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EFFICIENCY OF MUTUAL FUND COMPANIES: EVIDENCE FROM AN INNOVATIVE NETWORK SBM APPROACH

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ABSTRACT

This paper is the first DEA evaluation of the efficiency of a sample of mutual fund companies in a large Euro fund industry. Our novel network model links the efficiency of the core competency activities of a mutual fund company with the efficiency of its operational management function. Our results highlight the important networking effects at the marketing stage and question the prime role of the portfolio management skills in the overall efficiency of a mutual fund company. The application of non-parametric tests also provides a significant persistence phenomenon in the efficiency rankings obtained by our network model. Finally, the application of SBM Variation III (Tone, 2010) to our network complex allows us to find a large number of globally inefficient but locally efficient companies with reference to competitors with similar resources.

JEL CLASSIFICATION: G10, G20
KEYWORDS: Mutual fund companies; Network DEA; Portfolio Management Efficiency; Marketing Efficiency; Operational Management Efficiency.

1. INTRODUCTION

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1. INTRODUCTION

Over the last decades, the landscape for the financial sector has been subject to many structural changes which have transformed the overall competition map of the financial industry. This process has entailed changes in the efficiency of the financial institutions and in their diverse business units. Along with this challenging period, there has been an extensive literature of efficiency in financial institutions, basically focused on banking and insurance.

Data Envelopment Analysis (DEA) has been one of the most popular frontier methods in this literature. The lack of DEA requirements to any functional form between the inputs and outputs used by this multi-dimensional method has made this non-parametric methodology quite common for assessing relative efficiency of financial institutions. Berger and Humphrey (1997), Berger (2007), Fethi and Pasiouras (2010) and Paradi and Zhu (2013) are some relevant survey papers which review DEA applications for the last decades in the banking industry across different techniques and countries.

However, while an extensive DEA analysis has been devoted to banking and insurance, scarce research has studied the efficiency of mutual fund companies. On the one hand, we find an increasing DEA research on individual mutual fund performance since the original contribution of Murthi et al. (1997)[1], but on the other hand only Zhao and Yue (2010) and Premachandra et al. (2012) use DEA to assess the relative efficiency of a sample of mutual fund companies in China and USA respectively.[2]

[1] These new DEA measures which assess relative efficiency of individual funds with multiple inputs and multiple outputs may be considered as an alternative approach to traditional performance models which assume functional relationships between return and risk (e.g. Treynor 1965; Sharpe, 1966; and Jensen, 1968). Lamb and Tee (2012) discuss possible shortcomings of these DEA techniques to evaluate performance of individual investment funds and provide further research topics in this field.

[2] Despite the importance of fund families for investors' decisions (e.g., Kempf and Ruenzi, 2008; Jank and Wedow, 2013), the literature review on other methodologies different from DEA techniques finds that research on the performance at individual fund level is also much more extended than at fund family level.

This scarce DEA literature in mutual fund companies is probably explained by the difficulty to identify specific models and variables for these institutions without replicating merely the well-known banking and insurance models. Furthermore, the complex interaction between the business unit decisions made by the mutual fund companies requires a more sophisticated approach than the mere aggregation of the variables used in the evaluation of the individual mutual funds within the same company. Some of these decisions are related to the number of mutual funds managed by the company, the fund types supplied by the company to the market, the outsourcing of management and selling funds, etc., which will result in pretty different strategies and efficiency consequences for the fund companies.

Our study fills this gap in the literature by analysing for the first time a major Euro mutual fund industry. Based on the governance structure addressed by Berkowitz and Qiu (2003), we assess the relative efficiency of a complete sample of Spanish mutual fund companies. We propose an innovative network structure where the core competency of a mutual fund company is divided into a portfolio management stage and a marketing management stage. Zhao and Yue (2010) also define a similar core competency but they omit any fluent interaction existing between both management stages. In our model, the mutual fund company is also responsible to its shareholders and therefore, its operational management efficiency is driven by the interacting efficiency between both core competency activities and the final results of the company. That is, the mutual fund company delegates responsibility for managing and selling their mutual funds to either external or internal agents to enlarge the total money under its management and thereby obtaining higher incomes. This core competency approach is also present in the operational management function proposed by Premachandra et al. (2012), where the company attempts to obtain its highest net asset value with the least amount of expenses associated to portfolio management and selling fund shares. However, this function does not detail which part of the net asset value of the company is obtained by the portfolio management activities and which part is gained due to the marketing and distribution of mutual funds.

Based on a network DEA structure proposed by Tone and Tsutsui (2009), our model includes a set of intermediate variables which details the link between the portfolio management efficiency and the marketing efficiency of the company as major drivers of the operational efficiency obtained by the company shareholders. Considering that investors make their mutual fund decisions based on an asymmetric perception of prior performance (e.g. Ippolito, 1992; Sirri and Tufano, 1998; Del Guercio and Tkac, 2002; Ferreira et al., 2012), our model captures how the portfolio management outputs may be considered as intermediate inputs in the selling process of mutual funds. This link between the portfolio management efficiency and the marketing efficiency, and the link between both core competency activities and the operational efficiency of the company should highlight the interest in our results of some relevant company stakeholders such as the company shareholders, the mutual fund unitholders, the mutual fund managers and the mutual fund sellers.

However, the important market concentration of the Spanish fund market could be a challenging feature to get an appropriate evaluation of the efficiency for this industry. Traditional DEA techniques may fail to identify the appropriate 'best practice' competitors when there are striking differences between their management resources and characteristics. That is, when the reference frontier is formed by mutual fund companies with extremely different characteristics than the target company to be analysed. This limitation could question the accuracy of DEA results in those industries with assorted competitors, such as the Spanish mutual fund industry. The selection of homogeneous competitors by dropping from the sample those fund companies which do not fulfil some requirements[3] could affect the accuracy of the results because the DEA scores are obtained relative to the other companies in the sample. That is, the exclusion from the sample of relevant companies in terms of efficiency could distort the reference frontier and affect the empirical results. We do not exclude any fund company due to minimum size requirement. Furthermore, our study overcomes this sample bias by using the barely explored variations of the well-known slacks-based measure (SBM) proposed by Tone (2001). The original SBM is an unoriented model which works with excess inputs and output shortfalls simultaneously and allows its application under constant (CRS) and variable returns-to-scale (VRS) assumptions. One of the novel aspects of the new SBM variations (Tone, 2010) is the appropriate comparison of fund companies with homogeneous frontier sets, thereby fitting fully to the assorted characteristics displayed by the Spanish mutual fund companies. Hence, the identification of 'locally efficient' companies for the core competency activities within sets of homogeneous competitors makes our efficiency analysis a novel and suitable approach in mutual fund markets with assorted competition characteristics.

The paper is set forth as follows. Section 2 presents the background of our research. Section 3 shows the major concepts of our network model. Appendix A and Appendix

[3] Premachandra et al. (2012) only evaluate large US mutual fund families with total assets under management of at least $1 billion USD. As a consequence of this requirement, 97 out of the 198 US fund families are dropped from the original sample.

B provide details about the formulation of the SBM and the Network SBM models respectively. Section 4 presents the discussion of the data, sample selection and the variables included in our model. Section 5 includes the empirical analysis, and Section 6 summarizes the findings of the paper.

2. BACKGROUND

By the end of 2013, the mutual fund industry in Spain ranks fourth in number of mutual funds and fifth in assets of the Euro Zone mutual fund market (European Fund and Asset Management Association, 2014). The top 5, the top 10 and the top 25 out of the existing 81 Spanish fund companies controlled for 55%, 74% and 92% of the total fund assets, respectively (Inverco, 2014). If we compare these figures with the largest fund market in the world, we find that competition in Spain is much more concentrated than in the US mutual fund industry, where the top 5, the top 10 and the top 25 out of the existing 801 companies manage about 40%, 53% and 72% of the total assets in 2013, respectively (Investment Company Institute, 2014). Furthermore, the Spanish fund industry has an average Herfindahl-Hirschman Index of 0.1001 for the last fifteen years, twice up from 0.0481 in the US market as of December 2013. This brief comparison highlights the need for addressing these differential market concentration issues and their consequences in the efficiency studies not focused on the top fund industry worldwide.

Previous DEA research on the efficiency of mutual fund companies does not discuss how the market concentration may affect their models and results. Premachandra et al. (2012) consider only large US mutual fund companies; thereby a vast number of US firms with a residual market share are dropped out from their final sample. Zhao and Yue (2010) do not report any standard by which they select their Chinese fund companies. Considering that DEA efficiency scores are obtained relative to all the competitors within the sample, the exclusion from the analysis of any fund company may involve biased results. That is, the systematic exclusion of fund companies from the final sample based on size requirements will result in a partial evaluation of the target industry which could be extremely biased in more concentrated markets than the US fund industry. Our approach overcomes this partial evaluation problem in two aspects. First, we do not exclude any fund company due to minimum size condition which allows for the evaluation of the whole set of competitors. Second, Variation III of the SBM model (Tone, 2010) identifies 'locally efficient' companies in reference to the efficient companies within the same cluster formed by homogeneous competitors. Thus, our paper evaluates separately the efficiency of the whole industry formed by assorted competitors and the efficiency of the different market segments which include mutual fund companies with homogeneous characteristics.

According to the concept models proposed in DEA literature of mutual fund companies, Zhao and Yue (2010) propose a multi-subsystem fuzzy DEA to evaluate the core competency of a sample of Chinese mutual fund companies. This core competency is divided into two subsystems: Investment and Research; and Marketing and Service. However, these authors omit any link between both core competency stages. We capture this fluent interaction using a network SBM structure based on Tone and Tsutsui (2009) with several linking variables.

Premachandra et al. (2012) also assess this interaction by using a general two-stage DEA model with intermediate variables. The overall efficiency of a sample of large US fund companies is decomposed into operational efficiency and portfolio efficiency components. The operational function covers the core competency of a fund company which attempts to obtain the highest net asset value with the least amount of marketing expenses and management fees. However, this operational function does not identify separately the influence of both the investment and the marketing activities on the net asset value of the company. We assess separately the relative efficiency of both the portfolio management and the marketing/selling activities, and their link with the operational management efficiency of the fund company.

3. THE MODEL

DEA is a non-parametric methodology which is extensively used to evaluate the relative efficiency of financial institutions, possibly due to the lack of any restrictions on the functional form between the multiple inputs and outputs allowed in this multi-dimensional framework. The selection of inputs and outputs in DEA, however, is largely controversial, especially in the banking literature. The well-known deposit dilemma may create inconsistency in the efficiency results across the two major approaches to treat bank liabilities: the production approach and the intermediation approach.[4]

[4] Fethi and Pasiouras (2010) provide a relevant survey about the selection of inputs and outputs in the banking literature. This survey finds that the intermediation approach is much more frequent, probably due to the difficulties in collecting the detailed transaction information required by the production approach.

Recent applications to financial institutions develop network DEA models which help to evaluate efficiency of each component of the whole management process. These models incorporate intermediate variables which link the different management stages of the financial institutions. As a result, these intermediate measures are considered as neither pure inputs nor pure outputs, thereby helping to solve the large controversy in the proper selection of inputs and outputs. Kao (2014) provides an exhaustive review of the network DEA models and the structures used in literature. This review finds that financial institutions have the largest number of network applications, mostly conducted by two-stage structures.[5] Some recent studies are Kao and Hwang (2008), Chen et al. (2009), Fukuyama and Weber (2010), Tsai and Wang (2010), Zha and Liang (2010), Holod and Lewis (2011), Tsolas (2011), Premachandra et al. (2012), Yang and Liu (2012), Wu and Birge (2012) and Akther et al. (2013).

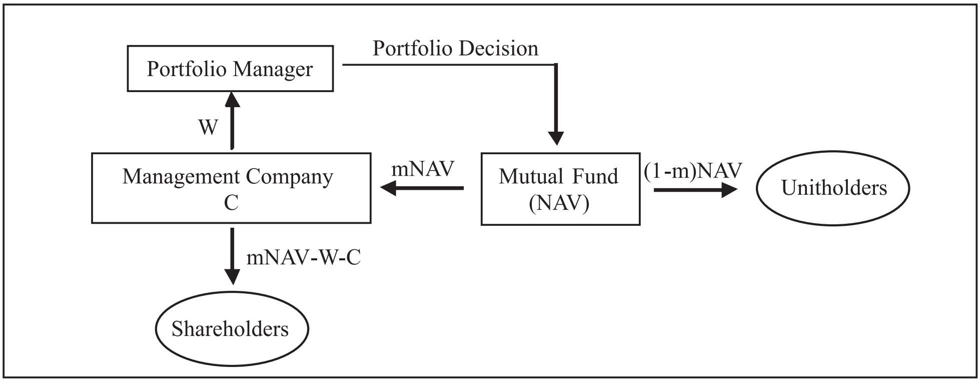
In our model structure, we capture the network effect between the core competency activities of a mutual fund company and their influence on the operational efficiency reported to the company shareholders. Our structure attempts to answer the following questions: 1) How efficient is the portfolio management process of a mutual fund company?, 2) How efficient is the selling process of mutual fund units?, and 3) How efficient is the operational management function of a fund company?.

The governance structure proposed by Berkowitz and Qiu (2003) helps us to preliminary approach these questions. Fig. 1 illustrates how a fund company is responsible to its shareholders and pays either an internal or external agent for managing mutual fund portfolios. These portfolio decisions will obviously affect the net asset value of the mutual fund. The results of this portfolio management will be provided to fund unitholders after subtracting management expenses by the company to recover wages paid to the portfolio manager and other operating expenses. As a result, the shareholders of the company will receive the final profits of this complex.

[5] Kao (2014) classifies five types of network structures: series, parallel, mixed, hierarchical, and dynamic. Basic two-stage and general two-stage systems are particular cases of series structures.

FIGURE 1

The mutual fund complex proposed by Berkowitz and Qiu (2003). Based on a governance structure approach, this complex reflects the relevant management interactions related to the mutual fund unitholders and the fund company shareholders. Where *C* is the operating expenses of the company, *W* represents the wages received by the portfolio manager, *m* is the management expense ratio of the company, and *NAV* is the net asset value of the mutual fund.



However, this complex omits any detailed influence of the marketing and selling activities on the net asset value of the mutual fund, and therefore on the management incomes earned by the company. This omission of the marketing effort to gain money flows into the mutual fund could severely bias this conceptual model. This bias could be especially relevant in those fund industries where the management expenses earned by the company are largely based on assets under management instead of performance-based fees, such as the Spanish mutual fund market (Díaz-Mendoza et al., 2014).

In our study, we overcome this problem by modelling both the portfolio management stage and the marketing stage as linking activities to explain the assets under management of a fund company. The following expression, which has been largely used in literature on mutual fund flows (e.g. Zheng, 1999; Sapp and Tiwari, 2004), reflects quite well the core competency of a mutual fund company which attempts to increase its total assets by means of both portfolio returns and money flows from the market.[6]

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[6] A more refined version of expression (1) corrects the increase in total assets due to fund mergers during period *t+1*.

$$TNA_{i,t+1}=TNA_{i,t}\,(1+R_{i,t+1})+MF_{i,t+1} \qquad (1)$$

where $TNA_{i,t}$ is the total net assets of fund i at the end of period t; $R_{i,t+1}$ is the return obtained by fund i during period $t+1$; and $MF_{i,t+1}$ are the net money flows into fund i during $t+1$.

Money flows into the mutual fund are obviously obtained by the marketing and selling activities of the company, but they cannot be considered as an independent stage of portfolio management because the results of these portfolio decisions influence investors to buy or to sell mutual fund units.[7] Furthermore, the operational management function of the company is also linked to both portfolio management and marketing activities. Expression (1) denotes that the asset-based fees earned by the company depend on the portfolio returns and on the selling process of mutual fund units. As a result, the efficiency of the operational cost structure to get the highest returns and the largest money flows as possible will determine the final profits received by the company shareholders.

Our model (Fig. 2) illustrates these management interactions within a mutual fund company j as a network structure with three relevant management stages: Portfolio Management Stage, Marketing and Selling Stage, and Operational Management Stage (hereinafter referred to as Portfolio Stage, Marketing Stage, and Operational Stage, respectively). Our network complex completes previous DEA structures in fund companies (Zhao and Yue, 2010; Premachandra et al. 2012) by detailing more clearly the links existing between core competency activities and their influence on the efficiency of the operational management structure of the company.

According to the review of Kao (2014), our network model corresponds to a series structure, which generalizes the two-stage complex previously proposed by Premachandra et al. (2012). At Portfolio Stage, labour (L_j) and capital resources (SE_j) of the company assume a specific level of risk (PR_j) to get higher gross returns (GR_j) in as many mutual funds (NF_j) and fund types (FT_j) as possible.[8] The rationale behind this

[7] Ferreira et al. (2012) analyse the flow-performance relationship across 28 countries, providing innovative evidence to the extensive literature on flow determinants in the US fund market.

[8] Inputs at Portfolio Stage assume that mutual funds are managed by the personnel and management resources of the company. This assumption makes sense because portfolio management outsourcing is a rare practice in our sample. In 2014 less than 3% of Spanish mutual funds were subadvised by external portfolio managers (Morningstar Direct).

stage is that a company with efficient portfolio management skills is one that is able to obtain higher gross returns than the competence with lower levels of risk for a large and well-diversified supply of mutual funds without assuming extra personnel expenses and capital resources.

At Marketing Stage, the fund company attempts to gain unitholders (UF_j) and money flows from (MF_j) the market into every fund managed by the company. The number and variety of mutual funds and their return records offered by the company to the market are hence very significant to aim this goal. Since these mutual fund records are determined by portfolio management activities, the outputs at Portfolio Stage are intermediate inputs at Marketing Stage, thereby linking both core competency activities of the company in our network complex.[9]

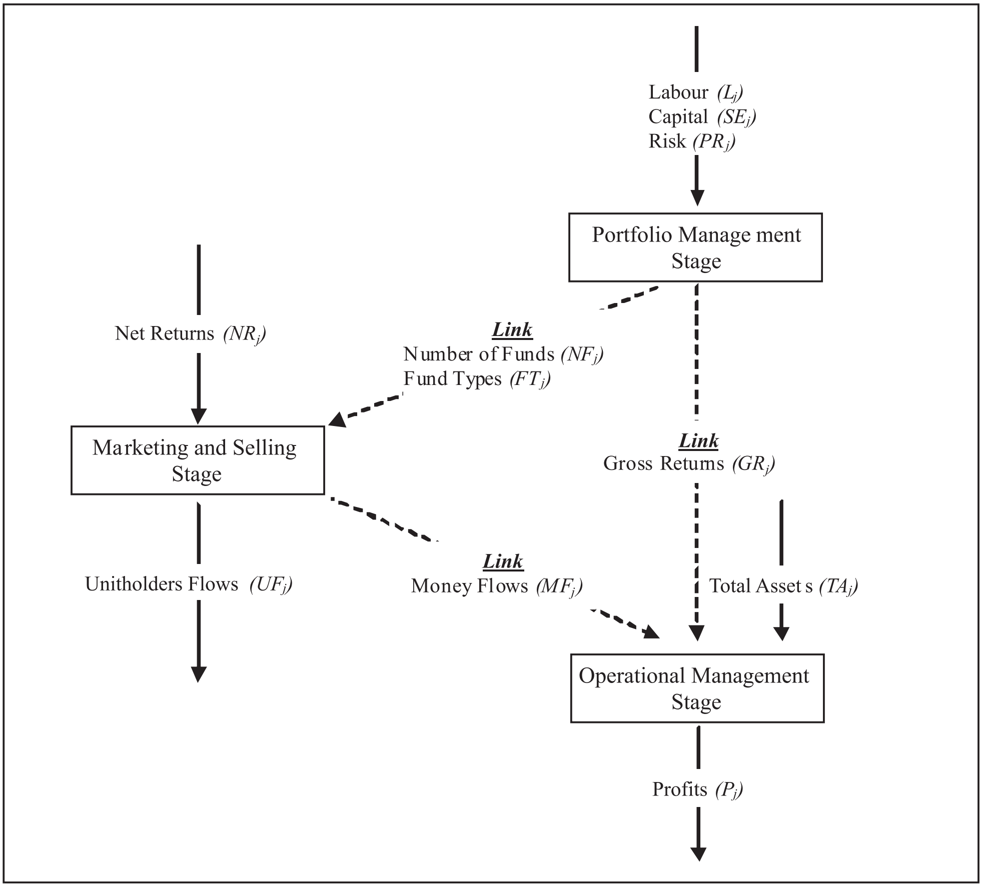
Finally, Operational Stage represents the operational management function of the fund company. This stage aims to obtain the highest profit (P_j) as possible to remunerate company shareholders. According to expression (1), the asset-based fees earned by the company are driven by gross returns (GR_j) at Portfolio Stage, by money flows (MF_j) at Marketing Stage, and by the assets managed by the company (TA_j) at the beginning of the analysed period. In our model, we use gross returns and money flows as intermediate inputs to link both Portfolio and Marketing Stages to Operational Stage respectively. A company with an efficient operational management structure will obtain a higher profit with fewer assets under management than competitors, being these assets a consequence of both portfolio management and marketing activities.

After defining our network structure, we describe the suitable procedure used in our research to model this complex. We work with a set of n fund companies ($j = 1, \ldots, n$) consisting of 3 stages ($k = 1, 2, 3$). Let m_k and r_k be the numbers of inputs and outputs to stage k, respectively. The link from stage k to stage h is denoted by (k,h) and the set of links by L. The inputs of company j at stage k are $\{x_j^k € R_+^{mk}\}$ ($j=1,\ldots, n$; $k = 1, 2, 3$); the outputs of company j at stage k are $\{\gamma_j^k € R_+^{r_k}\}$ ($j=1,\ldots, n$; $k=1, 2, 3$); the linking intermediate variables from stage k to stage h are $\{z_j^{(k,h)} € R_+^{t_{(k,h)}}\}$ ($j=1,\ldots, n$; $(k,h) € L$); where $t_{(k,h)}$ is the number of items in link (k,h). $\lambda^k € R_+^n$ is the intensity vector of stage k ($k = 1, 2, 3$); and s^{k+} and s^{k-} are the non-negative vectors of input excesses and output shortfalls, respectively.

[9] The returns supplied to the unitholders are computed after management fees and other expenses charged by the company. Therefore, net returnsinstead of gross returnsare considered as an input at Marketing Stage.

FIGURE 2

Network complex for evaluating the efficiency of mutual fund companies. The fund company j has three management stages: Portfolio Management, Marketing and Selling, and Operational Management. Thus, the overall efficiency of the fund company is decomposed into the efficiency of these three stages. Each stage utilizes its own inputs for obtaining its own outputs. L_j, SE_j, PR_j are the input variables at Portfolio Management Stage; NR_j is the input variable and UF_j is the output variable at Marketing and Selling Stage; TA_j is the input variable and P_j is the output variable at Operational Management Stage. But there are also four intermediate variables which link different activities of the company (dotted lines). NF_j, FT_j are outputs at Portfolio Management Stage which are utilized as inputs at Marketing and Selling Stage; GR_j is an output at Portfolio Management Stage which is considered as an input at Operational Management Stage; and MF_j is an output at Marketing and Selling Stage which is utilized as an input at Operational Management Stage.



Premachandra et al. (2012) justify the VRS hypothesis, as some of the variables included in their model (e.g., returns) can be negative. This is not the case for our innovatively constructed variables which will be described in the next section. However, we also assume VRS to better evaluate the efficiency when not all the fund companies are operating at the optimal scale. Thus, the production possibility set P is spanned by the convex hull of the existing companies.

$$P=\{(x^k,y^k,z^{(k,h)}) \setminus x^k \geq X^k \lambda^k,\ y^k \leq Y^k \lambda^k, z^{(k,h)} = Z^{(k,h)} \lambda^k, z^{(k,h)} = Z^{(k,h)} \lambda^h, e\lambda^k = 1, \lambda^k \geq 0\} \quad (2)$$

Notice that if we exclude from expression (2), the production possibility set P is defined under CRS assumption.

According to Tone and Tsutsui (2009), we have two major alternatives based on the SBM model (Tone, 2001)[10] for measuring the efficiency of a network complex such as Fig. 2: a Network SBM (NSBM) and a SBM-based separation model. NSBM proposed by Tone and Tsutsui (2009) employs the weighted SBM model (Cooper et al., 2007; Tsutsui and Goto, 2009) to decompose the overall efficiency of the fund company into partial ones for each management stage of a network structure. NSBM assumes that the overall efficiency is the weighted average of partial efficiencies where the weights are set exogenously. The original approach allows for the continuity of intermediate variables between management stages but it does not take into account the inefficiency of these intermediate variables. Therefore, NSBM does not integrate the slacks of the intermediate variables individually and independently into an efficiency score because these slacks are only considered through link constraints. We follow one of the NSBM extensions also proposed by Tone and Tsutsui (2009) to overcome this shortcoming. This extension incorporates slacks of the intermediate variables into the NSBM objective function.[11]

On the other hand, the SBM separation model evaluates stage efficiencies individually using the intermediate variables as ordinary inputs or outputs, thereby omitting any continuity of linking activities. That is, the SBM separation model computes efficiency scores for each stage considering the slacks of all variables included in the model as ordinary inputs and outputs but it does not capture the influence of the linking activities

[10] SBM is a non-radial model for measuring efficiency when inputs and outputs may change non-proportionally. See details of SBM model in Appendix A.

[11] Appendix B shows NSBM model and its extension. Further details of this NSBM extension are in section 6.1 of Tone and Tsutsui (2009).

on the model. The comparison of efficiency scores between NSBM and the SBM separation models will be especially important to identify what Tone and Tsutsui (2009) addressed as "networking effects" of the model.

4. DATA, SAMPLE SELECTION, AND VARIABLE CONSTRUCTION

The data on Spanish mutual fund companies are hand-collected from several databases. Financial data on companies are obtained from the Iberian Balance-sheets Analysis System (SABI) and the Spanish Official Business Registry. The information about mutual funds is obtained from the Spanish Securities Exchange Commission (CNMV) and the Spanish Association of Mutual and Pension Funds (Inverco). We work with all mutual fund companies registered in CNMV on 31st December of each year included in our sample period 2005-2012.

We consider all the funds in the company irrespective of their investment classification. Hedge funds are the only exception because of the striking differences between these portfolios and mutual funds. Hence we exclude all hedge funds and hedge fund companies from the sample to keep the objective of our study on companies primarily focused on the management and marketing of mutual funds. Also, mutual fund companies with inception dates close to year-end are dropped from the initial year to avoid any inception bias in the variables used in our model. These exclusions are residual in terms of year observations and economic relevance.[12]

Similarly to Premachandra et al. (2012), we consider multiple share classes of a mutual fund as separate mutual funds existing at the end of each year of our survey period.[13] Our work also assumes a minor survivorship bias because we work with those mutual funds existing at 31st December of each individual year analysed.[14]

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[12] Hedge funds still have a residual importance in the Spanish financial industry since its inception in 2006. A total of 316 (44) fund (company) year-end observations were dropped from the sample. These exclusions represent about 5% of company year-end observations and less than 1% in terms of assets managed by the Spanish fund industry.

[13] The consideration of share classes as separate mutual funds at Portfolio Stage could be controversial because the mutual fund portfolio at that stage is the same for all fund share classes. However, this issue is not important in our analysis because the different SBM efficiency scores at Portfolio Stage using both variables show a Spearman rank correlation higher than 99%. Details are available upon request.

[14] A total of 1,557 mutual funds have ceased operations during our survey period. This survivorship bias represents about 6% of total year-end observations and less than 1% of the total assets included in our sample.

Our final sample comprises a total of 736 company year observations which range from a minimum of 74 mutual fund companies in 2012 to a maximum of 102 in 2005 and 2006. Table 1 shows a large dispersion of the summary statistics for our sample, thereby highlighting the assorted characteristics of the Spanish mutual fund companies. Furthermore, the yearly evolution of these statistics since 2008 provides evidence of the significant impact of the worldwide financial crisis on the decreasing trend of the average magnitudes of the Spanish industry.

TABLE 1
SUMMARY STATISTICS OF SPANISH MUTUAL FUND COMPANIES

	2005	2006	2007	2008	2009	2010	2011	2012
Number of companies	102	102	95	93	95	89	86	74
Mutual funds per company	26 (43)	28 (48)	31 (53)	31 (54)	27 (42)	28 (41)	27 (40)	29 (41)
Unitholders per company	82,809 (255,312)	82,809 (260,916)	84,749 (241,650)	63,659 (177,150)	57,631 (154,350)	57,982 (144,351)	56,218 (136,048)	59,007 (128,529)
Assets in million €	2,569 (7,966)	2,651 (7,964)	2,682 (7,416)	1,888 (5,287)	1,795 (4,849)	1,616 (4,034)	1,539 (3,755)	1,663 (3,633)

This table illustrates the year-end average statistics per company of our sample. Standard deviation is in brackets.

Table 2 lists the input and output variables used in our network complex and how they are calculated. Some of these variables are obtained as aggregated values of individual mutual funds. However, a similar approach to variables associated with return and risk could distort the accuracy of these measures. We agree with Premachandra et al. (2012) that returns weighted by fund size do to some extent represent the portfolio skills of a company, but the different size and return patterns of the diverse investment categories covered by a company could distort the size-weighted returns and the levels of risk associated with a fund company. For instance, a company specialised in equity funds could obtain upwards biased size-weighted returns in years with bullish stock markets compared with a company specialised in bond funds. Zhue and Yue (2010) solve this potential problem by using a membership function to characterise fund types. In our case, we compare the daily average gross return for each mutual fund existing at 31st December with respect to all funds in the market included in the same investment category and during the same time period. Then we calculate the normalised value between 0 and 1 of these average gross returns and then compute the size-weighted average of these normalised values for every company. Hence, this positive return measure is consistent across the different fund types managed by a company. We follow a similar procedure for the normalised standard deviation of the daily gross returns as a relative measure of portfolio risk.

TABLE 2
INPUT, OUTPUT AND INTERMEDIATE VARIABLES

Portfolio Stage	*Inputs:*	*Outputs:*
	Labour (L_j) is the number of employees of company *j* at 31 st December. Capital (SE_j) is the stockholders capital of company *j* at 1st January. Portfolio Risk (PR_j) is the fund size-weighte adverage of the normalised value of the standard deviation of the daily gross returns of all funds managed by company *j* at 31st December.	**Number of Funds *(NF_j)*** is the number of funds managed by company *j* at 31st December. **Fund Types *(FT_j)*** is the number of investment categories covered by company *j* at 31st December according to the official classification of CNMV **Gross Returns *(GR_j)*** is he fund size-weighted average of the normalised value of the daily average gross returns of all funds managed by company *j* at 31st December.
Marketing Stage	*Inputs:*	*Outputs:*
	Number of Funds *(NF_j)* **Fund Types *(FT_j)*** Net Returns *(NR_j)* is the fund size-weighted average of the normalised value of the daily average net returns of all funds managed by company *j* at 31st December.	Unitholders Flows *(UF_j)* is the normalised value of unitholder inflows minus unitholder outflows for company *j* from 1st January to 31st December. **Money Flows *(MF_j)*** is the normalised value of the implied net money flows for company *j* from 1st January to 31st December.
Operational Stage	*Inputs:*	*Outputs:*
	Total Assets *(TA_j)* is the total assets managed by company *j* at 1st January. **Money Flows *(MNF_j)*** **Gross Returns *(GR_j)***	Profit *(P_j)* is the normalised value of the profit obtained by the company *j* from 1st January to 31st December.

Intermediate variables are printed in bold. (SE_j) is not influenced by the profit of the company during the analysed year. (GR_j) is computed as the fund size-weighted average of the normalised value between 0 and 1 of the average daily gross return for each mutual fund existing at 31st December with respect to all funds in the market included in the same investment category and during the same time period. (NR_j) is obtained as (GR_j) once the daily management and custodial fees charged by the company have been subtracted from the daily gross returns obtained by each fund. (PR_j) is computed as the fund size-weighted average of the normalised standard deviation between 0 and 1 of the average daily gross return for each mutual fund existing at 31st December with respect to all funds in the market included in the same investment category and during the same time period. (MF_j) is defined as monthly changes in the total assets of each fund net of returns and mergers, see expression (1). We follow the literature and assume that these flows occur at the end of the month for which we are computing this measure. Zheng (1999) determined that this approach is robust with other assumptions about the timing of these implied flows.

5. EMPIRICAL ANALYSIS

First, we compare the results obtained by the SBM separation model (Appendix A, model A2) with the extended NSBM model (Appendix B, model B6) for each management stage of our network complex illustrated by Fig. 2. Thereafter, we apply several non-parametric tests based on robust contingency tables to check for the persistence of the efficiency scores across time and mutual fund companies. Finally, we run an innovative SBM variant to obtain locally efficient fund companies with respect to competitors with homogeneous management characteristics.

5.1. Results of SBM separation and NSBM models

Panel A of Table 3 shows the results of the SBM separation model (under VRS) where the links between the management stages within a fund company are neglected. The efficiency for each management stage is separately obtained and the overall efficiency is obtained as the arithmetic average of the three individual efficiencies considered in our network complex. This equally-weighted hypothesis is also used in the extended NSBM model and it assumes an equal importance of Portfolio Stage, Marketing Stage and Operational Stage in the efficiency function of a fund company as a whole. Panel B of Table 3 shows the results of the NSBM extension (under VRS) which incorporates the link flows into the efficiency scores.[15]

We find several interesting patterns in these efficiency results. The last three columns of Table 3 show that there is not a significant change in the average efficiency scores before and after 2008, taken this year as a consensus frontier of the recent financial crisis. If we relate this result with the decreasing number of mutual fund companies competing in the Spanish fund industry (Table 1) we can conclude that crisis survivors are not increasing significantly the efficiency records of the Spanish fund industry. This similarity is also found in terms of variability of the efficiency scores obtained by both SBM approaches.

If we extend our attention to the efficiency scores weighted by the assets managed by each company at year-end, we find that these scores are significantly higher than the

[15] For the sake of brevity we omit the complete yearly rankings and detailed reference sets of all the mutual companies included in our empirical analysis. These results are available upon request.

equally-weighted measures with the only exception of Marketing Stage at SBM separation model. These results provide evidence that size seems to play a positive role in the efficiency of mutual fund companies. This finding is majorly explained by the good efficiency records of the 3 largest companies which manage about 45% of the assets of the Spanish mutual fund industry along our sample period. This evidence is robust across all years and management stages for both SBM separation and NSBM models.[16]

Finally, the comparison between Panel A and Panel B shows some differences in the efficiency patterns provided by both SBM separation and NSBM models. A further analysis of the Spearman rank correlations between the efficiency rankings obtained by both techniques (Table 4) will help us to better identify these differences.[17] Table 4 finds that the rankings obtained by both SBM separation and NSBM models are quite correlated, especially at the Operational Stage. However, the rankings are much more different at the Marketing Stage, where we find many years with independent rank correlations which support that the intermediate links affecting Marketing Stage are really important in our network model. These links are not properly captured by the SBM separation model which neglects them when they actually exist, thereby explaining the differences in efficiency and rankings with respect to NSBM approach. This networking effect makes sense according to our network complex (Fig. 1) where Marketing Stage plays a relevant intermediate role between the Portfolio Stage and Operational Stage.

[16] This evidence is also robust for the efficiency scores obtained under CRS assumption. We find an average Spearman correlation coefficient higher than 80% between the rankings provided under VRS and CRS hypotheses.
[17] Kendall rank correlations provide similar conclusions than those Spearman coefficients displayed by Table 4.

TABLE 3
EFFICIENCY SCORES FOR SBM SEPARATION AND NSBM MODELS UNDER VRS

Panel A SBM separation model	2005	2006	2007	2008	2009	2010	2011	2012	2005-2008	2009-2012	2005-2012
Portfolio Stage											
Number of Eff. companies	35	28	32	26	28	29	32	36	30	31	30
Equally-W efficiency score (Standard deviation)	0.658 (0.295)	0.578 (0.308)	0.628 (0.312)	0.555 (0.322)	0.623 (0.290)	0.595 (0.322)	0.585 (0.345)	0.740 (0.282)	0.604 (0.309)	0.635 (0.309)	0.620 (0.309)
Asset-W efficiency score	0.876	0.880	0.858	0.834	0.854	0.841	0.775	0.899	0.862	0.842	0.852
Marketing Stage											
Number of Eff. companies	6	10	11	9	7	4	8	14	9	8	8
Equally-W efficiency score (Standard deviation)	0.337 (0.232)	0.431 (0.255)	0.482 (0.229)	0.276 (0.280)	0.342 (0.225)	0.277 (0.190)	0.311 (0.271)	0.580 (0.256)	0.381 (0.249)	0.377 (0.235)	0.379 (0.242)
Asset-W efficiency score	0.422	0.391	0.303	0.141	0.221	0.248	0.245	0.339	0.314	0.263	0.288
Operational Stage											
Number of Eff. companies	15	19	14	10	14	8	12	15	14	12	13
Equally-W efficiency score (Standard deviation)	0.365 (0.304)	0.385 (0.332)	0.359 (0.301)	0.278 (0.270)	0.388 (0.287)	0.301 (0.265)	0.300 (0.308)	0.565 (0.256)	0.346 (0.301)	0.388 (0.279)	0.367 (0.290)
Asset-W efficiency score	0.633	0.719	0.626	0.666	0.723	0.542	0.617	0.739	0.661	0.655	0.658
Overall Efficiency											
Number of Eff. companies	2	1	3	2	0	1	0	1	2	1	1
Equally-W efficiency score (Standard deviation)	0.453 (0.178)	0.464 (0.157)	0.490 (0.172)	0.370 (0.170)	0.451 (0.156)	0.391 (0.147)	0.399 (0.172)	0.628 (0.129)	0.444 (0.169)	0.467 (0.151)	0.455 (0.160)
Asset-W efficiency score	0.644	0.663	0.596	0.547	0.599	0.543	0.546	0.659	0.612	0.586	0.599
Panel B Network SBM model	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2005-2008**	**2009-2012**	**2005-2012**
Portfolio Stage											
Number of Eff. companies	11	15	12	13	12	9	13	17	12	12	12
Equally-W efficiency score (Standard deviation)	0.494 (0.266)	0.501 (0.286)	0.487 (0.287)	0.566 (0.278)	0.552 (0.255)	0.505 (0.259)	0.548 (0.258)	0.737 (0.206)	0.512 (0.279)	0.586 (0.244)	0.549 (0.261)
Asset-W efficiency score	0.729	0.785	0.705	0.785	0.806	0.728	0.768	0.848	0.751	0.788	0.769
Marketing Stage											
Number of Eff. companies	14	14	15	13	13	10	15	16	14	14	14
Equally-W efficiency score (Standard deviation)	0.565 (0.247)	0.596 (0.264)	0.584 (0.262)	0.648 (0.227)	0.659 (0.195)	0.577 (0.236)	0.640 (0.224)	0.796 (0.150)	0.598 (0.250)	0.668 (0.201)	0.633 (0.226)
Asset-W efficiency score	0.760	0.826	0.744	0.822	0.869	0.793	0.834	0.895	0.788	0.848	0.818
Operational Stage											
Number of Eff. companies	18	22	19	16	17	12	17	18	19	16	17
Equally-W efficiency score (Standard deviation)	0.589 (0.257)	0.639 (0.264)	0.631 (0.261)	0.654 (0.239)	0.667 (0.203)	0.570 (0.243)	0.665 (0.224)	0.777 (0.153)	0.628 (0.255)	0.670 (0.205)	0.649 (0.230)
Asset-W efficiency score	0.772	0.840	0.758	0.827	0.879	0.784	0.822	0.852	0.799	0.834	0.817
Overall Efficiency											
Number of Eff. companies	10	12	9	11	11	8	12	15	11	11	11
Equally-W efficiency score (Standard deviation)	0.549 (0.244)	0.579 (0.256)	0.567 (0.255)	0.623 (0.234)	0.626 (0.200)	0.551 (0.234)	0.618 (0.219)	0.770 (0.151)	0.580 (0.247)	0.641 (0.201)	0.610 (0.224)
Asset-W efficiency score	0.754	0.817	0.736	0.811	0.851	0.768	0.808	0.865	0.780	0.823	0.801

TABLE 4
SPEARMAN RANK CORRELATION COEFFICIENTS BETWEEN SBM SEPARATION AND NSBM RANKINGS UNDER VRS

	2005	2006	2007	2008	2009	2010	2011	2012	2005-2008	2009-2012	2005-2012
Portfolio Stage	0.47**	0.26*	0.56**	0.50**	0.56**	0.37**	0.46**	0.38**	0.45**	0.44**	0.45**
Marketing Stage	0.42**	0.36**	0.26**	0.12	0.32**	-0.01	0.09	0.29*	0.28	0.17	0.23
Operational Stage	0.94**	0.77**	0.80**	0.60**	0.64**	0.75**	0.58**	0.72**	0.78**	0.67**	0.73**
Overall Efficiency	0.79**	0.73**	0.64**	0.64**	0.82**	0.63**	0.69**	0.70**	0.70**	0.71**	0.71**

* 5% significant; ** 1% significant.

TABLE 5
SPEARMAN RANK CORRELATION BETWEEN EFFICIENCY RANKINGS FOR SBM SEPARATION AND NSBM MODELS UNDER VRS

	2005			2006			2007			2008		
	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE
Portfolio Stage (PS)	-0.01	-0.07	0.58**	-0.30**	-0.23*	0.36**	-0.17	0.02	0.64**	-0.41**	0.01	0.63**
Marketing Stage (MS)	1	0.38**	0.50**	1	0.17	0.38**	1	0.18	0.31**	1	-0.20	0.08
Operational Stage (OpS)		1	0.64**		1	0.58**		1	0.58**		1	0.36**
Overall Efficiency (OvE)			1			1			1			1
	2009			2010			2011			2012		
	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE
Portfolio Stage (PS)	-0.23*	0.06	0.60**	-0.35**	-0.21*	0.66**	-0.14	0.03	0.61**	-0.21*	-0.23*	0.52**
Marketing Stage (MS)	1	0.06	0.23*	1	-0.05	-0.04	1	-0.21*	0.29**	1	0.04	0.41**
Operational Stage (OpS)		1	0.61**		1	0.37**		1	0.46**		1	0.43**
Overall Efficiency (OvE)			1			1			1			1
	2005			2006			2007			2008		
	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE
Portfolio Stage (PS)	0.76**	0.74**	0.89**	0.77**	0.77**	0.88**	0.76**	0.74**	0.87**	0.77**	0.74**	0.89**
Marketing Stage (MS)	1	0.95**	0.96**	1	0.98**	0.97**	1	0.99**	0.97**	1	0.93**	0.96**
Operational Stage (OpS)		1	0.95**		1	0.97**		1	0.97**		1	0.94**
Overall Efficiency (OvE)			1			1			1			1
	2009			2010			2011			2012		
	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE	MS	OpS	OvE
Portfolio Stage (PS)	0.59**	0.58**	0.85**	0.78**	0.71**	0.87**	0.67**	0.63**	0.84**	0.64**	0.62**	0.87**
Marketing Stage (MS)	1	0.83**	0.87**	1	0.95**	0.97**	1	0.92**	0.95**	1	0.88**	0.90**
Operational Stage (OpS)		1	0.88**		1	0.95**		1	0.92**		1	0.88**
Overall Efficiency (OvE)			1			1			1			1

* 5% significant; ** 1% significant.

According to Tone and Tsutsui (2009), the efficiency scores of the management stages cannot be fairly comparable because the number of inputs and outputs is different for the three management stages. The comparison between the efficiency rankings of the management stages provides therefore more accurate conclusions about the linking effects in our network model. Panel A of Table 5 finds new evidence which confirms that the omission of the networking effects may bias the efficiency rankings of a network structure. Spearman rank correlations show that most of the rankings obtained by the SBM separation model are independent and even negatively correlated. The only exception is in the Overall Efficiency as a consequence of its equally-weighted construction based on the scores of each individual management stage. This biased independence in the rankings may be explained as a consequence of the omission of the links by the SBM separation model when they are actually present in a fund company complex.

These former results are properly corrected after including the networking effects by the NSBM model. Panel B of Table 5 shows a significant increase in the similarity between the rankings as a consequence of the incorporation of link flows in efficiency measurements. However, the Spearman rank correlations between Marketing Stage and Operational Stage are significantly the largest between the three management stages. That is, efficiency at Marketing Stage is closely related to the efficiency at Operational Stage. In fact, efficiency at Marketing Stage is much more related to the efficiency at Operational Stage than Portfolio Stage. If we extend this correlation analysis to the Overall Efficiency rankings, we find that Marketing Stage and Operational Stage are more relevant to explain the Overall Efficiency of a company than the portfolio management skills. That is, the abilities for selling mutual funds seem to be more important to explain the Overall Efficiency of a fund company than the portfolio management skills of a fund company. This evidence is consistent for all years included in our sample period.

5.2. Persistence of efficiency scores across time and mutual fund companies

Mutual fund persistence refers to the compelling hypothesis that mutual funds with good (bad) performance records will keep these good (bad) results over time. Extensive literature has been devoted to this predictive phenomenon since the key early studies of Brown et al. (1992), Grinblatt and Titman (1992), Hendricks et al. (1993), and Goetzmann and Ibbotson (1994). We extend this persistence focus on the NSBM results obtained by the different management stages of a mutual fund company. That is, this section aims to be an original and further contribution to persistence literature and tests for whether fund companies maintain their relative NSBM rankings over time for the different management stages considered in our network model. If the persistence hypothesis is accepted, then those companies with high (low) NSBM efficiency rankings in a specific management stage will keep their high (low) efficiency rankings over time.

The use of non-parametric statistics based on contingency tables has been frequent in persistence literature since the first applications by Brown and Goetzmann (1995), Kahn and Rudd (1995) and Malkiel (1995) among others. However, the arbitrary determination of efficiency groups to be compared with other efficiency groups in subsequent years may be an important shortcoming of this non-parametric approach. That is, those groups based on efficiency medians and quartiles as usual could affect the accuracy of the persistence findings in the sense that adjacent groups may not have significant efficiency differences between them.[18]

Our approach to persistence is based on contingency tables, but efficiency groups are not exogenously determined through median or quartile breakpoints. We propose divisive clustering techniques to design robust efficiency groups rather than the mere consideration of median or quartile groups with the same number of companies. This divisive clustering approach starts with one large cluster containing all fund companies. This group is divided until selecting C representative efficiency clusters with the largest dissimilarity between any two of its efficiency observations.[19] According to standards in persistence literature, we initially identify two (C=2) consistent efficiency groups for each management stage and year, *Winners* companies (W) and *Losers* companies (L). Then, the divisive clustering technique splits up these groups to obtain four clusters (C=4) for each management stage and year (*Top Winners, Winners, Losers, and Bottom Losers*). Table 6 summarizes the average efficiency scores obtained by cluster and year. These statistics show that clusters are significantly different in efficiency terms to form accurate contingency tables to contrast for the persistence hypothesis.

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[18] Cortez et al. (1999) already noted how results from contingency tables for small mutual fund samples should be interpreted with caution.

[19] DIANA algorithm was applied to obtain the efficiency clusters. DIANA is included in the package 'Cluster' of the R project for Statistical Computing (Version 1.14.4, August 2013). This divisive approach seems to be more appropriate than agglomerative techniques in our concentrated sample because it initially finds few consistent large clusters from a unique efficiency group rather than combining the nearest efficiency observations until only one large cluster remains as agglomerative techniques do. In any case, the efficiency clusters obtained in our sample by both techniques are quite similar. Detailed cluster dendograms are available upon request.

TABLE 6
SUMMARY STATISTICS OF THE EFFICIENCY CLUSTERS

	2005	2006	2007	2008	2009	2010	2011	2012
Portfolio Stage								
Top Winners	0.98 (16)	0.97 (19)	0.97 (16)	0.96 (23)	0.96 (18)	0.98 (13)	0.99 (14)	0.97 (22)
Winners	0.75 (7)	0.67 (11)	0.71 (12)	0.70 (13)	0.67 (15)	0.70 (16)	0.77 (5)	0.75 (28)
Losers	0.45 (44)	0.47 (26)	0.44 (28)	0.46 (34)	0.44 (41)	0.43 (30)	0.52 (29)	0.57 (17)
Bottom Losers	0.23 (31)	0.23 (39)	0.23 (36)	0.23 (23)	0.22 (14)	0.23 (25)	0.29 (26)	0.32 (7)
Marketing Stage								
Top Winners	0.97 (18)	0.96 (24)	0.96 (21)	0.97 (19)	0.99 (15)	0.98 (15)	0.98 (17)	0.99 (18)
Winners	0.76 (13)	0.71 (15)	0.73 (15)	0.79 (16)	0.84 (10)	0.77 (11)	0.82 (9)	0.85 (20)
Losers	0.51 (26)	0.53 (21)	0.49 (32)	0.54 (50)	0.59 (44)	0.54 (28)	0.58 (19)	0.71 (22)
Bottom Losers	0.34 (41)	0.31 (35)	0.29 (24)	0.24 (8)	0.43 (19)	0.34 (30)	0.43 (29)	0.58 (14)
Operational Stage								
Top Winners	0.98 (23)	0.99 (26)	0.97 (25)	0.97 (24)	0.99 (19)	0.99 (16)	0.99 (21)	1.00 (18)
Winners	0.78 (7)	0.75 (13)	0.74 (15)	0.77 (12)	0.85 (5)	0.77 (8)	0.84 (3)	0.91 (4)
Losers	0.51 (31)	0.55 (27)	0.54 (27)	0.56 (39)	0.61 (39)	0.56 (26)	0.61 (22)	0.72 (39)
Bottom Losers	0.35 (37)	0.33 (29)	0.33 (25)	0.32 (18)	0.46 (25)	0.34 (34)	0.46 (28)	0.57 (13)
Overall efficiency								
Top Winners	0.96 (17)	0.98 (16)	0.96 (15)	0.94 (24)	0.97 (16)	0.95 (16)	0.97 (15)	0.99 (17)
Winners	0.76 (12)	0.76 (20)	0.75 (21)	0.70 (19)	0.78 (8)	0.70 (15)	0.78 (11)	0.85 (6)
Losers	0.51 (25)	0.52 (25)	0.48 (31)	0.47 (45)	0.58 (37)	0.48 (23)	0.52 (32)	0.73 (32)
Bottom Losers	0.34 (44)	0.30 (34)	0.29 (25)	0.15 (5)	0.43 (27)	0.32 (30)	0.38 (16)	0.59 (19)

This table illustrates the average efficiency scores per cluster and year. These statistics are shown for those companies included in the persistence analysis. Number of companies for each cluster is in brackets.

The comparison of the initially obtained *W* and *L* groups in two consecutive years allows the identification of the 2x2 contingency tables displayed by Table 7. Several non-parametric tests previously used in the persistence literature are applied to these contingency tables. Table 7 shows a significant persistence phenomenon in NSBM efficiency rankings for all the management stages and years considered in our network complex, although less significance is observed between 2008-2009 and 2011-2012. This finding is robust across all the non-parametric 2x2 tests. In addition, Cochran's Y-test also confirms this persistence for the whole period from 2005 to 2012. That is, the best (worst) managed companies at the different management stages included in our network model are usually the same during our sample period.

To look more deeply at the persistence effect using non-parametric measures, we use the 4x4 contingency tables that result when comparing the four efficiency clusters (*Top Winners,*

Winners, Losers, and Bottom Losers) in two consecutive years. Table 8 presents the main results. First, we find a significant value of the chi-square test for each management stage for nearly all consecutive periods. Again, this result provides evidence of a strong persistence phenomenon in the NSBM efficiency rankings obtained by the Spanish fund companies in our sample period. Similarly to 2x2 contingency tables, this 4x4 analysis also finds a decrease in the significance of this persistence between 2008-2009 and 2011-2012. Financial crisis and a new industry competition map could be behind of these results, respectively. In any case, future studies are necessary to properly justify these potential explanations.

TABLE 7
NSBM EFFICIENCY PERSISTENCE BASED ON 2X2 CONTINGENCY TABLES

PortfolioStage	WW	WL	LW	LL	Malkiel Z-test Winners	Malkiel Z-test Losers	B&G Z-test	K&R χ2-test	Cochran Y-test
2005-2006	17	6	13	62	4.506**	2.495*	4.613**	26.528**	
2006-2007	19	11	10	55	3.902**	2.651**	4.401**	22.252**	
2007-2008	24	4	11	53	5.196**	3.437**	5.310**	38.806**	
2008-2009	19	17	16	41	1.875	1.490	2.363*	5.739*	10.235**
2009-2010	16	17	13	42	1.898	1.470	2.360*	5.764*	
2010-2011	17	12	5	50	3.972**	2.884**	4.405**	24.097**	
2011-2012	15	4	35	20	1.060	0.623	1.212	1.511	
Marketing Stage	WW	WL	LW	LL	Malkiel Z-test Winners	Malkiel Z-test Losers	B&G Z-test	K&R χ2-test	Cochran Y-test
2005-2006	24	7	15	52	4.280**	2.911**	4.760**	26.790**	
2006-2007	24	15	13	43	2.893**	2.414*	3.649**	14.200**	
2007-2008	22	14	12	44	3.003**	2.407*	3.709**	14.811**	
2008-2009	14	21	12	46	1.588	1.233	1.982*	4.041*	9.789**
2009-2010	15	10	11	52	3.338**	2.102*	3.723**	15.559**	
2010-2011	17	9	10	48	3.629**	2.430*	4.088**	19.077**	
2011-2012	19	7	19	29	2.216*	1.631	2.674**	7.573**	
OperationalStage	WW	WL	LW	LL	Malkiel Z-test Winners	Malkiel Z-test Losers	B&G Z-test	K&R χ2-test	Cochran Y-test
2005-2006	24	6	14	54	4.634**	3.078**	5.010**	30.950**	
2006-2007	25	14	16	40	2.641**	2.204*	3.354**	11.831**	
2007-2008	23	17	12	40	2.535*	2.223*	3.282**	11.366**	
2008-2009	15	21	11	46	1.833	1.457	2.297*	5.481*	9.629**
2009-2010	15	9	9	55	3.875**	2.373*	4.188**	20.646**	
2010-2011	15	9	10	50	3.508**	2.219*	3.885**	17.227**	
2011-2012	11	13	11	39	1.726	1.196	2.060*	4.409*	
OverallEfficiency	WW	WL	LW	LL	Malkiel Z-test Winners	Malkiel Z-test Losers	B&G Z-test	K&R χ2-test	Cochran Y-test
2005-2006	22	7	13	56	4.512**	2.925**	4.897**	28.916**	
2006-2007	25	11	12	47	3.752**	2.931**	4.505**	22.673**	
2007-2008	26	10	16	40	3.201**	2.566*	3.938**	16.828**	
2008-2009	15	28	10	40	1.184	1.098	1.598	2.606	10.123**
2009-2010	16	8	15	49	3.224**	1.975*	3.582**	14.295**	
2010-2011	20	11	7	46	3.859**	2.952**	4.488**	23.608**	
2011-2012	12	14	11	37	1.661	1.222	2.028*	4.251*	

The 2x2 contingency tables are obtained by comparing the efficiency clusters W and L of two consecutive years. Therefore, WW (LL) shows the number of winners (losers) in two consecutive years. WL (LW) indicates the number of winners (losers) in the first year being losers (winners) in the next year. The following non-parametric tests use the information provided by these 2x2 contingency tables. Z-test applied by Malkiel (1995) compares the number of winners (losers) in two consecutive years with the number of winners (losers) in the first year. The Z-test~N(0,1) contrasts for the persistence hypothesis including the probability of a winner (loser) being a winner (loser) in the next year. This probability takes different values for each compared year, because the number of winners and losers is different due to our clustering approach. Brown and Goetzmann (1995) propose an odds ratio which represents the number of persistent companies to those that are not. Brown and Goetzmann (1995) develop a Z-test~N(0,1) to contrast for the persistence hypothesis based on this odds ratio. Kahn and Rudd (1995) originally apply a chi-square test~$\chi^2_{(1)}$ to contrast for the persistence hypothesis. This statistic is based on both actual and expected number of companies being WW, WL, LW and LL in two consecutive years. Similarly to the Z-test applied by Malkiel(1995), the expected frequencies are calculated in our sample for each year. Finally, Cochran (1954) uses aggregate information of 2x2 contingency tables to provide a persistence test for the entire sample period. This Cochran's Y-test~N(0,1) is based on the number of 2x2 contingency tables, the number of winners (losers) in the first year, and the relation between persistent companies and those that are not.

* 5% significant; ** 1% significant.

TABLE 8
NSBM EFFICIENCY PERSISTENCE BASED ON 4X4 CONTINGENCY TABLES

	Portfolio Stage					Marketing Stage					Operational Stage					Overall Efficiency				
2006 2005	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	7**	4	3	2**	42.4**	8*	5	4	1**	49.5**	12**	6*	4	1**	41.8**	6*	8**	2	1**	47.6**
W	3	3**	0	1		8**	3	2	0**		4*	2	1	0		2	6**	3	1*	
L	6	4	19**	15		6	3	11**	6		6	3	15*	7		3	4	13**	5	
Bot L	3	0*	5	23**		2**	4	6	29**		3**	2	11	21**		4	2**	10	28**	
2007 2006	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	7*	4	5	3*	37.7**	10*	4	8	2*	36.2**	13**	3	7	3*	39.5**	5	5	5	1*	41.2**
W	6**	2	3	0**		7*	3	3	2		5	4	2	2		8**	7	3	2*	
L	3	2	12*	9		2	7*	9	3		6	7	11	3*		2	5	14**	4	
BotL	1**	4	8	26**		3*	1**	12	19**		2**	1*	7	19**		1**	4	9	20**	
2008 2007	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	13**	2	1**	0*	54.6**	10**	3	6**	2	25.7**	14**	2	5**	4	23.5**	11**	3	1**	0	35.7**
W	4	5**	3	0*		3	6**	6	0		3	4	6	2		8	4	7	2	
L	4	3	12	9		5	4	21	2		5	2	14	6		3*	8	19	1	
BotL	1**	3	18*	14*		1*	2	17	4		1**	4	14	6		1**	4	18**	2	
2009 2008	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	8*	6	7	2	16.1	7**	3	6	3	19.1*	8**	4	10	2	16.6	9**	2	10	3*	15.8
W	3	2	7	1		2	2	11	1		1	2	5	4		1	3	6	9	
L	4	5	21*	4		3**	6	28	13		2*	5	24	8		5	3	21	16	
Bot L	3	4	8	8**		3	0	2	3		4	0	8	6		1	1	1	2	
2010 2009	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	7**	5	1**	5	24.3**	10**	0	2*	3	44.1**	12**	1	3	3*	48.4**	9**	4	1*	2*	31.8**
W	3	1	9	2		1	4**	5	0*		0	2*	2	1		3	0	3	2	
L	1**	8	20	12		2**	6	18	18		2**	5	18*	14		2**	7	16*	12	
Bot L	2	2	4	6		2	1	7	9		2	0	6	17**		2	4	7	14*	
2011 2010	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	8**	1	1*	3	40.5**	8**	3	0**	4	30.1**	10**	1	0**	5	28.9**	10**	2	0**	4	48.5**
W	4	4**	5	3		4	2	4	1*		3	1	4	0*		2	6**	7	0*	
L	1**	1	18**	10		3	3	12*	10		5	1	12	8		2	1	10	10**	
Bot L	3	0	7	15**		4	0*	7	19**		4*	0	11	19**		3	1	20**	6	
2012 2011	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test	Top W	W	L	Bot L	χ2 test
Top W	9**	2*	2	1	19.5*	7	5	2	3	12.6	9*	2	7*	3	12.6	7*	2	3*	3	17.1*
W	3	1	1	0		3	4	1	1		0	0	3	0		3	0	5	3	
L	6	16*	4	3		4	6	7	2		5	2	12	3		6	4	17	5	
Bot L	4*	9	10*	3		4	5	12	8		4	0	17	7		1	0	7	8*	

The 4x4 contingency tables are obtained by comparing number of mutual fund companies included in the four efficiency clusters (Top W, W, L and Bot L) of two consecutive years. The following non-parametric tests use the information provided by these 4x4 tables. Similarly to 2x2 tables, a new chi-square test~$\chi^2_{(9)}$ is now applied to 4x4 tables to check for the persistence hypothesis. This test is based on both actual and expected number of companies for each one of the 16 efficiency combinations in two consecutive years. The expected frequencies are calculated in our sample for each year. Finally, we apply the residual analysis of Haberman (1973) to identify those efficiency categories responsible for a significant chi-square value. This test computes an adjusted residual d~N(0,1) based on both actual and expected number of companies for each one of the 16 cells of a 4x4 contingency table. The adjusted residuals for each contingency table cell are not displayed for the sake of brevity but its statistical significance is considered for each cell. Similarly to the chi-square test, the expected frequencies are calculated for each year.

* 5% significant; ** 1% significant.

Finally, the analysis of residuals of Haberman (1973) identifies those efficiency groups responsible for the persistence phenomenon. Table 8 provides very insightful evidence of this test in our sample. We find a significantly higher persistence of those companies included in the *Top W* clusters than in other 4x4 contingency table cells. This result is robust across nearly all time periods and management stages. This evidence indicates that the 4x4 persistence results are strongly caused by the best mutual fund companies in efficiency terms, being this result robust for portfolio management, for marketing and distribution of mutual funds as well as for the operational efficiency of the fund company.

Furthermore, following to Premachandra et al. (2012) if we pay more detailed attention to the number of companies that have performed consistently well, Table 9 shows that very few companies are able to perform excellent over our whole sample period. This finding proves the great difficulty to get excellent efficiency records during a long time horizon. In our sample, only 4, 5, and 6 fund companies have performed consistently excellent over periods longer than 6 years at Portfolio Stage, Marketing Stage and Operational Stage, respectively. In this small and selective group we find large bank-owned fund companies managing many mutual funds and fund types together with small independent companies specialized in few mutual funds and fund types.[20] This result may indicate that both diversification and specialization strategies may be successful in efficiency terms if these strategies are properly developed.

[20] Detailed information about these companies is not shown for the sake of brevity, but it is available upon request.

Table 9
NUMBER OF PERSISTENT TOP WINNER-TOP WINNER COMPANIES OVER DIFFERENT SAMPLE PERIODS

	Over 2-year	Over 3-year	Over 4-year	Over 5-year	Over 6-year	Over 7-year	Over 8-year
Portfolio Stage	15	3	2	2	2	0	2
Marketing Stage	7	7	1	2	3	1	1
OperationalStage	10	9	1	3	1	3	2
OverallEfficiency	12	4	2	2	2	1	1

5.3. The search for locally efficient mutual fund companies

Finally, according to the important concentration of the Spanish fund industry we follow an innovative approach proposed by Tone (2010) to identify locally efficient companies which are going to be referred to the best practice frontier formed by fund companies with similar management characteristics.

In our SBM-based separation model, the intermediate variables and therefore the inefficiencies associated to them must be all included in the sets of ordinary inputs $X^k=(x_1^k,\dots,x_n^k)\in R^{m_k\times n}$ or ordinary outputs $Y^k=(y_1^k,\dots,y_n^k)\in R^{r_k\times n}$ for each stage k. However, Tone (2010) states that the objective function expressed by the original SBM might project the evaluated company onto a very remote point on the reference frontier because SBM aims to find the worst efficiency score associated with the relatively maximum slacks under the constraints of the model (Appendix A, model A1). These remote projections could be sometimes hard to interpret in terms of appropriate efficiency comparisons. In order to overcome this limitation, Tone (2010) explores the supporting hyperplanes (Facets) of the production possibility set to define the existence of a facet which includes efficient linear combinations of the companies analysed. In most DEA models, the production possibility set is a polyhedral convex set whose vertices correspond to the efficient companies found by the corresponding DEA method. Tone (2010) argues that a polyhedral convex set can be defined by its vertices or by its supporting hyperplanes and recommends four variants of the original SBM which are based on the hyperplanes instead of the vertices.[21] SBM Variation III proposed by Tone

[21] SBM Variation I aims to obtain the minimum slacks-based measure point on the facets that the SBM finds for the objective company. That is, to find the nearest referent point on the efficient frontier. Then, SBM Variation II extends this approach to consider all facets of the production possibility set. Finally, there are two additional variants because the exhaustive enumeration of all facets required in Variation II may

(2010) is the most suitable model for our research purposes. This variant aims to find the nearest referent point on the efficient frontier by clustering all facets of the production possibility set. This model uses groups of homogeneous competitors to identify globally inefficient but locally efficient companies within these clusters.

Variation III requires four steps. First, we classify all companies in homogeneous clusters. Second, we obtain the *s* efficient companies for each management stage *k* according to the SBM separation model (A1), thereby identifying the inputs $\xi^k=(\xi_1^k,\dots,\xi_s^k)\in R^{m_k\times n}$ and outputs $\eta^k=(\eta_1^k,\dots,\eta_s^k\in R^{r_k\times s}$ for these SBM efficient companies. Third, we enumerate all facets of the production possibility set and only select the clustered *maximal friends* facets (m_k=1,…, M_k) composed by combinations of SBM efficient companies at stage *k* within the same cluster.[22] Finally, for every stage *k* SBM Variation III looks for the nearest point on the reference frontier by minimizing the slacks-based measure from each clustered *maximal friends* facet. The formulation of SBM Variation III under VRS is defined as follows

$$\rho_o^{m_k}=\max_{\lambda^k,s^{k-},s^{k+}}\frac{1-\frac{1}{m_k}\left(\sum_{i=1}^{m_k}\frac{s_i^{k-}}{x_{io}^k}\right)}{1+\frac{1}{r_k}\left(\sum_{r=1}^{r_k}\frac{s_r^{k+}}{y_{ro}^k}\right)}$$

subject to (3)

$$\xi_o^{m_k}\lambda^k+s^{k-}=x_o^k$$

$$\eta^{m_k}\lambda^k-s^{k+}=y_o^k$$

$$e\lambda^k=1$$

$$\lambda^k,s^{k-},s^{k+}\geq 0,$$

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need huge computing: Variation III clusters all facets and Variation IV makes a random search of these facets.

22 Tone (2010) defines an algorithm for finding the *maximal friends* facets. A subset of SBM efficient companies is called *friends* if a CRS or VRS linear combination of this subset is also efficient. Then, *maximal friends* facets are those *friends* facets when any addition of an efficient company (not in the *friends*) to the *friends* is not more *friends*. Finally, a *friends* facet is a *dominated friends* facet if it is a subset of others. Detailed explanations of this algorithm and the definitions of *friends*, *dominated friends* and *maximal friends* can be found in Tone (2010).
If none of companies in the cluster analysed is efficient, Tone (2010) proposes to pick up the efficient companies in the adjacent clusters to form the *maximal friends* facets.

where $\eta^k = (\eta_1^k, \ldots, \eta_s^k \in R^{r_k \times s}$ is the set of inputs and outputs of those efficient companies that span each clustered *maximal friends* facet (m_k) selected in the third step of this variant. That is, we solve model (3) at stage k for each clustered *maximal friends* facet. After that, the efficiency score $\rho_o^{VarIII_k}$ at stage k is finally computed as the maximum $\rho_o^{m_k}$ obtained for all the clustered *maximal friends* facets (M_k). If model (3) finds no feasible solution for the new within-cluster facets, the company is efficient in its cluster, that is, globally inefficient but locally efficient in relation to the companies with common characteristics. Notice that if we delete the constraint $e\,\lambda^k = 1$, the model (3) would be solved under CRS assumption.

According to Tone (2010), one of the major merits of this SBM Variation III is that the efficiency score is acquired in reference to the efficient companies in the same cluster. The results are more accurate because the companies are compared with competitors with common cluster characteristics. This advantage is especially helpful to find locally efficient companies in mutual fund markets with assorted competitors such as the Spanish fund industry.

Our clustering proposal is based on the assets managed by the fund companies in our sample, where a large number of small fund companies manage a residual market asset share and a reduced number of huge fund companies dominate the industry. We assume the hypothesis that companies with clustering-homogeneous size should have quite similar management resources to reach efficiency at every management stage in our network complex. We propose 5 size clusters based on homogeneous dendogram heights.[23] Table 10 highlights the assorted size statistics of these five clusters. That is, these extreme size differences will also correspond to different management resources under our clustering hypothesis.

The search for the maximal friend facets has been quite different for each stage and cluster. A total of 19,112 reference combinations were examined to find the *maximal friends* facets required to apply SBM Variation III. For the case of clusters with a small number of efficient companies the *maximal friends* were easily found according to the algorithm proposed by Tone (2010). On the other hand, those clusters including more efficient companies involve much higher computational resources. As an example, if we

[23] Similarly to the identification of contingency tables in the persistence analysis, we follow the divisive clustering approach proposed by DIANA algorithm to find robust size clusters. Cluster dendograms are available upon request.

find 13 efficient companies at Portfolio Stage (Cluster 5 in 2007), then in the worst case we run ${}_7C_6$=1,716 SBM models to search for *maximal friends* facets.

The analysis of efficiency restricted to homogeneous competitors reveals that a relevant percentage of globally inefficient companies are now considered as locally efficient. Table 10 shows that this finding is valid for most of management stages and years. That is, we generally find that a relevant number of Spanish fund companies may be considered efficient according to size-homogeneous reference companies. This result supports that most of these fund companies are not considered inefficient in relation to competitors with similar management characteristics despite the inefficient scores obtained in relation to all the industry. Table 10 also shows that the relevance of both globally and locally efficiency levels within each cluster is generally more important in large companies than in small companies at every management stage. That is, efficiency seems to be positively affected by the fund company size. This result confirms the previous evidence provided by Table 3.

Finally, this large number of globally inefficient but locally efficient companies across management stages and years could reveal that the evaluation of the efficiency in concentrated fund markets should consider carefully appropriate reference frontiers with similar management resources to avoid misinterpreting efficiency conclusions. Further research on this issue is necessary to extend this evidence.

TABLE 10
EFFICIENCY BY SIZE CLUSTERS

	2005	2006	2007	2008	2009	2010	2011	2012
Cluster 1								
Companies (Average assets)	7 (23,075)	7 (24,623)	6 (27,335)	7 (23,080)	7 (16,415)	11 (9,394)	7 (11,735)	5 (12,869)
Portfolio Stage-GE (LE)	5 (0)	7 (0)	5(1)	6 (1)	6 (1)	6 (5)	5 (0)	4 (0)
Marketing Stage-GE (LE)	2 (5)	3 (3)	1(5)	1 (6)	1 (3)	1 (6)	1(5)	0 (0)
Operational Stage-GE (LE)	2 (5)	4 (2)	3 (3)	4 (3)	3 (4)	2 (6)	4 (1)	3 (2)
Cluster 2								
Companies (Average assets)	19 (2,309)	18 (3,093)	19 (3,807)	17 (3,346)	14 (2,455)	20 (1,096)	12 (2,319)	14 (2,842)
Portfolio Stage-GE (LE)	5 (11)	4 (12)	5 (8)	3 (8)	2 (12)	4(15)	3 (5)	10 (0)
Marketing Stage-GE (LE)	1 (9)	3 (3)	3(4)	0 (17)	1 (9)	0 (19)	2 (4)	4 (7)
Operational Stage- GE (LE)	2 (5)	3 (11)	2 (17)	2 (12)	3 (11)	4 (3)	3 (5)	3 (10)
Cluster 3								
Companies (Average assets)	22 (972)	28 (921)	28(936)	29 (851)	32 (671)	20 (706)	31 (599)	20 (673)
Portfolio Stage-GE (LE)	8 (3)	6 (12)	5 (18)	9 (5)	8 (16)	6 (4)	9 (4)	7 (9)
Marketing Stage-GE (LE)	1 (21)	0 (6)	1 (27)	3 (15)	1 (27)	0 (7)	1 (30)	2 (18)
Operational Stage- GE (LE)	2 (6)	4 (5)	2 (15)	1 (1)	3 (1)	1 (17)	3 (1)	4 (10)
Cluster 4								
Companies (Average assets)	22 (278)	18 (244)	15 (224)	16 (256)	12 (182)	14(176)	17 (162)	13 (221)
Portfolio Stage-GE (LE)	5 (13)	5 (6)	4 (11)	1 (8)	2 (8)	4 (10)	5 (9)	4 (9)
Marketing Stage-GE (LE)	2 (11)	2 (7)	2 (11)	2 (7)	3 (0)	2 (4)	2 (15)	2 (7)
Operational Stage- GE (LE)	3 (16)	4 (5)	3 (9)	1 (11)	2 (9)	0 (11)	2 (11)	2 (10)
Cluster 5								
Companies (Average assets)	32 (94)	31 (63)	27 (106)	24 (123)	30 (95)	24 (80)	19 (69)	22 (108)
Portfolio Stage-GE (LE)	11 (3)	6 (14)	13 (1)	7 (4)	10 (9)	9 (6)	10 (0)	11 (4)
Marketing Stage-GE (LE)	0 (9)	2 (6)	4 (16)	3 (0)	1 (26)	1 (10)	2 (6)	6 (12)
Operational Stage- GE (LE)	6 (24)	4 (17)	4 (19)	2 (20)	3 (24)	1 (15)	0 (14)	3 (7)

This table shows the number of companies included for each size cluster and year together with the average assets in million euros managed per company. GE represents the number of globally efficient companies found by the SBM separation model (Tone, 2001) for each size cluster, management stage and year. LE represents the number of globally inefficient but locally efficient companies found by SBM Variation III (Tone, 2010) for each size cluster, management stage and year.

6. CONCLUSIONS

This study is the first evaluation of the efficiency of mutual fund companies in a relevant Euro fund industry, i.e. Spain. Based on a Network SBM approach proposed by Tone and Tsutsui (2009), our paper develops an innovative model which includes three interacting management stages within a fund company: Portfolio Stage, Marketing Stage, and Operational Stage.

The efficiency results of this network model show that the linking effects between the management stages in a company are especially relevant at Marketing Stage. In addition, we find that the abilities for selling mutual funds seem to be more important to explain the efficiency of a fund company than the portfolio management skills. We also find that company size seems to play a positive role in the efficiency of Spanish fund companies. Finally, we do not detect a significant change in the efficiency patterns before and after financial crisis.

According to efficiency rankings drawn by our network model, we find a significant persistence phenomenon for all the management stages and years, although less significance is observed since financial crisis. This finding is robust across all the non-parametric tests. We find that this evidence may be especially driven by the best fund companies in efficiency terms.

Finally, the application of the innovative SBM Variation III (Tone, 2010) to the concentrated Spanish fund industry finds a large number of globally inefficient but locally efficient companies across different management stages and years. This empirical result supports the application of specific techniques which consider homogeneous reference frontiers in those highly concentrated fund industries, such as the Spanish mutual fund market.

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Appendix A. SBM model

According to the non-oriented and VRS version of the SBM model (A1) proposed by Tone (2001), an objective company $\{x_o^k, y_o^k\}$ will be considered as efficient at stage k in terms of Pareto-Koopmans when it has no input excesses and no output shortfalls for any optimal solution, i.e., $\rho_o^{SBM_k}=1$.

$$\rho_o^{SBM_k}=\min_{\lambda^k, s^{k-}, s^{k-}} \frac{1-\frac{1}{m_k}\left(\sum_{i=1}^{m_k}\frac{s_i^{k-}}{x_{io}^k}\right)}{1+\frac{1}{r_k}\left(\sum_{r=1}^{r_k}\frac{s_r^{k}}{y_{ro}^k}\right)}$$

subject to (A1)

$$X^k\lambda^k+s^{k-}=x_o^k$$

$$Y^k\lambda^k-s^{k+}=y_o^k$$

$$e\lambda^k=1$$

$$\lambda^k, s^{k-}, s^{k+}\geq 0,$$

where $X^k=(x_1^k,\cdots,x_n^k)\in R^{m_k\times n}$; $Y^k=(y_1^k,\cdots,y_n^k)\in R^{r_k\times n}$. In this approach, the link variables $Z^{(k,h)}$ and their slacks must be included in the sets of ordinary inputs X^k or outputs Y^k previously defined. If we delete the constraint $e\,\lambda^k=1$, we deal with the CRS version of the SBM model.

Let an optimal solution of the above model (A1) be $\left(\lambda_o^{k*}, s_o^{k-*}, s_o^{k+*}\right)$. The reference set R_o to the target company at stage k is defined as those companies corresponding to positive values of the intensity vector.

$$R_o=\left\{j|\lambda_j^{k*}>0,\ j=1,\ldots n\right\} \tag{A2}$$

According to Tone (2001), the objective company $\{x_o^k, y_o^k\}$ can be projected in terms of the companies included in the reference set R_o at stage k as follows

$$\bar{x}_o^k=x_o^k-s_o^{k-*}=\sum_{j\in R_o}x_j\lambda_j^* \qquad \bar{y}_o^k=y_o^k+s_o^{k+*}=\sum_{j\in R_o}y_j\lambda_j^* \tag{A3}$$

Appendix B. Network SBM model and extension

After setting exogenously the relative importance w^k of stage k in the overall efficiency measure, NSBM (Tone and Tsutsui, 2009) evaluates the non-oriented overall efficiency of a target company $\{x_o^k, y_o^k, z_o^{(k,h)}\}$ under VRS assumption as follows

$$\rho_o^{NSBM} = \min_{\lambda^k, s^{k-}, s^{k}} \frac{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k}\right)\right]}{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_r^{k+}}{y_{ro}^k}\right)\right]}$$

subject to (B1)

$$X^k \lambda^k + s^{k-} = x_o^k \qquad Y^k \lambda^k - s^{k+} = y_o^k \qquad e\lambda^k = 1 \qquad (k=1,2,\ldots,K)$$

$$\lambda^k, s^{k-}, s^{k+} \geq 0 \qquad \forall k$$

where $X^k = (x_1^k, \cdots, x_n^k) \in R^{m_k \times n}$; $Y^k = (y_1^k, \cdots, y_n^k) \in R^{r_k \times n}$; $\sum_{k=1}^{K} w^k = 1$, $w^k \geq 0$ $\forall$k. Notice that if we delete the constraint $\lambda^k=1$, we assume the CRS version of the NSBM model.

According to Tone and Tsutsui (2009), the restrictions related to link variables $z_o^{(k,h)}$ can be added to the above model (B1) as following

$$Z^{(k,h)} \lambda^h = Z^{(k,h)} \lambda^k \qquad \forall k,h \tag{B2}$$

or

$$Z^{(k,h)} \lambda^h = z_o^{(k,h)} \; Z^{(k,h)} \lambda^k = z_o^{(k,h)} \qquad \forall k,h \tag{B3}$$

where $Z^{(k,h)} = \left(z_1^{(k,h)}, \cdots, z_n^{(k,h)}\right) \in R^{t(k,h) \times n}$

Restriction (B2) corresponds to the "free" case where the linking activities are freely determined and keep continuity between input and output. That is, the link flow may vary in the optimal solution of model (B1). Restriction (B3) corresponds to the "fixed" case, i.e. the linking activities do not change. An objective company will be considered as overall efficient when $\rho_o^{NSBM} = 1$, and therefore an objective company will be considered as efficient at stage k when $\rho_o^{NSBM_k}=1$, being the non-oriented efficiency at stage k defined by

$$\rho_o^{NSBM_k}=\frac{1-\frac{1}{m_k}\left(\sum_{i=1}^{m_k}\frac{s_i^{k-*}}{x_{io}^k}\right)}{1+\frac{1}{r_k}\left(\sum_{r=1}^{r_k}\frac{s_r^{k+*}}{y_{ro}^k}\right)} \quad (k=1,2,\ldots,K) \tag{B4}$$

where s^{k-*}, s^{k+*} are the optimal input and output slacks at model (B1). The reference set to the target company evaluated in (B1) at stage k is defined as the set of companies corresponding to positive values of the intensity vector.

$$R_o=\left\{j \backslash \lambda_j^{k*}>0,\ j=1,\ldots n\right\} \tag{B5}$$

Furthermore, Tone and Tsutsui (2009) propose to extend the original NSBM model to incorporate the inefficiency of the intermediate variables into the objective function. This extension includes the slacks $s^{(f,k)-}$ of the intermediate input to stage k at link (f,k), and the slacks $s^{(k,h)+}$ of the intermediate output from stage k at link (k,h). The extension of the non-oriented version of the NSBM model under VRS is set as follows

$$\rho_o^{NSBM'}=\min_{\lambda^k,s^{k-},s^{k+},s^{(f,k)-},s^{(k,h)+}}\frac{\sum_{k=1}^{K}w^k\left[1-\frac{1}{m_k+\sum_{f\in P_k}t_{(f,k)}}\left(\sum_{i=1}^{m_k}\frac{s_i^{k-}}{x_{io}^k}+\sum_{f\in P_k}\frac{s_f^{(f,k)-}}{z_{fo}^{(f,k)}}\right)\right]}{\sum_{k=1}^{K}w^k\left[1+\frac{1}{r_k+\sum_{h\in F_k}t_{(k,h)}}\left(\sum_{r=1}^{r_k}\frac{s_r^{k+}}{y_{ro}^k}+\sum_{h\in F_k}\frac{s_h^{(k,h)+}}{z_{ho}^{(k,h)}}\right)\right]}$$

subject to (B6)

$$\begin{array}{llll}
X^k\lambda^k+s^{k-}=x_o^k & Y^k\lambda^k-s^{k+}=y_o^k & e\lambda^k=1 & (k=1,2,\ldots,K)\\
Z^{(f,k)}\lambda^k+s^{(f,k)-}=z_o^{(f,k)} & Z^{(f,k)}\lambda^f=Z^{(f,k)}\lambda^k & \forall f,k & \\
Z^{(k,h)}\lambda^k-s^{(k,h)+}=z_o^{(k,h)} & Z^{(k,h)}\lambda^h=Z^{(k,h)}\lambda^k & \forall k,h & \\
\lambda^k,s^{k-},s^{k+},s^{(f,k)-},s^{(k,h)+}\geq 0 & & \forall f,k,h &
\end{array}$$

where P_k is the set of stages having the link $(f,k) \in L$ (antecessor of stage k) and $t_{(f,k)}$ is the number of intermediate variables in that link; and F_k is the set of stages having the link $(k,h) \in L$ (successor of stage k) and $t_{(k,h)}$ is the number of intermediate variables in that link. A company will be overall efficient at model (B6) when the optimal input and output slacks (s^{k-*}, s^{k+*}) together with optimal intermediate input and output slacks $(s^{(f,k)-*}, s^{(k,h)+*})$ result in $\rho_o^{NSBM'} - 1$.

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