How do US equity funds perform when it comes to risk?

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 show that US no-load equity funds display varying levels of efficiency over time but also depending 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: US fund performance, stochastic frontier analysis, panel VAR, risk.

JEL Classification: G11, G12, G14, G23.
1. INTRODUCTION

One of the greatest developments in the modern financial markets is their domination by institutional investors. Mutual funds are probably the most important member of institutional investors managing a significant part of savings and channeling them to profitable investments. Despite their appeal to retail investors offering numerous advantages such as access to professional management, risk diversification and liquidity there exist costs that come with these advantages. Such costs are justified by 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. Fundamentally, the issue 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. This paper offers for the first time in the literature parametric measurement of fund performance using stochastic frontier analysis.

Accurate measurement of fund performance has been a rather challenging task and has attracted the focus of the academic literature over the past 40 years with the main finding being that on average mutual funds underperform relatively to their passive benchmarks approximately by the size of costs charged to their shareholders (Gruber 1996, Carhart 1997, Fama and French 2010). Recent attempts of a more reliable performance measurement include among others the studies of Homma & Pigorsch (2012) and Angelidis et al (2013). Hence the skills of fund managers as a whole to offer superior risk adjusted returns have been seriously disputed. Although there is substantial 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 examined portfolio to the returns of an unmanaged portfolio of comparable risk (see following section of stylized facts for an extensive discussion). Several drawbacks of these metrics such as their inability to incorporate funds’ transaction costs or the issue of selecting the proper benchmark have fueled the introduction of performance measures that rely on frontier analysis in the spirit of Koopmans (1951) and Farrell (1957). Following the seminal work of Koopmans (1951), and Farrell (1957), there is a burgeoning literature that employs frontier analysis for the purpose of investment funds’ performance evaluation.
Before we proceed with the relevant literature, it would be useful to distinguish between the two main paths of frontier-based methodologies that appear in the relevant studies: parametric approach and nonparametric approach. Berger and Humphrey (1997) pointed out that the crucial differences between the 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. Another significant discrepancy between these methods lies in the form of the craved efficiency. In particular, nonparametric models are usually employed for measuring technical efficiency while parametric models are adopted for gauging overall efficiency (Bauer, Berger, Ferrier, and Humphrey 1998).

Moreover, in the context of measuring efficiency by means of data envelopment analysis (DEA) researchers generally employ mutual funds’ cost and risk variables as inputs and a well-defined indicator of return as one of the outputs (see Murthi et al. 1997 and Murthi and Choi, 2001, and Basso and Funari, 2001, Lozano and Gutierrez, 2008). 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. As for markets outside US, measuring the performance of Italian funds by means of various DEA-based models was the focus of. 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. Galagadera and Silvapulle (2002) analyzed relative performance of Australian mutual funds employing loads, expenses, minimum initial investment and portfolio risk as inputs and gross performance as output. It should be noted that portfolio risk and funds’ gross performance were calculated for varying holding periods. 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 along with a series of frontier estimators Kerstens et al (2011) proposed the use of the shortage function as an efficiency measure which they believed accommodates 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.

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. In particular, larger funds appeared more efficient than small funds indicating the presence of economies of scale, but it may also be related to relatively larger capital inflows into successful funds. Unlike these two characteristics, fund age appeared to be irrelevant for fund efficiency. Finally, their findings revealed that underperformers tend to be less efficient in a subsequent period. 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.

To this end, the purpose of our study is threefold. First, we attempt to broaden the findings of the relatively few studies measuring fund performance using stochastic frontier analysis for the first time in the literature for an up to date set concerning US no-load mutual funds. Second, in order to account for possible time variation in efficiency scores, we provide efficiency scores over time. Third, we opt for 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. We offer an analysis that allow us to observe the direction of causality between US no-load funds performance as
measured by efficiency and some key variables such as risk, flows and size. Finally, we believe that in the context of our VAR analysis we provide novel findings with respect to managers’ risk shifting behaviour given the inconclusive heated debate in the literature (see inter alia Brown, Harley and Starks 1996, Chevallier & Ellison 1997, Bosse 2001, Huang et al 2011, Schwarz (2012) and Cullen et al 2012).

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%.

A snick review of our results reveals a positive relationship between fund performance and risk. Examining the reverse causation we infer that the response of fund’s risk to efficiency innovation is negative.

The rest of the paper is organized as follows: Section 2 outlines the main hypotheses to be tested. Section 3 describes the employed methodology and data while Section 4 discusses empirical results. Finally, Section 5 provides some concluding remarks and policy implications.

2. 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 characterize 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 (Chevallier 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 Chevallier 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 efficiency causes an increase in fund’s risk level.

Following the moral hazard hypothesis of Gorton and Rosen (1995) we claim that managers of efficient financial institutions are more inclined to adopt an expansionary strategy that could subsequently be proved rather risky. In other words, related to rationale of Berk and Green (2004) managers of successful funds are willing to assume greater risk in order to attract larger inflows and therefore increase their asset-based compensation. Since funds are priced at the net asset value the most skilled managers are expected to receive larger compensation through managing more assets. The more efficient a fund becomes the more flexible is to engage in a riskier investment strategy.

In addition to the above hypotheses, we also examine the relationship between fund’s asset size and performance. To this end, two additional hypotheses are of relevance.

Hypothesis 3: 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.

**Hypothesis 4**: An increase in fund’s asset size results in a decrease in fund’s efficiency.

Departing from the hypothesis of economies of scale liquidity considerations coupled with organizational structure frictions present in the fund management industry could distort fund performance rendering larger funds with a disadvantage compared to their smaller counterparts. Stated differently, according to Chen et al (2004) smaller funds could be more flexible and could place all their available monies into their best ideas achieving thus superior risk-adjusted returns.

### 3. Empirical methodology and data.

#### 3.1 US funds data

Our sample consists of more than 500 no-load domestic US equity mutual funds that were in existence for at least one year under the period of analysis 2002-2010. Only no-load funds have been included in our analysis so as to avoid the complexity of the variety of expenses charged in different fund share classes. 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 input-output data variables is the comprehensive Morningstar Direct database whereas the macroeconomic variables have been retrieved from Thomson Datastream. Within the 9-year period we have collected annual raw returns, total year-end assets and various funds’ operational characteristics including expense ratio, turnover ratio and 3-year fund star 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.
For the estimation of funds’ performance we follow the relevant studies conducted in a non-parametric framework namely Murthi et al (1997), Basso and Funari (2001, 2003), Daraio and Simar (2006) that employ as input variables fund’s costs and mean fund return as output. In particular, in order to measure funds’ efficiency we specify two inputs expense ratio and turnover ratio and one output mean return. Fund shareholders are charged with various costs that are associated with managing, administrative, operating, advertising or marketing expenses such as 12b-1 fees. Therefore, a typical measure of a fund’s expenses is the annual expense ratio that is expressed as a portion of fund’s average assets. Turnover ratio is considered as an additional input variable (Murthi et al 1997) and gages the information-induced trading activity of a fund manager during a year. The success of a fund obtains when its manager achieves superior portfolio risk-adjusted returns through buying and selling securities in a cost-effective manner. Although, a high turnover ratio indicates an active manager that engages into market timing or/and stock picking strategies in the pursuit of profitable investment opportunities this might entail increased costs that ultimately erode fund returns (Elton et al., 1993, Indro et al., 1999).

In the context of the second stage analysis we include fund’s risk, total assets under management, Morningstar star rating and normalized flows. Annualized standard deviation of fund returns has been included as risk variable. Star rating is an innovative risk-adjusted, peer-group fund performance evaluation system that has been proved to exert significant influence on retail mutual fund investors (Del Guercio and Tkac JFDA, 2008). To control for the riskiness 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 (DMR) of the whole sample.

Finally, we have computed annual flow for each fund at year $t$ following the percentage asset growth rate net of appreciation, namely \(\frac{(TNA_t - (1+r_t)TNA_{t-1})}{TNA_{t-1}}\), where $TNA_t$ represents the fund’s total assets at the end of year $t$ and $r_t$ is its return over year $t$. Our sample spans 20 different investment categories defined by Morningstar.
3.2 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. In this paper we opt for the parametric estimation as in Aigner et al. (1977). To this end, we employ a function for US fund’s return that takes the form:

\[
R_{it} = f(N, Z) + v_{it} + u_{it}
\]

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 two inputs: expense ratio and turnover ratio and one output mean return. \(Z\) 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.

The above specification has been applied in the literature, but in the context of non-parametric analysis (DEA) where fund return is considered the key output variable (see Murthi et al. 1997 and Murthi and Choi, 2001, and Basso and Funari, 2001, Lozano and Gutierez, 2008). To this end, the present functional form of Equation (1) represents the underlying production function of a typical fund.
In addition, in the empirical estimations we fit a flexible translog specification that takes into account non-linearities. The translog function takes the form:

\[
\ln(R_i) = \alpha_0 + \sum_i a_i \ln N_i + \frac{1}{2} \sum_i \sum_j a_{ij} \ln N_i \ln N_j + \\
\sum_i \zeta_i \ln Z_i + \frac{1}{2} \sum_i \sum_j \zeta_{ij} \ln Z_i \ln Z_j + \frac{1}{2} \sum_i \sum_j \theta_{ij} \ln N_i \ln Z_j + \\
\sum_i \sum_j \mu_{it} + \frac{1}{2} \mu_{it}^2 + \sum_i \nu_{it} \ln N_i + \sum_i \rho_{it} \ln N_i + \\
+ \sum \phi_i D_i + u_i \pm v_i
\]

(2)

where as above 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.

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.

The stochastic frontier model of Equation (2) is estimated via a maximum likelihood procedure parameterized in terms of the variance parameters

\[
\sigma_e^2 = \sigma_u^2 + \sigma_v^2 \text{ and } \lambda = \frac{\sigma_u}{\sigma_e}.
\]

3.3 US funds efficiency scores

Table 2 presents the average efficiency scores of US funds over the period examined. We also report the evolution of mean efficiency score of our sample funds for the period of analysis.
Table 2: US funds’ efficiency over time.

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>0.582</td>
<td>0.107</td>
<td>0.867</td>
<td>0.116</td>
</tr>
<tr>
<td>2003</td>
<td>0.885</td>
<td>0.035</td>
<td>0.980</td>
<td>0.679</td>
</tr>
<tr>
<td>2004</td>
<td>0.789</td>
<td>0.052</td>
<td>0.921</td>
<td>0.554</td>
</tr>
<tr>
<td>2005</td>
<td>0.752</td>
<td>0.052</td>
<td>0.928</td>
<td>0.503</td>
</tr>
<tr>
<td>2006</td>
<td>0.820</td>
<td>0.048</td>
<td>0.910</td>
<td>0.512</td>
</tr>
<tr>
<td>2007</td>
<td>0.749</td>
<td>0.076</td>
<td>0.956</td>
<td>0.404</td>
</tr>
<tr>
<td>2008</td>
<td>0.394</td>
<td>0.092</td>
<td>0.656</td>
<td>0.078</td>
</tr>
<tr>
<td>2009</td>
<td>0.878</td>
<td>0.046</td>
<td>0.973</td>
<td>0.667</td>
</tr>
<tr>
<td>2010</td>
<td>0.828</td>
<td>0.045</td>
<td>0.920</td>
<td>0.410</td>
</tr>
<tr>
<td>Average</td>
<td>0.741</td>
<td>0.061</td>
<td>0.901</td>
<td>0.435</td>
</tr>
</tbody>
</table>

Note: estimations of US fund efficiency using a stochastic frontier analysis. The efficiency scores are derived from parameter estimates of a translog function specification. Source: Authors’ estimations.

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 74%, 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 light of the influential studies of Sharpe (1992) and Brown and Goetzmann (1997) that provide evidence of the importance of style on fund performance mean efficiency scores across different categories of funds are reported in Table 3. Preliminary evidence on a positive relation between asset size and efficiency obtains from the last column of Table 3 since funds that belong to 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.

Table 3: US funds’ efficiency per investment category

<table>
<thead>
<tr>
<th>Morningstar category</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communications</td>
<td>0.385</td>
<td>0.897</td>
<td>0.748</td>
<td>0.707</td>
<td>0.818</td>
<td>0.739</td>
<td>0.272</td>
<td>0.889</td>
<td>0.789</td>
<td>0.694</td>
</tr>
<tr>
<td>Consumer Discretionary</td>
<td>0.559</td>
<td>0.882</td>
<td>0.784</td>
<td>0.707</td>
<td>0.833</td>
<td>0.628</td>
<td>0.428</td>
<td>0.892</td>
<td>0.879</td>
<td>0.732</td>
</tr>
<tr>
<td>Consumer Staples</td>
<td>0.668</td>
<td>0.857</td>
<td>0.839</td>
<td>0.706</td>
<td>0.851</td>
<td>0.800</td>
<td>0.530</td>
<td>0.862</td>
<td>0.832</td>
<td>0.772</td>
</tr>
<tr>
<td>Equity Energy</td>
<td>0.580</td>
<td>0.787</td>
<td>0.863</td>
<td>0.900</td>
<td>0.700</td>
<td>0.869</td>
<td>0.208</td>
<td>0.869</td>
<td>0.689</td>
<td>0.718</td>
</tr>
<tr>
<td>Financial</td>
<td>0.709</td>
<td>0.897</td>
<td>0.818</td>
<td>0.757</td>
<td>0.863</td>
<td>0.626</td>
<td>0.389</td>
<td>0.840</td>
<td>0.830</td>
<td>0.748</td>
</tr>
<tr>
<td>Health</td>
<td>0.570</td>
<td>0.880</td>
<td>0.814</td>
<td>0.808</td>
<td>0.791</td>
<td>0.794</td>
<td>0.514</td>
<td>0.872</td>
<td>0.804</td>
<td>0.761</td>
</tr>
<tr>
<td>Industrials</td>
<td>0.555</td>
<td>0.885</td>
<td>0.816</td>
<td>0.769</td>
<td>0.838</td>
<td>0.751</td>
<td>0.379</td>
<td>0.838</td>
<td>0.882</td>
<td>0.746</td>
</tr>
<tr>
<td>Large Blend</td>
<td>0.637</td>
<td>0.874</td>
<td>0.802</td>
<td>0.768</td>
<td>0.850</td>
<td>0.769</td>
<td>0.441</td>
<td>0.877</td>
<td>0.823</td>
<td>0.760</td>
</tr>
<tr>
<td>Large Growth</td>
<td>0.574</td>
<td>0.879</td>
<td>0.786</td>
<td>0.767</td>
<td>0.818</td>
<td>0.804</td>
<td>0.416</td>
<td>0.883</td>
<td>0.827</td>
<td>0.750</td>
</tr>
<tr>
<td>Large Value</td>
<td>0.660</td>
<td>0.879</td>
<td>0.811</td>
<td>0.761</td>
<td>0.860</td>
<td>0.735</td>
<td>0.458</td>
<td>0.862</td>
<td>0.821</td>
<td>0.761</td>
</tr>
<tr>
<td>Mid-Cap Blend</td>
<td>0.621</td>
<td>0.891</td>
<td>0.806</td>
<td>0.755</td>
<td>0.806</td>
<td>0.700</td>
<td>0.406</td>
<td>0.877</td>
<td>0.827</td>
<td>0.743</td>
</tr>
<tr>
<td>Mid-Cap Growth</td>
<td>0.550</td>
<td>0.884</td>
<td>0.787</td>
<td>0.754</td>
<td>0.811</td>
<td>0.777</td>
<td>0.364</td>
<td>0.877</td>
<td>0.849</td>
<td>0.739</td>
</tr>
<tr>
<td>Mid-Cap Value</td>
<td>0.628</td>
<td>0.891</td>
<td>0.816</td>
<td>0.754</td>
<td>0.826</td>
<td>0.671</td>
<td>0.375</td>
<td>0.894</td>
<td>0.813</td>
<td>0.741</td>
</tr>
<tr>
<td>Miscellaneous Sectors</td>
<td>0.566</td>
<td>0.858</td>
<td>0.765</td>
<td>0.671</td>
<td>0.809</td>
<td>0.676</td>
<td>0.316</td>
<td>0.882</td>
<td>0.850</td>
<td>0.710</td>
</tr>
<tr>
<td>Small Blend</td>
<td>0.618</td>
<td>0.901</td>
<td>0.799</td>
<td>0.734</td>
<td>0.816</td>
<td>0.684</td>
<td>0.380</td>
<td>0.877</td>
<td>0.846</td>
<td>0.739</td>
</tr>
<tr>
<td>Small Growth</td>
<td>0.531</td>
<td>0.911</td>
<td>0.760</td>
<td>0.725</td>
<td>0.788</td>
<td>0.733</td>
<td>0.344</td>
<td>0.881</td>
<td>0.842</td>
<td>0.724</td>
</tr>
<tr>
<td>Small Value</td>
<td>0.638</td>
<td>0.897</td>
<td>0.801</td>
<td>0.709</td>
<td>0.808</td>
<td>0.647</td>
<td>0.401</td>
<td>0.871</td>
<td>0.846</td>
<td>0.735</td>
</tr>
<tr>
<td>Technology</td>
<td>0.343</td>
<td>0.917</td>
<td>0.668</td>
<td>0.665</td>
<td>0.753</td>
<td>0.742</td>
<td>0.245</td>
<td>0.929</td>
<td>0.792</td>
<td>0.673</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.515</td>
<td>0.853</td>
<td>0.853</td>
<td>0.770</td>
<td>0.910</td>
<td>0.809</td>
<td>0.414</td>
<td>0.789</td>
<td>0.835</td>
<td>0.750</td>
</tr>
<tr>
<td>Natural Resources</td>
<td>0.611</td>
<td>0.853</td>
<td>0.774</td>
<td>0.823</td>
<td>0.786</td>
<td>0.805</td>
<td>0.181</td>
<td>0.890</td>
<td>0.787</td>
<td>0.723</td>
</tr>
</tbody>
</table>

No. of observations          | 366   | 396   | 439   | 453   | 472   | 489   | 504   | 507   | 507   |

Note: estimations of US fund efficiency using a stochastic frontier analysis. The efficiency scores are derived from parameter estimates of a translog function specification.
Source: Authors’ estimations.

The above efficiency scores are derived from a stochastic frontier analysis and to the best of our knowledge are reported for the first time in the literature, as previous funds efficiency scores have been based on non-parametric methods. Murthi et al. (1997) were the first to apply the DEA method to fund performance, whilst Murthi and Choi (2001) followed similar methodology. Efficiency scores are similar to ours, though they are not entirely comparable due to differences in the sample. Moreover, Sengupta (2003) focus on portfolios performance and reported that 70% of the examined portfolios were relatively efficient, but with significant deviations depending on the category of funds. Other studies focusing on US funds include Anderson et al. (2004) who examined the efficiency of real estate funds. Gregoriou (2003) and Gregoriou et al. (2005) focus on the hedge fund, whilst Kerstens et al
(2011) have employed a large database of US and European mutual funds. In a recent paper Premachandra et al. (2012) opt for a semi-parametric two-stage DEA model that decomposes the overall efficiency of a decision-making unit into two components and demonstrated its applicability by assessing the relative performance of 66 large mutual fund families in the US over the period 1993–2008.


3.4 Revealing the underlying dynamics: a Panel-Var model

Having derived US funds performance we turn next our attention to its main underlying determinants whilst we tackle issues related to underlying dynamics and endogeneity that have not been addressed in the literature. To this end, 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 autoregression (VAR) model for a panel data set. The VAR specification fits the purpose of this paper, given the absence of

---

1 An important drawback of estimating causal relationships between efficiency and its main determinants that have not been dealt in the literature is the resulted endogeneity bias equation (6) due to use a 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 able to resolve the causality among them.
concrete 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\(^2\):

\[
X_{it} = \mu_i + \Phi X_{it-1} + e_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T. \tag{3}
\]

, where \(X_{it}\) is a vector, for example in this particular case, of four random variables. Namely, \(X_{it}\) is a vector could include the efficiency (\(EFF_{it}\)), flows (\(flow_{it}\)), assets (\(assets_{it}\)) and most importantly (\(risk_{it}\)). Thus, \(\Phi\) is an 4x4 matrix of coefficients, \(\mu_i\) is a vector of \(m\) individual effects and \(e_{it}\) 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 risk or deviation of 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 (see Lütkepohl, H., 2005) allows all variables within a system of equations to enter as endogenous, whilst also the short run dynamic relationships could be revealed. Essentially, the VAR would allow us to explore the underlying causal relationships between our main variables: efficiency 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 impact upon, for example, fund size or would it be the case of vice versa, but also a bi-directional one.

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

---

\(^2\) For purposes of simplicity of the exposition we present a first order 4x4 panel-VAR.
must be orthogonal. We
Under the endogeneity assumption the residuals will be correlated and therefore
estimation:
the panel-VAR

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 \(e_i, e_2, e_3 \) and \(e_4 \) from the panel-VAR estimation:

\[
\begin{align*}
EFF_{it} &= \gamma_{10} + \sum_{j=1}^{J} \beta_{11} e_{it-j} + \sum_{j=1}^{J} \beta_{12} e_{2it-j} + \sum_{j=1}^{J} \beta_{13} e_{3it-j} + \sum_{j=1}^{J} \beta_{14} e_{4it-j} + \sum_{j=1}^{J} \beta_{15} e_{5it-j} \\
flow_{it} &= \gamma_{20} + \sum_{j=1}^{J} \beta_{21} e_{it-j} + \sum_{j=1}^{J} \beta_{22} e_{2it-j} + \sum_{j=1}^{J} \beta_{23} e_{3it-j} + \sum_{j=1}^{J} \beta_{24} e_{4it-j} + \sum_{j=1}^{J} \beta_{25} e_{5it-j} \\
assets_{it} &= \gamma_{30} + \sum_{j=1}^{J} \beta_{31} e_{it-j} + \sum_{j=1}^{J} \beta_{32} e_{2it-j} + \sum_{j=1}^{J} \beta_{33} e_{3it-j} + \sum_{j=1}^{J} \beta_{34} e_{4it-j} + \sum_{j=1}^{J} \beta_{35} e_{5it-j} \\
risk_{it} &= \gamma_{40} + \sum_{j=1}^{J} \beta_{41} e_{it-j} + \sum_{j=1}^{J} \beta_{42} e_{2it-j} + \sum_{j=1}^{J} \beta_{43} e_{3it-j} + \sum_{j=1}^{J} \beta_{44} e_{4it-j} + \sum_{j=1}^{J} \beta_{45} e_{5it-j}
\end{align*}
\]

Under the endogeneity assumption the residuals will be correlated and therefore the coefficients of the MA representation are not interpretable. As a result, the residuals must be orthogonal. 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:

\[
\begin{align*}
EFF_{it} &= \delta_{10} + \sum_{j=1}^{J} \beta_{11} e_{it-j} + \sum_{j=1}^{J} \beta_{12} e_{2it-j} + \sum_{j=1}^{J} \beta_{13} e_{3it-j} + \sum_{j=1}^{J} \beta_{14} e_{4it-j} + \sum_{j=1}^{J} \beta_{15} e_{5it-j} \\
flow_{it} &= \delta_{20} + \sum_{j=1}^{J} \beta_{21} e_{it-j} + \sum_{j=1}^{J} \beta_{22} e_{2it-j} + \sum_{j=1}^{J} \beta_{23} e_{3it-j} + \sum_{j=1}^{J} \beta_{24} e_{4it-j} + \sum_{j=1}^{J} \beta_{25} e_{5it-j} \\
assets_{it} &= \delta_{30} + \sum_{j=1}^{J} \beta_{31} e_{it-j} + \sum_{j=1}^{J} \beta_{32} e_{2it-j} + \sum_{j=1}^{J} \beta_{33} e_{3it-j} + \sum_{j=1}^{J} \beta_{34} e_{4it-j} + \sum_{j=1}^{J} \beta_{35} e_{5it-j} \\
risk_{it} &= \delta_{40} + \sum_{j=1}^{J} \beta_{41} e_{it-j} + \sum_{j=1}^{J} \beta_{42} e_{2it-j} + \sum_{j=1}^{J} \beta_{43} e_{3it-j} + \sum_{j=1}^{J} \beta_{44} e_{4it-j} + \sum_{j=1}^{J} \beta_{45} e_{5it-j}
\end{align*}
\]
with

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

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

\[
\begin{pmatrix}
\text{Cov}(e_{1it}, e_{1it}) & \text{Cov}(e_{1it}, e_{2it}) & \text{Cov}(e_{1it}, e_{3it}) & \text{Cov}(e_{1it}, e_{4it}) \\
\text{Cov}(e_{2it}, e_{1it}) & \text{Cov}(e_{2it}, e_{2it}) & \text{Cov}(e_{2it}, e_{3it}) & \text{Cov}(e_{2it}, e_{4it}) \\
\text{Cov}(e_{3it}, e_{1it}) & \text{Cov}(e_{3it}, e_{2it}) & \text{Cov}(e_{3it}, e_{3it}) & \text{Cov}(e_{3it}, e_{4it}) \\
\text{Cov}(e_{4it}, e_{1it}) & \text{Cov}(e_{4it}, e_{2it}) & \text{Cov}(e_{4it}, e_{3it}) & \text{Cov}(e_{4it}, e_{4it})
\end{pmatrix}
= PP^{-1}
\] (8)

Using the above panel-VAR individual heterogeneity in the levels is ensured by introducing fixed effects in the model, denoted \( \mu_i \). 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).

4. Empirical Results of panel-VAR.

4.2 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.
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. 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. Our findings provide evidence in favor of Hypothesis 1. This result is of some importance as it reveals the dynamic response of funds performance to risk. Focusing on a static framework could bias results. Huang et al (2011) in a static long run model show that funds that increase their risk impede their performance.

**Figure 1: Impulse Response Function; the impact of risk.**

<table>
<thead>
<tr>
<th>Impulse-responses for 1 lag VAR of eff assets dmr risk</th>
<th>Errors are 5% on each side generated by Monte-Carlo with 10 reps</th>
</tr>
</thead>
<tbody>
<tr>
<td>response of eff to eff shock</td>
<td>response of eff to assets shock</td>
</tr>
<tr>
<td>response of eff to dmr shock</td>
<td>response of eff to risk shock</td>
</tr>
<tr>
<td>response of assets to eff shock</td>
<td>response of assets to assets shock</td>
</tr>
<tr>
<td>response of assets to dmr shock</td>
<td>response of assets to risk shock</td>
</tr>
<tr>
<td>response of dmr to eff shock</td>
<td>response of dmr to assets shock</td>
</tr>
<tr>
<td>response of dmr to dmr shock</td>
<td>response of dmr to risk shock</td>
</tr>
<tr>
<td>response of risk to eff shock</td>
<td>response of risk to assets shock</td>
</tr>
<tr>
<td>response of risk to dmr shock</td>
<td>response of risk to risk shock</td>
</tr>
</tbody>
</table>

Source: Authors’ estimations.
Note: eff: funds’ SFA efficiency score, essets: funds’ total, end-year assets, dmr: funds’ deviation from median return, risk: funds’ annualized standard deviation of returns.
Each diagram shows the responses of a variable to its own shock of one standard deviation and shocks of one standard deviation of the rest of the variables.
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 that is Hypothesis 2, we find evidence against this hypothesis and in line with Huang et al (2011). This result is quite powerful and reveals that funds by improving their performance achieve subsequently lower levels of risk through effective risk diversification. However, it is interesting to note that during the first two years 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 and the science of covariance.

There is an extended literature that focuses also on risk (see Sengupta, 2003, Anderson et al., 2004, Gregoriou, 2003, Gregoriou et al., 2005, Basso and Funari, 2001, yet it 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.

Table 4 reports variance decompositions (VDCs). Moreover, 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, 17.3% of the forecast error variance of risk is explained by efficiency, whilst 11.6% 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 (Brown, Harlow and Starks 1996, Chevallier and Ellison 1997) may be motivated either by agency issues or by stock selection/timing abilities of fund managers. 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.

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Eff</strong></td>
<td><strong>Assets</strong></td>
<td><strong>DMR</strong></td>
<td><strong>Risk</strong></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.80340</td>
<td>0.00387</td>
<td>0.00016</td>
<td>0.19257</td>
</tr>
<tr>
<td>10</td>
<td>0.18181</td>
<td>0.51157</td>
<td>0.00040</td>
<td>0.30622</td>
</tr>
<tr>
<td>10</td>
<td>0.14784</td>
<td>0.00663</td>
<td>0.84408</td>
<td>0.00145</td>
</tr>
<tr>
<td>10</td>
<td>0.21842</td>
<td>0.04192</td>
<td>0.00038</td>
<td>0.73928</td>
</tr>
<tr>
<td>20</td>
<td>0.31258</td>
<td>0.06852</td>
<td>0.00044</td>
<td>0.61846</td>
</tr>
<tr>
<td>20</td>
<td>0.22812</td>
<td>0.05156</td>
<td>0.00024</td>
<td>0.72009</td>
</tr>
<tr>
<td>20</td>
<td>0.14620</td>
<td>0.01841</td>
<td>0.83338</td>
<td>0.00200</td>
</tr>
<tr>
<td>20</td>
<td>0.17392</td>
<td>0.11638</td>
<td>0.00059</td>
<td>0.70912</td>
</tr>
</tbody>
</table>

Source: Authors’ estimations.
Note: Eff: funds’ SFA efficiency score, Assets: funds’ total, end-year assets, DMR: Funds’ deviation from median return, Risk: Funds’ annualized standard deviation of returns.

We opt for a simulation of 10 and 20 periods ahead, noted by ‘s’.
The table reports the forecast error variance decomposition of each variable in the panel-VAR.

4.2 Does asset size, deviation from median return and Morningstar rating matter?

Figure 2, first line of diagrams, reports the response of efficiency to shocks of one plus/minus standard deviation in assets; funds’ deviation from median return; and lastly Morningstar 3-year star rating. Figure 1 report 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 ratting and fund performance.

**Figure 2: Impulse Response Functions: fund efficiency, assets, deviation from return and Morning 3-year rating.**

Source: Authors’ estimations.
Note: eff: funds’ SFA efficiency score, assets: funds’ total, end-year assets, dmr: funds’ deviation from median return, rate: Morningstar 3-year star rating.
Each diagram shows the responses of a variable to its own shock of one standard deviation and shocks of one standard deviation of the rest of the variables.

Contrary to the findings of Annaert et al (2003) for the whole sample we document negative relationship between fund efficiency and asset size, see first row, second sub-diagram from the right. That is to say the response of efficiency on one standard deviation shock in assets is negative, but only in the very short run as it converges to zero thereafter. This finding provides some evidence in favor of Hypothesis 2 and is consistent with previous studies see inter alia Chen et al (2004) documenting the existence of a negative effect of assets on funds’ performance.
From the first row of Figure 2 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 some marked 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. 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.

Table 5: Variance Decomposition; the impact of Morningstar rating.

<table>
<thead>
<tr>
<th></th>
<th>s</th>
<th>eff</th>
<th>assets</th>
<th>dmr</th>
<th>rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>eff</td>
<td>10</td>
<td>0.94430</td>
<td>0.00162</td>
<td>0.01586</td>
<td>0.03821</td>
</tr>
<tr>
<td>assets</td>
<td>10</td>
<td>0.04649</td>
<td>0.84009</td>
<td>0.00768</td>
<td>0.10574</td>
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<tr>
<td>dmr</td>
<td>10</td>
<td>0.16702</td>
<td>0.00368</td>
<td>0.82554</td>
<td>0.00376</td>
</tr>
<tr>
<td>rate</td>
<td>10</td>
<td>0.04871</td>
<td>0.05363</td>
<td>0.12655</td>
<td>0.77111</td>
</tr>
<tr>
<td>eff</td>
<td>20</td>
<td>0.94428</td>
<td>0.00164</td>
<td>0.01587</td>
<td>0.03822</td>
</tr>
<tr>
<td>assets</td>
<td>20</td>
<td>0.04943</td>
<td>0.81359</td>
<td>0.01009</td>
<td>0.12689</td>
</tr>
<tr>
<td>dmr</td>
<td>20</td>
<td>0.16685</td>
<td>0.00483</td>
<td>0.82433</td>
<td>0.00399</td>
</tr>
<tr>
<td>rate</td>
<td>20</td>
<td>0.04873</td>
<td>0.05504</td>
<td>0.12632</td>
<td>0.76991</td>
</tr>
</tbody>
</table>

Source: Authors’ estimations.
Note: eff: funds’ SFA efficiency score, assets: funds’ total, end-year assets, dmr: Funds’ deviation from median return, Rate: Morningstar 3-year star rating.
We opt for a simulation of 10 and 20 periods ahead, noted by ‘s’.
The table reports the forecast error variance decomposition of each variable in the panel-VAR.

4.3 Does the 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 our best of knowledge, no study before has explicitly addressed the relationship between fund flows and efficiency under this framework. It is also worth noting that the panel-VAR dimension in this instance is 5x5.

From the first row, second diagram from the left, of Figure 3 we observe 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 (row 2, first left hand side, Figure 3) 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.

Figure 3: Impulse Response Function; the impact of flows

Errors are 5% on each side generated by Monte-Carlo with 10 reps

Source: Authors’ estimations.
Note: eff: funds’ SFA efficiency score, flow: funds’ percentage inflow/outflow; assets: funds’ total, end-year assets, dmr: funds’ deviation from median return, risk: funds’ annualized standard deviation of returns. Each diagram shows the responses of a variable to its own shock of one standard deviation and shocks of one standard deviation of the rest of the variables.

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.
Table 6: Variance Decomposition; the impact of flows.

<table>
<thead>
<tr>
<th></th>
<th>s</th>
<th>Eff</th>
<th>Flow</th>
<th>Assets</th>
<th>DMR</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Eff</strong></td>
<td>10</td>
<td>0.79679</td>
<td>0.00002</td>
<td>0.00576</td>
<td>0.00515</td>
<td>0.19228</td>
</tr>
<tr>
<td><strong>Flow</strong></td>
<td>10</td>
<td>0.00116</td>
<td>0.99843</td>
<td>0.00016</td>
<td>0.00015</td>
<td>0.00010</td>
</tr>
<tr>
<td><strong>Assets</strong></td>
<td>10</td>
<td>0.15345</td>
<td>0.00002</td>
<td>0.75421</td>
<td>0.00166</td>
<td>0.09067</td>
</tr>
<tr>
<td><strong>DMR</strong></td>
<td>10</td>
<td>0.11505</td>
<td>0.00003</td>
<td>0.00125</td>
<td>0.87543</td>
<td>0.00825</td>
</tr>
<tr>
<td><strong>Risk</strong></td>
<td>10</td>
<td>0.35887</td>
<td>0.00007</td>
<td>0.02645</td>
<td>0.01685</td>
<td>0.59776</td>
</tr>
<tr>
<td><strong>Eff</strong></td>
<td>20</td>
<td>0.63860</td>
<td>0.00002</td>
<td>0.02922</td>
<td>0.00905</td>
<td>0.32311</td>
</tr>
<tr>
<td><strong>Flow</strong></td>
<td>20</td>
<td>0.00117</td>
<td>0.99838</td>
<td>0.00019</td>
<td>0.00015</td>
<td>0.00012</td>
</tr>
<tr>
<td><strong>Assets</strong></td>
<td>20</td>
<td>0.23294</td>
<td>0.00002</td>
<td>0.47873</td>
<td>0.00697</td>
<td>0.28133</td>
</tr>
<tr>
<td><strong>DMR</strong></td>
<td>20</td>
<td>0.11801</td>
<td>0.00003</td>
<td>0.00278</td>
<td>0.86054</td>
<td>0.01864</td>
</tr>
<tr>
<td><strong>Risk</strong></td>
<td>20</td>
<td>0.31825</td>
<td>0.00005</td>
<td>0.06165</td>
<td>0.01725</td>
<td>0.60279</td>
</tr>
</tbody>
</table>

Source: Authors’ estimations.
Note: eff: funds’ SFA efficiency score, assets: funds’ total, end-year assets, flow: funds’ percentage inflow/outflow, dmr: Funds’ deviation from median return, risk: funds’ annualized standard deviation of returns.
We opt for a simulation of 10 and 20 periods ahead, noted by ‘s’.
The table reports the forecast error variance decomposition of each variable in the panel-VAR.

4.4 Robustness analysis; a general panel-VAR

As part of testing the robustness of our results we opt in this section a general panel-VAR specification with dimensions 6x6.

To this end, Figure 4 reports the IRFs resulting from a panel-VAR formulation incorporating all variables of interest. The results are in line with the ones reported above and provide further evidence favoring the importance of risk in explaining the variation of funds efficiency. Estimated IRFs are consistent with Hypothesis 3 and 4.
Similarly, Table 7 reports 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%. 

Source: Authors’ estimations. 
Note: Eff: funds’ SFA efficiency score, Assets: Funds’ total, end-year assets, Flow: Funds’ percentage inflow/outflow, DMR: Funds’ deviation from median return, Risk: Funds’ annualized standard deviation of returns 
Each diagram shows the responses of a variable to its own shock of one standard deviation and shocks of one standard deviation of the rest of the variables.
Table 7: Variance Decomposition

<table>
<thead>
<tr>
<th></th>
<th>s</th>
<th>Eff</th>
<th>Flow</th>
<th>Assets</th>
<th>DMR</th>
<th>Risk</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eff</td>
<td>10</td>
<td>0.63105</td>
<td>0.00000</td>
<td>0.00150</td>
<td>0.03781</td>
<td>0.28787</td>
<td>0.04177</td>
</tr>
<tr>
<td>Flow</td>
<td>10</td>
<td>0.00190</td>
<td>0.99602</td>
<td>0.00001</td>
<td>0.00030</td>
<td>0.00155</td>
<td>0.00021</td>
</tr>
<tr>
<td>Assets</td>
<td>10</td>
<td>0.14294</td>
<td>0.00005</td>
<td>0.71600</td>
<td>0.01021</td>
<td>0.12145</td>
<td>0.00934</td>
</tr>
<tr>
<td>DMR</td>
<td>10</td>
<td>0.11992</td>
<td>0.00004</td>
<td>0.00092</td>
<td>0.84833</td>
<td>0.02464</td>
<td>0.00616</td>
</tr>
<tr>
<td>Risk</td>
<td>10</td>
<td>0.23519</td>
<td>0.00002</td>
<td>0.00403</td>
<td>0.07725</td>
<td>0.60367</td>
<td>0.07984</td>
</tr>
<tr>
<td>Rating</td>
<td>10</td>
<td>0.09038</td>
<td>0.00041</td>
<td>0.01815</td>
<td>0.15182</td>
<td>0.12802</td>
<td>0.61122</td>
</tr>
<tr>
<td>Eff</td>
<td>20</td>
<td>0.38995</td>
<td>0.00000</td>
<td>0.00710</td>
<td>0.06662</td>
<td>0.46321</td>
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</tr>
<tr>
<td>Flow</td>
<td>20</td>
<td>0.00323</td>
<td>0.98915</td>
<td>0.00010</td>
<td>0.00092</td>
<td>0.00571</td>
<td>0.00089</td>
</tr>
<tr>
<td>Assets</td>
<td>20</td>
<td>0.19090</td>
<td>0.00002</td>
<td>0.33294</td>
<td>0.04843</td>
<td>0.37688</td>
<td>0.05082</td>
</tr>
<tr>
<td>DMR</td>
<td>20</td>
<td>0.12661</td>
<td>0.00003</td>
<td>0.00201</td>
<td>0.77973</td>
<td>0.07708</td>
<td>0.01454</td>
</tr>
<tr>
<td>Risk</td>
<td>20</td>
<td>0.20609</td>
<td>0.00001</td>
<td>0.01041</td>
<td>0.08628</td>
<td>0.60407</td>
<td>0.09314</td>
</tr>
<tr>
<td>Rating</td>
<td>20</td>
<td>0.13414</td>
<td>0.00025</td>
<td>0.01345</td>
<td>0.12732</td>
<td>0.31266</td>
<td>0.41217</td>
</tr>
</tbody>
</table>

Source: Authors’ estimations.
We opt for a simulation of 10 and 20 periods ahead, noted by ‘s’.
The table reports the forecast error variance decomposition of each variable in the panel-VAR.

4.5 IRFs and VDCs for funds grouped according to size

Asset size remains a fundamental issue in the process of professional money management. 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.
Figures 5 to 8 present IRFs for funds that belong to the various asset groups while Table 8 summarizes the respective VDCs. From the first row of Figure 5 we infer that the effect of one standard deviation shock of risk on funds’ efficiency is positive and relatively large in magnitude for smaller funds. 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 it is negative implying a reverse feedback. This means that a shock that would increase fund’s efficiency reduces portfolio risk.

**Figure 5: Impulse Response Function, Small Funds**

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 Chevallier and Ellison (1997) who argue that funds flow-
performance relationship could serve as an implicit incentive scheme for management companies to increase or decrease riskiness with the aim of attracting new money. So, in light of the well-documented relationship between flows and risk we see from line 2, the diagram on the right hand side, of Figure 5 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 (see Figures 6-8) we observe a negative response of flows to risk. This means that an increase in funds’ total riskiness reduces flows. Thus, funds flows respond to risk (Chevallier and Ellison 1997) but not in unique way, as the size of funds is detrimental.

**Figure 6: Impulse Response Function, Small- medium funds**

Impulse-responses for 1 lag VAR of eff flow dmr risk

Errors are 5% on each side generated by Monte-Carlo with 500 reps

Source: Authors’ estimations.
Note: Eff: funds’ SFA efficiency score, Flow: Funds’ percentage inflow/outflow, DMR: Funds’ deviation from median return, Risk: Funds’ annualized standard deviation of returns.
Each diagram shows the responses of a variable to its own shock of one standard deviation and shocks of one standard deviation of the rest of the variables.
Figure 7: Impulse Response Function, medium large funds

Impulse-responses for 1 lag VAR of eff flow dmr risk

<table>
<thead>
<tr>
<th>Response</th>
<th>5% (p 5)</th>
<th>95% (p 95)</th>
</tr>
</thead>
<tbody>
<tr>
<td>response of eff to eff shock</td>
<td>-0.0434</td>
<td>0.1788</td>
</tr>
<tr>
<td>response of eff to flow shock</td>
<td>-0.0072</td>
<td>0.0020</td>
</tr>
<tr>
<td>response of eff to dmr shock</td>
<td>-0.0100</td>
<td>0.0121</td>
</tr>
<tr>
<td>response of eff to risk shock</td>
<td>0.0000</td>
<td>0.0644</td>
</tr>
<tr>
<td>response of flow to eff shock</td>
<td>-0.0094</td>
<td>0.0994</td>
</tr>
<tr>
<td>response of flow to flow shock</td>
<td>-0.0116</td>
<td>0.4266</td>
</tr>
<tr>
<td>response of flow to dmr shock</td>
<td>-0.0279</td>
<td>0.0215</td>
</tr>
<tr>
<td>response of flow to risk shock</td>
<td>-0.1405</td>
<td>0.0119</td>
</tr>
<tr>
<td>response of dmr to eff shock</td>
<td>-0.0168</td>
<td>0.0374</td>
</tr>
<tr>
<td>response of dmr to flow shock</td>
<td>-0.0064</td>
<td>0.0373</td>
</tr>
<tr>
<td>response of dmr to dmr shock</td>
<td>-0.0141</td>
<td>0.0943</td>
</tr>
<tr>
<td>response of dmr to risk shock</td>
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<td>1.8676</td>
</tr>
<tr>
<td>response of risk to eff shock</td>
<td>-8.5455</td>
<td>0.0000</td>
</tr>
<tr>
<td>response of risk to flow shock</td>
<td>-0.9705</td>
<td>0.2529</td>
</tr>
<tr>
<td>response of risk to dmr shock</td>
<td>0.0000</td>
<td>1.8676</td>
</tr>
<tr>
<td>response of risk to risk shock</td>
<td>0.0000</td>
<td>13.0984</td>
</tr>
</tbody>
</table>

Errors are 5% on each side generated by Monte-Carlo with 500 reps

Source: Authors’ estimations.
Note: Eff: funds’ SFA efficiency score, Assets: Funds’ total, end-year assets, Flow: Funds’ percentage inflow/outflow, DMR: Funds’ deviation from median return, Risk: Funds’ annualized standard deviation of returns.
Source: Authors’ estimations.
From the above it is evident that efficiency and risk are strongly related and consistent with this finding is the behaviour of VDCs for the two variables reported in Table 8. 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 risk whereas 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. If we examine the dependence between efficiency and risk we will observe that is more pronounced in the first and third asset quartile whereas in the rest quartile appears weakened. In particular, among largest funds a shock in the risk accounts for only 8% of the variation in efficiency levels compared to 40% in the smallest funds.
Table 8: VDCs for funds sub-groups.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Panel B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Small funds</strong></td>
<td><strong>Small-medium funds</strong></td>
</tr>
<tr>
<td>Eff</td>
<td>Flow</td>
</tr>
<tr>
<td>Eff</td>
<td>0.57279</td>
</tr>
<tr>
<td>Flow</td>
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<tr>
<td>DMR</td>
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</tr>
<tr>
<td>Risk</td>
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</tr>
<tr>
<td>Eff</td>
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</tr>
<tr>
<td>Flow</td>
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<tr>
<td>DMR</td>
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</tr>
<tr>
<td>Risk</td>
<td>0.25354</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C</th>
<th>Panel D</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Medium-large funds</strong></td>
<td><strong>Large funds</strong></td>
</tr>
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<td>Eff</td>
<td>Flow</td>
</tr>
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</tr>
<tr>
<td>Risk</td>
<td>0.34831</td>
</tr>
</tbody>
</table>

Source: Authors’ estimations.
Note: Eff: funds’ SFA efficiency score, Flow: Funds’ percentage inflow/outflow, Assets: Funds’ total, end-year assets, DMR: Funds’ deviation from median return, Risk: Funds’ annualized standard deviation of returns.
We opt for a simulation of 10 and 20 periods ahead, noted by ‘s’.
The table reports the forecast error variance decomposition of each variable in the panel-VAR.

5. CONCLUSIONS

This paper reveals for the first time US no-load mutual fund industry performance using stochastic frontier analysis. We also examine the relationship between efficiency and some key covariates, notably risk. Our results show substantial heterogeneity in efficiency over time. In addition funds efficiency varies across different funds based on size and investment style.
The panel VAR analysis show the response of funds performance to a shock in risk is positive. This result is consistent with the Hypothesis 1 that funds taking large bets are more likely to end-up with a superior performance. The reverse causal relationship cannot be excluded although the empirical evidence is not as strong. Our results offer evidence that risk-taking behaviour could be associated with high levels of efficiency. In addition, it is worth noting that the dependence between efficiency and risk is more pronounced among smallest funds. In particular, among smaller funds we found that 40% of the variation in efficiency is attributed to a shock in risk. Among the rest of the employed variables asset size, and contrary to the findings of Annaert et al (2003), affects adversely fund performance. This finding is consistent with a lack of economies of scale in the US no-load equity funds during the analyzed period.

The reported results have some implications for investors, professional managers and regulators. The revealed relationships could be part of investors’ information set when select a fund whereas fund managers could benefit from the knowledge of what enhances their portfolio performance. Finally, regulators and supervisory authorities whose task is to safeguard a secure and well-functioning financial system may take into account that risk improves fund performance and this may convey valuable information regarding managers’ incentives.
References


Cullen G., Gasbarro D., Monroe G.S., Zumwalt J. K., 2012, Changes to mutual fund risk: Intentional or mean reverting?.Journal of Banking & Finance 36, 112-120


