to be tested

Hypothesis 1: An increase in fund's risk causes an increase in fund's efficiency.

Managers' risk behavior and their response to risk incentives has been a central topic in the process of understanding the agency related problem that characterizes mutual fund industry. Retail investors opt for a fund that employs its resources in the most effective manner to maximize risk-adjusted returns. Contrary to investors' preferences mutual fund companies are motivated by their own profits and when actions of mutual fund companies are not aligned to those aiming at maximizing expected risk-adjusted returns then we expect some inefficiencies to arise. Therefore, managers can engage into risk shifting strategies of their portfolios acting as if they are competing in a tournament (Brown, Harlow and Starks 1996, BHS hereafter) interpreting the flow-performance relationship as an implicit incentive contract (Chevalier and Ellison 1997). In particular, according to BHS tournament model fund managers that were losers in the first period were likely to increase fund volatility in the latter part of the evaluation period to a greater degree than interim winners and this is exactly what they found. Evidence against BHS claims were provide by Chevalier and Ellison (1997) and Qui (2003) who argued that it is winners rather than losers who gamble. In a related study Huang et al. (2011) employing a holdings-based measure of risk shifting show that highly risky funds perform poorly compared to funds with stable risk exposure. In general, fund managers are expected to shift the degree of risk in their portfolio so as to manipulate their performance and thus reap a greater portion of investors' flows.

Hypothesis 2: An increase in fund's asset size results in an increase in fund's efficiency.

This hypothesis has been heavily examined in the relevant literature with contradictory results so far. On the one hand, there is a line of arguments that has been put forward by Chen et al. (1992) and Indro et al. (1999) linking the notion of asset growth in fund management industry with the positive effects of economies of scale. In other words, larger funds operate more efficiently than smaller due to better and more effective allocation of the available resources. Larger funds have better skills in processing available information whereas can achieve substantially lower trading commissions due to the block of trades that characterize their transactions. As a result, lower expenses lead to better performance and increased efficiency.

4. Methodology and data.

4.1 Description of US funds data

Our sample includes no-load domestic US equity mutual funds that operated at least for one year during the period of our analysis, i.e. from 2002 to 2010. As discussed earlier, traditional mutual funds are classified either as load or no-load depending on their distribution channel. No-load funds are directly distributed to investors and charge no sales fees. On the other hand, investors in load funds are faced with different sales fees such as front-end load, deferred sales load that vary with the fund's share class. A natural question that arises is whether sales loads should be included in funds' operating cost. In the context of our analysis we opt for funds' total operating cost as an input of funds' SFA functional form. Thus as Gil-Bazo and Ruiz- Verdú (2009) point out caution is needed when it comes to various loads paid by investors since they reflect fund's ownership cost and not fund's operating cost. With the above in mind, we focus on no-load funds in which operating expenses represent the 100% of all fees[1]. Moreover, index funds, exchange traded funds (ETFs) and other non-traditional mutual funds such as target date funds have been excluded from the current sample. The source of data variables is the comprehensive Morningstar Direct database whereas the macroeconomic variables have been retrieved from Thomson Datastream. We use the following variables: raw returns, total year-end assets and various funds' operational characteristics including expense ratio, turnover ratio and Morningstar 3-year fund star

[1] Morey (2003) comparing the performance of load and no-load funds in the US market has concluded that no-load funds offer superior risk-adjusted return than load funds.

ratings. A thorough review of the available data for reporting errors, outliers and other discrepancies leave us with an unbalanced panel of observations which includes a total of 507 distinct funds.

Our sample spans the entire fund universe defined by Morningstar. We restrict our attention on US-domiciled equity funds that keep at least 70% of their assets in domestic stocks. Domestic equity funds are classified into nine distinct categories based on the style and size of their stock holdings over the last three years. In particular, US-domiciled funds are grouped into one of the nine categories: large growth, large blend, large value, medium growth, medium blend, medium value, small growth, small blend, small value. For example, a large growth fund tends to favor large capitalization, growth-oriented stocks. Moreover, Morningstar assigns US-based equity funds that focus on a particular sector of the market to a specialty category: communications, consumer staples, consumers discretionary, equity energy, financials, health care, industrials, natural resources, technology, utilities, and miscellaneous.

4.2 Description of variables

Although non-parametric frontier methods have been widely employed in order to assess the performance of professionally managed portfolios these methods have a significant shortcoming. Frontier-based methods have gained their popularity mainly through their ability to combine simultaneously multiple input-output variables into a single numeric value called the efficiency score. However, as Kerstens et al. (2011) convincingly point out when a researcher decides to appeal to a non-parametric frontier method so as to assess the performance of a portfolio will shortly realize that there is no a priori criterion for selecting the proper input-output variables.

This has triggered numerous relevant studies to rely on various aspects. From a quick review of the relevant studies we can summarize the following variables that are mostly used as inputs: loads, expense ratio, turnover ratio and risk (either standard deviation of returns or beta) and a measure of portfolio return as output. We refer inter alia to Murthi et al. (1997) who were the first to apply the DEA method to fund performance evaluation in the US funds' market with standard deviation of returns, expense ratio, loads and turnover as inputs and mean gross return as output and to Murthi and Choi (2001). At this point it is worth mentioning that there are investors who pay more attention to the first two moments of the returns distribution (mean, standard deviation),while others may be more sensitive with extreme values such as skewness or/and kurtosis. This fact has given birth to specifications that account for higher order moments of the returns distribution (Joro and Na, 2006 Guo et al., 2012). Incorporating higher order moments as input–output variables essentially accounts for investor preferences in the performance evaluation process in way similar to the use of the first two moments (Briec and Kerstens, 2010). Along these lines there are studies that opt for both low and high moments of the distribution of funds. Matallín-Sáez et al. (2014) in their specification employed the standard deviation of the daily returns, the beta of the fund, the expense ratio as well as kurtosis as inputs, whilst as outputs they consider the mean daily return and the skewness of the returns[2].

The selection of inputs and outputs of this paper is driven by modeling funds in the context of a SFA functional form in line with Murthi et al. (1997), Basso and Funari (2001, 2003), Daraio and Simar (2006), Matallín-Sáez et al. (2014). Thus, with respect to inputs we identify managerial skill as the employed human capital, whilst as fixed capital we consider building, offices, brand name. We extract information regarding human and fixed capital expenditure from expenses such as fixed costs, custodian costs and marketing and advertising costs. These expenses are included in each individual fund's expense ratio. In addition, portfolio turnover ratio provides information for the cost of management, given that fund's management aims to generate positive alpha for fund's shareholders so as to achieve systematically a higher risk-adjusted return than the market or a passive investment strategy (Jensen, 1968)[3] .

Thus, and in line with Murthi et al. (1997), Basso and Funari (2001, 2003), Daraio and Simar (2006), Matallín-Sáez et al.(2014), we opt for fund's expense ratio and turnover ratio as explanatory and fund's monthly mean return as dependent variable.[4] In some detail; expense ratio is expressed as a portion of fund's average assets during a year.

[2] Furthermore, the list of candidate for selection is not limited to measures of the returns distribution or cost components. For example, Galagedera and Silvapulle (2002) include the minimum initial investment as an additional variable while other studies employ variables associated with the size or the portfolio composition of the fund: Daraio and Simar (2006) include total assets under management as an additional input, Haslem and Scheraga (2006) include the percentage of stocks.

[3] Also, fund's management adjust the degree of risk in response to market-wide movements in line with market timing practices (Treynor and Mazuy, 1966). These practices reflect strategic asset allocation whereas portfolios based on positive alpha refer to the tactical asset allocation.

[4] There is some evidence (see inter alia Glawischnig and Sommersguter-Reichmann, 2010; Matallín-Sáez et al. 2014) suggesting that mutual fund investors should consider higher moments of fund returns such as skewness and kurtosis. As robustness of the empirical measures of performance we also opt for the third and fourth moment of fund returns respectively in line with the above studies.

Expense ratio includes managing, administrative, operating, advertising (such as 12-b1 fees) and marketing expenses. The various sales charges are excluded from the calculation of the expense ratio. Turnover ratio provides information regarding the time period a manager keeps a stock into his/her portfolio. The ratio is computed by taking the lesser of purchases or sales and dividing by average monthly net assets. Higher turnover ratio implies an active manager who changes the portfolio composition frequently imposing probably larger transaction fees to funds' shareholders. Turnover ratio is considered as an additional input variable (Murthi et al., 1997). The empirical results on the relationship between fund performance and turnover ratio are contradictory. For example, Wermers (2000) provides evidence in favor of a positive relationship between turnover ratio and fund performance. On the other hand, Elton et al. (1993), Indro et al. (1999) represent the view that superior fund performance is associated with lower turnover ratio.

In the context of the second stage analysis that investigates the impact of key determinants of fund's performance, we include fund's total risk, total assets under management, Morningstar star rating and normalized flows. Total risk is defined as the annualized standard deviation of fund returns and reflects the variability of fund returns with respect to its mean return. In order to control for the degree of risk of the fund relative to the market we opt for an annual market-adjusted return of the fund. The annual market adjusted return is calculated as the deviation of fund return from the median return of the whole sample. This variable represents the fund's total asset base and is an indicator of the size of the fund. The structure of traditional open-end funds allows investors to buy or redeem their shares without restrictions. A measure of the money flowing in or out of the fund provides useful information about fund's behavior. Thus, we have calculated inflow/outflow for each fund at year t following the percentage asset growth rate net of appreciation, namely $(TNA_t - (1 + r_t)TNA_{t-1}) / TNA_{t-1}$, where TNA_t represents the fund's total net assets at the end of year t and r_t is its return over year t. Morningstar star rating is a famous fund ranking system that has been proved to exert significant influence on retail mutual fund investors (Del Guercio and Tkac, 2008). Morningstar assigns one to five stars to mutual funds according to their risk-adjusted performance within its relative peer-group. Stars are computed virtually for all funds that are in existence provided that are at least three years old. Best funds within the category are assigned five stars whereas the worst funds receive one star.

4.3 Stochastic frontier specification for US funds efficiency

Studies that attempt to measure operational efficiency are branched into two paths that is parametric approach incorporating econometric models (Stochastic Frontier Approach, Thick Frontier Approach, and Distribution Free Approach) and non-parametric approaches applying linear programming techniques (Data Envelopment Analysis and Free Disposal Hull Analysis). Yet, no consensus has been reached about the appropriate estimation methodology.

The stochastic frontier approach (SFA) was proposed by Aigner, Lovell and Schmidt (1977), and Meeusen and Van den Broeck (1977). Based on this framework a flexible functional form, whether cost, profit or the production function, is employed as a frontier that also includes random error given the parametric nature of such approach. Inefficiencies can, then, be identified through the error term. Moreover, the predicted standard functional form represents the frontier, whereas inefficiency is estimated through the error term, orthogonal to the predicted frontier. The orthogonality implies that the estimated inefficiency scores are uncorrelated with the regressors and any scale economies (Ferrier and Lovell, 1990). A number of different parametric approaches have been proposed in the literature for the estimation of efficiency, each of which has its individual strengths and weaknesses (see Koutsomanoli and Mamatzakis 2009 and Greene 2008). The main drawback of the standard stochastic frontier approach is that it heavily relies on the assumption regarding the underlying distribution of the error terms. In most applications, the half normal distribution is employed which in our case might be rather restrictive.

Given that the Stochastic Frontier Analysis necessitates a given underlying distribution whilst fund returns might follow a non-normal distribution, we employ the Distribution Free Approach (DFA thereafter), see Berger (1993). This approach is a particularly attractive technique due to its flexibility as it does not impose a-priori any specific shape on the distribution (DeYoung, 1997). Based on Berger (1993) the estimation of the functional form is separate for each year of panel data. This procedure essentially provides composed error terms, that in turn when subsequently are averaged over each year of the sample for each fund the random error terms would be averaged out. Thus the remaining error term is a measure of efficiency across the sample of funds.

Moreover, by averaging the residuals to estimate fund-specific efficiency, DFA estimates how well a fund performs relative to its competitors over a range of conditions over time, rather than its relative efficiency at any one point in time (DeYoung, 1997). This is useful for the industry, since relative efficiencies among different funds or clusters of funds may shift somewhat over time because of changes in management, technical change, regulatory reform, exogenous shocks, and other environmental influences. However, the rationality of the DFA assumptions depends on the length of period studied. Empirical investigation (i.e., DeYoung, 1997, Mester, 2003) into the number of years that may be needed to strike a balance between the benefits from having an additional observation to help average the random error and the costs associated with adding extra information, which increases the likelihood that the efficiency in the extra year might drift further away from its long term level, shows that a ten year period reasonably balances these concerns.

To this end, we employ a function for US fund's return that takes the form:

$$R_{it} = f\,(N_{it}, Z_{it}) + v_{it} + u_{it} \tag{1}$$

where R_{it} denotes observed fund return for i at year t, N is a vector of fund specific variables affecting this return and Z is a vector of control variables. N includes expense ratio and turnover ratio. Z comprises the CBOE implied volatility index VIX that reflects market perception of the future returns and a bond quality spread measure that is calculated as the difference between BAA-rated bonds and AAA-rated bonds. We have included these two variables so as to capture both behavioral considerations and market-wide credit risk conditions that are crucial for portfolio managers' decisions. The last components of equation 1 are of particular interest for this paper as v_{it} corresponds to random fluctuations and is assumed to follow a symmetric normal distribution around the frontier whereas u_{it} accounts for the fund's efficiency compared to the best-practice level within the industry and follows a half-normal distribution.

In addition, in the empirical estimations we fit a flexible translog specification that takes into account non-linearities. The translog function takes the form:

$$ln(R_i) = \alpha_0 + \sum_i \alpha_i lnN_i + {}^1\!/_2 \sum_i \sum_j \alpha_{ij} lnN_i lnN_j +$$

$$\sum_i \zeta_i lnZ_i + {}^1/_2 \sum_i \sum_j \zeta_{ij} lnZ_i lnZ_j + {}^1/_2 \sum_i \sum_j \theta_{ij} lnN_i lnZ_j$$

$$+ \sum_i \sum_j + \mu_1 t + {}^1/_2 \mu_2 t^2 + \sum_i \nu_i t lnN_i + \sum_i + \sum_i \rho_i t lnN_i +$$

$$+ \sum_\iota \varphi_i D_i + u_i + v_i \qquad (2)$$

where, as above, R_{it} denotes observed fund return for *i* at year *t*, N is a vector of fund specific variables affecting this return and Z is a vector of control variables.

Standard linear homogeneity and symmetry restrictions in all quadratic terms of the translog specification are imposed, whilst we also include dummies to capture any differences across specific groups (clusters) of US funds and time effects.

$\sigma_\varepsilon^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u / \sigma_\varepsilon$.

The stochastic frontier model of Equation (2) is estimated using Seemingly Unrelated Regression (SUR) estimation technique.

4.4 Revealing the underlying dynamics: a Panel-VAR model

We turn next our attention to its main underlying determinants whilst we tackle issues related to underlying dynamics and endogeneity that have not been previously addressed in the literature. An important drawback of estimating causal relationships between efficiency and its main determinants that has not been dealt in the literature is the resulted endogeneity bias equation (6) due to the use of standard OLS. We tackle endogeneity bias here by employing a more flexible framework using a panel-VAR analysis that will also reveal underlying short run dynamics. Essentially all variables in the panel-VAR are entering as endogenous so as to resolve the causality among them (Lütkepohl, 2005).

We examine the underlying causality links between US funds’ efficiency and some key variables specific to the industry such as fund flows, size, risk and Morningstar ratings.

We opt for a vector autoregresion (VAR) model for a panel data set that accounts for unobserved heterogeneity among sample units. This method has found applications in various topics including Koutsomanoli-Filippaki and Mamatzakis (2009) who examine the underlying relationship between bank efficiency and risk and Love and Zicchino (2006) who explore the relation between financial conditions and investment at a firm level. The VAR specification fits the purpose of this paper, given the absence of precise prior knowledge of which Hypotheses proposed by the literature, and discussed above, hold in the case of US funds, and thereby it deals with the issue of endogeneity of the variables. Such a model takes the form[5]:

$$X_{it} = \mu_i + \Phi X_{it-1} + e_{it}, \;\; i = 1,\ldots, \mathrm{N},\; t = 1,\ldots,\mathrm{T}. \qquad (3)$$

where X_{it} is a vector, for example in this particular case, of four random variables. Namely, X_{it} is a vector that includes the efficiency (EFF_{it}), flows ($flow_{it}$), assets ($assets_{it}$) and most importantly risk ($risk_{it}$). Thus, Φ is an 4x4 matrix of coefficients, μ_i is a vector of m individual effects and $e_{i,t}$ are iid residuals.

As an extension to the 4x4 panel-VAR specification we would also include a fifth variable in our model that is either Morningstar rating or deviation from median return (DMR).

In some detail the system of equation (3) builds on the seminal work of Sims's (1980) Vector Autoregressive (VAR) methodology. This methodology allows all variables within a system of equations to enter as endogenous, whilst also the short run dynamic relationships could be revealed see, for example, Lütkepohl (2005). The VAR would allow us to explore the underlying causal relationships between our main variables: efficiency scores derived from the Distribution Free Approach and key fund specific variables. In this type of models there are no restrictions imposed concerning the direction of causality. For example, we would be able to observe whether fund efficiency impacts upon, for example, fund size or would it be the case of vice versa, but also a bi-directional one.

[5] For purposes of simplicity of the exposition we present a first order 4x4 panel-VAR.

In the first empirical application of the panel-VAR, we opt for the following form:

$$
\begin{aligned}
EFF_{it} &= \mu_{10} + \sum_{j=1}^{J} \alpha_{11} EFF_{it-j} + \sum_{j=1}^{J} \alpha_{12}\, flow_{it-j} + \sum_{j=1}^{J} \alpha_{13}\, assets_{it-j} + \sum_{j=1}^{J} \alpha_{14}\, risk_{it-j} + e_{1i,t} \\
flow_{it} &= \mu_{20} + \sum_{j=1}^{J} \alpha_{21} EFF_{it-j} + \sum_{j=1}^{J} \alpha_{22}\, flow_{it-j} + \sum_{j=1}^{J} \alpha_{23}\, assets_{it-j} + \sum_{j=1}^{J} \alpha_{24}\, risk_{it-j} + e_{2i,t} \\
assets_{it} &= \mu_{30} + \sum_{j=1}^{J} \alpha_{31} EFF_{it-j} + \sum_{j=1}^{J} \alpha_{32}\, flow_{it-j} + \sum_{j=1}^{J} \alpha_{33}\, assets_{it-j} + \sum_{j=1}^{J} \alpha_{34}\, risk_{it-j} + e_{3i,t} \\
risk_{it} &= \mu_{40} + \sum_{j=1}^{J} \alpha_{41} EFF_{it-j} + \sum_{j=1}^{J} \alpha_{42}\, flow_{it-j} + \sum_{j=1}^{J} \alpha_{43}\, assets_{it-j} + \sum_{j=1}^{J} \alpha_{44}\, risk_{it-j} + e_{4i,t}
\end{aligned}
\tag{4}
$$

The moving averages (MA) form of the model sets EFF_{it}, $flow_{it}$, $assets_{it}$ and $risk_{it}$ equal to a set of present and past residuals e_1, e_2, e_3 and e_4 from the panel-VAR estimation:

$$
\begin{aligned}
EFF_{it} &= \gamma_{10} + \sum_{j=1}^{J} b_{11} e_{1it-j} + \sum_{j=1}^{J} b_{12} e_{2it-j} + \sum_{j=1}^{J} b_{13} e_{3it-j} + \sum_{j=1}^{J} b_{14} e_{4it-j} + e_{1i,t} \\
flow_{it} &= \gamma_{20} + \sum_{j=1}^{J} b_{21} e_{1it-j} + \sum_{j=1}^{J} b_{22} e_{2it-j} + \sum_{j=1}^{J} b_{23} e_{3it-j} + \sum_{j=1}^{J} b_{24} e_{4it-j} + e_{2i,t} \\
assets_{it} &= \gamma_{30} + \sum_{j=1}^{J} b_{31} e_{1it-j} + \sum_{j=1}^{J} b_{32} e_{2it-j} + \sum_{j=1}^{J} b_{33} e_{3it-j} + \sum_{j=1}^{J} b_{34} e_{4it-j} + e_{3i,t} \\
risk_{it} &= \gamma_{40} + \sum_{j=1}^{J} b_{41} e_{1it-j} + \sum_{j=1}^{J} b_{42} e_{2it-j} + \sum_{j=1}^{J} b_{43} e_{3it-j} + \sum_{j=1}^{J} b_{44} e_{4it-j} + e_{4i,t}
\end{aligned}
\tag{5}
$$

Under the endogeneity assumption the residuals will be correlated and therefore the coefficients of the MA representation are not interpretable. We orthogonalize the residuals by multiplying the MA representation with the Cholesky decomposition of the covariance matrix of the residuals. The orthogonalized, or structural, MA representation is:

$$EFF_{it} = \delta_{10} + \sum_{j=1}^{J} \beta_{11}\varepsilon_{1it-j} + \sum_{j=1}^{J} \beta_{12}\varepsilon_{2it-j} + \sum_{j=1}^{J} \beta_{13}\varepsilon_{3it-j} + \sum_{j=1}^{J} \beta_{14}\varepsilon_{4it-j}$$

$$flow_{it} = \delta_{20} + \sum_{j=1}^{J} \beta_{21}\varepsilon_{1it-j} + \sum_{j=1}^{J} \beta_{22}\varepsilon_{2it-j} + \sum_{j=1}^{J} \beta_{23}\varepsilon_{3it-j} + \sum_{j=1}^{J} \beta_{24}\varepsilon_{4it-j}$$

$$assets_{it} = \delta_{30} + \sum_{j=1}^{J} \beta_{31}\varepsilon_{1it-j} + \sum_{j=1}^{J} \beta_{32}\varepsilon_{2it-j} + \sum_{j=1}^{J} \beta_{33}\varepsilon_{3it-j} + \sum_{j=1}^{J} \beta_{34}\varepsilon_{4it-j}$$

$$risk_{it} = \delta_{40} + \sum_{j=1}^{J} \beta_{41}\varepsilon_{1it-j} + \sum_{j=1}^{J} \beta_{42}\varepsilon_{2it-j} + \sum_{j=1}^{J} \beta_{43}\varepsilon_{3it-j} + \sum_{j=1}^{J} \beta_{44}\varepsilon_{4it-j} \qquad (6)$$

with

$$\begin{pmatrix} \beta_{11j}\beta_{12j}\beta_{13j}\beta_{14j} \\ \beta_{21j}\beta_{22j}\beta_{23j}\beta_{24j} \\ \beta_{31j}\beta_{32j}\beta_{33j}\beta_{34j} \\ \beta_{41j}\beta_{42j}\beta_{43j}\beta_{44j} \end{pmatrix} = \begin{pmatrix} b_{11j}b_{12j}b_{11j}b_{12j} \\ b_{21j}b_{22j}b_{23j}b_{24j} \\ b_{31j}b_{32j}b_{33j}b_{34j} \\ b_{41j}b_{42j}b_{43j}b_{44j} \end{pmatrix} P \begin{pmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \\ \varepsilon_{3it} \\ \varepsilon_{4it} \end{pmatrix} = P^{-1} \begin{pmatrix} e_{1it} \\ e_{2it} \\ e_{3it} \\ e_{4it} \end{pmatrix} \qquad (7)$$

where P is the Cholesky decomposition of the covariance matrix of the residuals:

$$\begin{pmatrix} Cov(e_{1it}, e_{1it}) Cov(e_{1it}, e_{2it}) Cov(e_{1it}, e_{3it}) Cov(e_{1it}, e_{4it}) \\ Cov(e_{2it}, e_{1it}) Cov(e_{2it}, e_{2it}) Cov(e_{2it}, e_{3it}) Cov(e_{2it}, e_{4it}) \\ Cov(e_{3it}, e_{1it}) Cov(e_{3it}, e_{2it}) Cov(e_{3it}, e_{3it}) Cov(e_{3it}, e_{4it}) \\ Cov(e_{4it}, e_{1it}) Cov(e_{4it}, e_{2it}) Cov(e_{4it}, e_{3it}) Cov(e_{4it}, e_{4it}) \end{pmatrix} = PP^{-1} \qquad (8)$$

Using the above panel-VAR individual heterogeneity in the levels is ensured by introducing fixed effects in the model, denoted μ_i. Variables within the panel-VAR are forward mean-differenced using the Helmert procedure (Love and Zicchino, 2006). In addition, standard errors of the impulse response functions are calculated and confidence intervals generated with Monte Carlo simulations (Love and Zicchino, 2006).

5. Empirical Results

5.1 US funds efficiency scores

Table 1 presents the average efficiency scores of US funds over the period examined derived by a Distribution Free Approach (DFA) described in earlier section. We also report the evolution of mean efficiency score of our sample funds for the period of analysis.

Insert Table 1 here

The results highlight that with the exception of two years, 2002 and 2008, a year which was marked by the effects of the global financial crisis throughout the financial system, funds' mean efficiency remains at relatively high levels. The average efficiency score across all US funds is 81%, a quite high value. Another interesting feature is revealed by the dispersion of efficiency scores, which reaches its highest values during 2002 and 2008 as previously indicating substantial heterogeneity of funds in terms of efficiency. This does not come as a surprise given the cataclysmic effects in financial markets if the recent credit crunch. There is also some efficiency variability across US no-load mutual funds. In Table 2, we report mean efficiency scores across different categories of funds. We find a positive relation between asset size and efficiency that we show in the last column of Table 2. The three Large categories (Large Blend, Large Value and Large Growth) exhibit the highest average efficiency scores. On the other hand, Technology Funds exhibit the lowest levels of efficiency a result that contradicts the findings of Sengupta (2003). Finally, it appears that portfolios of no-load funds invested in Financial Sector have performed relatively well considering the unfavourable events that unfolded during 2008 crisis in the particular sector. The latter could probably be credited to skilful management on the part of mutual fund managers of the specific category [6].

Insert Table 2 here

[6] It should be noted that we have conducted robustness test using alternative schemes incorporating skewness and kurtosis. Results remain consistent and are available upon request.

The above efficiency scores are derived from a stochastic frontier analysis. As we have already mentioned previous studies on funds efficiency have been based on non-parametric methods. Murthi et al. (1997) were among the first to apply the DEA method to fund performance, whilst Murthi and Choi (2001) followed similar methodology. If we compare our findings with those studies we may see that efficiency scores are similar to ours, though they are not entirely comparable due to differences in the sample. Moreover, Sengupta (2003) focused on portfolios' performance and reported that 70% of the examined portfolios were relatively efficient, but with significant deviations depending on the category of funds.

5.2 Empirical Results of panel-VAR.

5.2.1 Does risk impact upon fund efficiency?

Next we report the Impulse Response Functions (IRFs thereafter). IRFs plot the response of each variable within the panel VAR framework to its own innovation and to the innovations of the other variables.

Insert Figure 1 here

From the first row of Figure 1, right hand side corner, we observe that a one standard deviation shock of risk on efficiency is positive a finding consistent with Hypothesis 1.It is worth noting that the impact follows an upward path that persists throughout the period of analysis. In effect this finding indicates that the causal relationship runs from risk to funds' performance and carries a positive sign. Funds that take large bets are more likely to finish with a superior performance. This result is of some importance as it reveals the dynamic response of funds performance to risk. Focusing on a static framework could bias the results. Huang et al. (2011) in a static long run model show that funds that increase their risk end-up with a lower performance.

Overall, the underlying degree of risk emerges as an important element of funds performance, especially in light of the increased volatility that has accompanied the outburst of the recent financial turmoil. Examining the reverse causation we infer that the response of funds risk to efficiency innovation is negative, significant and big in magnitude. According to Gorton and Rosen (1995) an increase in efficiency causes an increase in risk level, we cannot confirm this hypothesis and our results are in line with Brown et al. (1996). This finding has implications since it reveals that a decline in fund's efficiency is associated with a respective increase in fund's total riskiness.

Our argument is clearly related to Hypothesis 1 stating that funds that increase their risk levels achieve ultimately greater performance. Thus, our findings provide substantial evidence in favor of this Hypothesis.

However, it is interesting to note that during the first two years of our analysis the impact of efficiency on risk is shrinking but grows in the third period whereas it diverges away from equilibrium thereafter. This variability highlights the complexities involved in the relationship between risk and funds' performance, and in particular the underlying shifts in the direction of causality.

There is a voluminous literature that focuses on risk aspects of mutual funds (see Sengupta, 2003, Anderson et al., 2004, Gregoriou, 2003, Gregoriou et al., 2005, Basso and Funari, 2001). Yet, this is for the first time that US funds' efficiency is directly related to risk in this framework. Moreover, in contrast to Murthi et al. (1997) hypothesis that efficiency is negatively correlated with funds' systematic risk we find evidence that the response of US funds' efficiency to risk is positive. This finding resembles the argument by Berk and Green (2004) stating that managers of successful funds assume higher risk in order to attract larger inflows and therefore increase their asset-based compensation. However, the present evidence goes further to suggest that risky managers are also highly efficient.

In Table 4, we report variance decompositions (VDCs) that provide further evidence in favor of the previous findings. From the first row, last column, we observe that 19.2% of the forecast error variance of US funds efficiency is explained by risk. This is a quite dominant result and highlights with great emphasis that US funds' efficiency is predominantly determined by risk. On the other hand and similarly, 21.8% of the forecast error variance of risk is explained by efficiency, whilst 4.2% of risk's forecast error variance is explained by asset size. To this end, it is worth noting that both US funds' performance and assets explain portfolio risk.

Risk shifting may be motivated either by agency issues or by stock selection/timing abilities of fund managers (Brown, Harlow and Starks 1996, Chevalier and Ellison 1997). In the latter case, risk shifting may be proved beneficial for investors when active managers trade in order to exploit their superior skills and perform better. Following this conjecture funds that increase their riskiness would deliver superior performance to their investors. It should also be noted that the impact of a time varying risk strategy is strongly related to the motivation of such a strategy. This would imply that when fund managers are engaging into risk shifting strategies spurred by self-interested motives then we should expect no superior performance.

Insert Table 4 here

5.2.2 Do fund size, deviation from median return and Morningstar rating matter?

In Figure 2, we report the response of efficiency to shocks of one plus/minus standard deviation in fund size; funds' deviation from median return; and lastly Morningstar 3-year star rating. We show three additional lines of diagrams of the responses of the remaining variables in the panel-VAR. This the first time in the literature that evidence is provided for the relationship between rating and fund performance measured in this way.

Insert Figure 2 here

Contrary to the findings of Annaert et al. (2003), we report, for the whole sample, a negative relationship between fund efficiency and fund size, see in Figure 2, the first row, second sub-diagram from the right. The findings provide indications that Hypothesis 2 may not be valid. That is to say the response of efficiency on one standard deviation shock in assets under management is negative, but only in the very short run as it converges to zero thereafter. This finding is also consistent with previous studies see inter alia Chen et al. (2004) that show the existence of a negative effect of fund size on funds' performance. Furthermore, we observe that a one standard deviation shock of the funds deviation from median return on efficiency is positive in the first period but then there is a certain degree of fluctuation before converging.

Interestingly the impact of Morningstar rating on US funds efficiency is persistently negative over the whole period, though its main impact takes place within the first two years and converges gradually thereafter. This is an important result as it demonstrates that a shock in Morningstar rating, let say a downgrade, will result in a decline in efficiency of US funds. Similarly, the impact of a shock in funds efficiency on Morningstar rating is positive, and big in magnitude, over the whole period (see last row, first diagram from the left). This finding resembles the hypothesis of Murthi et al. (1997), who argue that efficiency is negatively correlated with funds' systematic risk indicating that high-risk funds are characterized with low efficiency. In the literature, it is for the first time that the Morningstar rating is linked to US performance as measured by SFA efficiency scoring. Yet in the literature there are studies, see Sharpe (1998), that examined the properties of Morningstar's measure and showed that the risk-adjusted rating (RAR) generated by Morningstar caters results similar to the well-known excess return Sharpe ratio. Blake and Morey (2000) also tested the hypothesis that the Morningstar rating system provides information on future mutual fund performance for a sample of US domestic equity funds and reached weak evidence that Morningstar's highest-rated funds outperform the next-to-highest and median-rated funds. In addition, Del Guercio and Tkac (2008) documented a significant inflow for 5-star funds and a remarkable sensitivity of investors to 'star' upgrades or downgrades that is gauged by inflows and outflows experienced by funds.

Next we provide more details into the underlying relationships between the variables of the panel-VAR by means of variance decompositions (VDCs), see Table 5. In particular, variance decompositions indicate the percentage of the variability in the variable of interest, i.e. US funds' efficiency, that is attributed to another variable, i.e. Morningstar rating. These results provide further light to IRFs, revealing the importance of the various determinants in explaining the variation of funds' efficiency. We report the overall aggregated effect over 10 and 20 years. From the first row, last column, we observe that 3.8% of the forecast error variance of US funds efficiency is explained by Morningstar rating. Assets and funds' deviation from median return assert a much lower contribution. On the other hand, 4.8% of the forecast error variance of

Morningstar rating is explained by US funds efficiency, insinuating a two-way causal relationship, in line with the findings of the IRFs above.

Insert Table 5 here

5.2.3 Do flows affect fund efficiency?

Studies focusing on fund flows range from investor's reaction to fund performance, to the relationship between market movements and fund flows and to the interaction between fund costs and fund flows. To the best of our knowledge, no study before has explicitly addressed the relationship between fund flows and efficiency under this framework.

We find that a one standard deviation shock of flows on efficiency is positive. It is worth noting that the impact follows an upward path in the first two periods but then converges to zero, whilst its magnitude is also low. On the other hand, the impact of efficiency on flows is negative which contradicts earlier findings of Smith (1978), Ippolito (1992) and others that improved performance attracts new money to funds. However, observing the response of flows to a shock on efficiency we can again infer that the negative effect is only transitory and then fades away. This could be just the result of the significant outflows experienced by mutual funds in light of the outburst of financial crisis and this probably requires further exploration.

Table 6 reports variance decompositions (VDCs). Moreover, from the first row, last column, we observe, once more, that 19.2% of the forecast error variance of US funds efficiency is explained by risk. This is the dominant result, whilst flows explain little of the forecast error variance of US funds efficiency.

Insert Table 6 here

Next, we provide the results for the robustness of the general panel-VAR. In Table 7, we report VDCs that provide evidence in line with the one reported above. Once more, risk is the dominant determinant of US funds' efficiency as 28.7% of the latter is explained by the former. Morningstar rating also plays an important role as 4.1% of efficiency is explained by the rating. Interestingly we observe that for longer horizons the variability of US funds' efficiency attributed to risk amounts to 46.32%.

Insert Table 7 here

5.3. IRFs and VDCs for funds grouped according to size

Fund size remains a fundamental issue in our understanding of the delegated money management industry. Several studies have highlighted the relationship between fund size and performance see inter alia Grinblatt and Titman (1989), Berk and Green (2004), Chen et al. (2004) all reaching contradictory results. In some cases, smaller funds achieve superior performance because they can buy/sell securities without affecting adversely their prices. On the other hand, a few researchers (Golec, 1996) believe that smaller funds may be confronted with higher transaction costs resulting from diseconomies of scale that erode performance. Therefore, we set off to hypothesize a different relationship between the variables under examination across various fund sizes. Murthi et al. (1997) found that funds' efficiency scores derived from a DEA approach were not related to asset size. To this end, we divide our sample into four groups (quartiles) on the basis of fund size and report the relevant IRFs and VDCs for each subgroup.

Table 8 summarizes the respective VDCs. We find that that the effect of one standard deviation shock of risk on funds' efficiency is positive and relatively large in magnitude for smaller funds. This result is in line with Hypothesis 1. The peak response of efficiency to a shock in risk occurs after two years while it converges to equilibrium thereafter. However, if we examine the response of risk to a shock in efficiency we observe that is negative implying a reverse feedback. This means that a shock that would increase fund's efficiency reduces portfolio risk.

As for the rest variables, a large part of fund's flows variation is explained by changes in the total riskiness of the portfolio especially for the biggest funds. This finding is related to the conjecture of Chevalier and Ellison (1997) who argue that funds flow-performance relationship could act as an implicit incentive scheme for management companies to increase or decrease riskiness with the aim of attracting 'fresh' money. So, in light of the well-documented relationship between flows and risk we can report that a one standard deviation shock in risk on fund flows is positive and large in magnitude for small funds. However, it is interesting to note that for the other categories of funds, namely small medium, medium-large, and large we observe a negative response of flows to risk. This means that an increase in funds' total riskiness reduces flows. Thus, funds' flows appear sensitive to risk (Chevalier and Ellison, 1997) but not in unique way, as the size of funds is detrimental.

Insert Table 8 here

6. Conclusions

This paper explores for the first time the performance of US no-load mutual funds using stochastic frontier analysis. The underlying dynamics of the relationship between derived efficiency scores and some key covariates, notably risk are also examined. Our results reveal substantial heterogeneity in efficiency scores over time and across funds. In addition funds' efficiency appears to depend heavily on the size and the investment style of the funds. Highest efficiency scores are concentrated in the Consumer Staples category whereas Technology Funds exhibit the lowest levels of efficiency a result that contradicts the findings of Sengupta (2003).

This paper sheds new light into the performance of no-load funds in US, the largest industry of that type in the world, and also on the underlying dynamics of some key determinants of the performance such as risk and flows. Based on our findings key players in the market could gain additional information on the performance of the no-load funds across various sub-groups.

IRFs show that the causal relationship runs from risk to funds' performance and carries a positive sign which is in line with Hypothesis 1. Funds that take large bets are more likely to finish with a superior performance. The reverse causal relationship cannot be excluded although the empirical evidence is not as strong. This finding is consistent with the argument put forward by Berk and Green (2004) that managers of successful funds are willing to pursue riskier strategies in order to attract larger inflows and therefore increase their asset-based compensation. Moreover, the current evidence goes further to suggest that risky managers are also highly efficient

Most interestingly, the dependence between efficiency and risk is more pronounced among funds in the lowest size quartile. In particular, among smaller funds we found that 40% of the variation in efficiency is attributed to a shock in risk. As for the rest of the fund characteristics fund size, and contrary to the findings of Annaert et al. (2003), affects adversely fund performance. The findings provide indications that Hypothesis 2 may not be valid. Moreover, funds in the top size quartile achieve lower levels of efficiency and vice versa. This result points to the absence of economies of scale in the US no-load equity funds during the analyzed period.

We show that efficiency and risk are strongly related and consistent with this finding is the behaviour of VDCs. In particular, the results provide further evidence favouring the relationship between efficiency and risk since almost 40% of forecast error variance of efficiency is explained by fund's risk whereas fund's deviation from median return accounts for only 2%. In the same lines, the results show that 27% of the forecast error variance of funds' risk is explained by efficiency level. Examining the interaction between efficiency and risk we observe that it is more pronounced in the first and third asset quartile whereas in the rest quartile appears weakened. In particular, in the case of largest funds a shock in the risk accounts for only 8% of the variation in efficiency levels compared to 40% in the smallest funds.

Our results could have possible policy implications for investors, professional managers and market regulators. Investors should be aware that larger funds are characterized by reduced flexibility and thus might experience inferior performance especially during periods of market turbulence. Therefore fund size is an important consideration for investors and shareholders. Fund size and its negative effect on fund performance contain valuable information for fund managers as well who are required to maintain an optimal fund size and deliver superior risk-adjusted returns. Unveiling the dynamic component of fund managers' risk-taking behaviour entails important implications. Related to the above, regulators and supervisory authorities whose task is to safeguard a secure and well-functioning financial system and ultimately shareholders interests should monitor the risk-taking behaviour of money managers.

Moreover, observed misalignment in incentive structures of management of the funds (see Berk and Green, 2004) could have contributed to an understatement of true risk, generating mispricing of fund's net asset value. In light of this, our analysis permits to examine whether the underlying relationship between risk and performance is subject to variability, and in particular what is the response of performance to shocks in risk. This is an issue of particular importance as the recent crisis has demonstrated that shocks, due to risk, may hold the key for understanding the underlying reasons for the malfunctions in the industry.

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