EFFICIENCY ASSESSMENT OF BALTIC PENSION FUND MANAGEMENT COMPANIES

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Abstract
Purpose. This research paper focuses on the operational efficiency of Baltic pension fund management companies from the perspective of competitiveness of small and medium-size companies with no or low exposure to non-pension fund management business compared to other companies in the marketplace. The purpose is to assess whether small and medium-size pension fund management companies operating in Estonia, Latvia and Lithuania are capable of competitive efficiency compared to companies with bigger assets under management and a bigger share of non-pension fund management income.
Methods. The methods used in the empirical part of the research are: data envelopment analysis as well as main trend analysis, cluster analysis, development indicators, relative and absolute indicators. Data used for empirical research are from pension fund management companies in Latvia, Lithuania and Estonia. The research period covers the post-financial crisis years from 2009 to 2014.
Findings. The research outcome is reasoning why non-diversified small and medium-size pension fund management companies are capable of achieving competitive efficiency compared to their peers with bigger assets under management, which can be both non-diversified as well as more diversified companies.
Originality. In the context of a general lack of studies on the topic in the Baltic countries, the research paper provides a comprehensive quantitative assessment of the efficiency of pension fund management companies in the region with a focus on competitiveness of small and medium-size companies.

Keywords: *Pension fund management, data envelopment analysis, efficiency.*

INTRODUCTION

Stakeholder theory asserts that managers should make decisions that take into account the interests of all the firm's stakeholders. This will include shareholders, employees, suppliers, customers, local communities, the government and the environment (Pike, Neale 2009). The pension fund management marketplace is a typical business example where the interests of shareholders, customers and the government (via regulators) have to be balanced. Both too low and too high operational efficiency can lead to market distortions, which will have a negative impact on sustainability in the long run. The research problem is to assess whether small and medium-size pension fund management companies operating in Estonia, Latvia and Lithuania are capable of generating competitive efficiency compared to companies with bigger assets under management and a bigger share of non-pension fund management income. The research hypothesis is that companies with such a profile are competitive despite possible lack of economies of scale and scope. Pension fund management companies domiciled in the Baltics are generally owned by international financial groups of Nordic origin, which puts the research in the context of efficiency and sustainable development of multinational companies. The methods used in the empirical part of the research to process the abovementioned data are mathematical programming, mainly DEA and main trend analysis, cluster analysis, development indicators, relative and absolute indicators and other methods.

Literature Review

The performance management problem has triggered a fair amount of scientific discussion. Typically, measurements based on an accounting, market, economic value added or balances scorecard are used for performance assessment purposes. Accounting and market-based performance indicators prevail in diversification research. Accounting performance measurements can also be used when non-listed firms are included. However, their main drawback is looking backward as well as the risk that they can be subject to managerial manipulation. Bank efficiency studies are considered to be fairly abundant by now (Deutsche Bundesbank 2006). But only a few apply two or more techniques to an identical data set, especially European data (Weill 2004). Studies that compare parametric and non-parametric techniques include Ferrier and Lovell (1990), Sheldon (1994), Resti (1997), Bauer et al. (1998), Casu and Girardone (2002) and Beccalli et al. (2006). An early study that compares alternative frontier techniques is Ferrier and Lovell (1990). The researchers analysed the cost structure of 575 US banks for the year 1984 using both the Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) methodologies. They find higher efficiency scores with DEA compared to SFA, namely 80% and 74% respectively. They conclude that DEA is sufficiently flexible to envelop the data more closely than the translog cost frontier. However, efficiency scores are not significantly correlated, thus indicating that other factors not controlled for may drive the obtained wedge between the two measures. European evidence is provided by Sheldon (1994). He analysed the cost efficiency of Swiss banks with SFA and DEA in the period of 1987 to 1991. While results from DEA indicate that the average degree of cost efficiency is about 56%, SFA yielded only 3.9% mean efficiency. This substantial deviation from the usually obtained magnitudes of around 80%, obtained for US and European studies, casts some doubt as to an appropriate specification of the cost function (Amel et al. 2004). Likewise, he reports an insignificant rank-order correlation of 1%, indicating that no relationship exists between the two groups of efficiency scores. These results – that two alternative methods to implement an identical theoretical cost minimization problem should not be correlated – are remarkable. And, in fact, Resti (1997) provides very different results. He analysed the cost efficiency of 270 Italian banks over the period of 1988-1992. He compares the parametric and non-parametric efficiency scores and finds that the econometric and linear programming results do not differ substantially. Moreover, contrary to Ferrier and Lovell (1990) and Sheldon (1994), he reports higher efficiency scores between 81% and 92% for SFA as opposed to DEA scores between 60% and 78%. Rank correlation between SFA and DEA is statistically significant at the 1% level and ranges from 44% to 58%. The rank ordering of firm-specific inefficiency is strongly correlated over time, although it is more persistent with DEA than with SFA. The Bauer et al. (1998) study is the most significant of all, given the application of four approaches – SFA, DEA, Thick Frontier Analysis (TFA) and Distribution Free Analysis (DFA) – on a data set of 683 US banks over the period of 1977-1988. They suggest six consistency conditions to analyse the robustness of frontier efficiency measures. They compare the efficiency distributions, the rank order correlation of the efficiency distributions, the correspondence of best-practice and worst-practice banks across techniques, the stability of measured efficiency over time, the consistency of efficiency with market-competitive conditions and the consistency with standard non-frontier performance measures. For each approach, they calculate a measure of single-year efficiency and a measure of total-years efficiency based on one set of banks over the entire time period. Mean efficiency of parametric techniques averages 83% while mean efficiency for the nonparametric approaches is only around 30%. Nonparametric and parametric techniques present only a very weak consistency ranking with each other: rank-order correlation is 10%. All the methods are stable over time, although DEA generally shows slightly better stability than the parametric methods. On the other hand, the parametric efficiency scores are generally consistent with the standard performance measures, while DEA efficiency scores are much less so. In sum, Bauer et al. (1998) conclude that there is no single correct approach to specify an efficient frontier. Instead, both measures seem to react to varying degrees to particularities of the data. Thus, reporting methodological cross-checks is important to ensure that policymakers are aware of the different information contained in efficiency measures derived with alternative methods. In their study, Casu and Girardone (2002) evaluated the cost characteristics, profit efficiency and productivity change of Italian financial conglomerates during the 1990s using SFA, DFA and DEA. Efficiency measures from stochastic and deterministic frontiers are reasonably similar in magnitude and also show similar variation in efficiency levels. Despite these similarities in range and variance of the efficiency score, the trend in the DEA cost efficiency increases between 1996 and 1998 and shows a rather sharp decrease in 1999. In turn, SFA estimates exhibit a steady improvement in cost efficiency. Not surprisingly, DFA efficiency estimates are consistent with the DEA scores rather than with the SFA scores and display a decreasing trend of efficiency. Weill (2004) also checks the robustness of SFA, DFA and DEA. He measures the cost efficiency of 688 banks from five European countries (France, Italy, Germany, Spain, and Switzerland) over the period of 1992-1998. He compares mean efficiencies, correlation coefficients between methodologies and the correlation with standard measures of performance. Efficiency scores do not differ substantially across techniques and are positively correlated between SFA and DFA. At the same time, there is no positive relationship between any parametric approach and DEA. All approaches provide efficiency scores that are correlated with standard measures of performance. Beccalli et al. (2006) measure the cost efficiency of stock-market-listed European banks in 1999 and 2000. They investigate the link between efficiency measures and the market performance of financial institutions by means of SFA and DEA and find that percentage changes in stock prices reflect percentage changes in cost efficiency, particularly those derived from DEA. Furthermore, SFA efficiency scores are slightly higher than DEA scores, namely 85% versus 83%, and DEA efficiency scores are more dispersed compared to SFA scores. In sum, more recent studies find that SFA efficiency scores are generally higher compared to DEA scores. This may reflect the different treatment of stochastic noise and the ability to control for heterogeneity. At the same time, studies that investigate the differences across methods more systematically show that efficiency measures differ not only in terms of mean industry efficiency. Because of the scope of and other limitations of this article, the authors employ DEA CRS and VRS models to assess operational efficiency. SFA is left out of the scope.

Theoretical Framework

Foundations of the Data Envelopment Analysis

The mathematical programming approach to construction of frontiers and measurement of efficiency relative to constructed frontiers goes by the descriptive title of data envelopment analysis, with the acronym DEA (Fried et al. 2008). It truly does envelop a data set; it makes no accommodation for noise, and so does not "nearly" envelop a data set the way the deterministic kernel of a stochastic frontier does. Moreover, subject to certain assumptions about the structure of production technology, it envelops the data as tightly as possible. Data Envelopment Analysis was first coined by Charnes, Cooper and Rhodes (1978) and had an input-oriented model with constant return to scale (CRS). This method, which is currently known as basic DEA, was an extension of "Farrell's measure to multiple – input multiple – output situations and operationalised it using mathematical programming" (Emrouznejad 2000). Recent scientific publications worldwide confirm that DEA is applied widely in different branches of scientific research (Liu et al. 2016). DEA has been applied for simultaneous analysis of production and investment performance of Canadian life and health insurance companies (Wu et al. 2007), for analysis of efficiency and productivity in the Swiss insurance industry (Biener et al. 2016), on bank branch efficiency (Paradi et al. 2011), and on efficiency evaluation of equity funds (Babalos et al. 2012). It is widely used for rankings (Adler et al. 2002), for research evaluation (Meng et al. 2008), and on requirements and challenges for application of DEA (Hatami-Marbini et al. 2011).

So as to illustrate the basic DEA model mathematically, let's assume that all the decision-making units (DMUs) use m inputs for the production of n outputs in a given technology level. denotes the amount of input i (i=1,2,…...,m) produced by jth DMU (j=1,2,….,k), whereas represents the quantity of output s (s=1,2,…..,n) produced by jth DMU (j=1,2,….,k). The variables (r=1, 2,….,n) and (i=1,2,……,m) are weights of each output and input respectively. The technical efficiency of can be written as:

$$Max \frac{\sum_{r=1}^{n} u_r Y_{r0}}{\sum_{i=1}^{m} w_i X_{i0}}$$

subject to:

$$\frac{\sum_{r=1}^{n} u_r Y_{rj}}{\sum_{i=1}^{m} w_i x_{ij}} \leq 1$$

for j=1,2,….,k, whereas u_r and $w_i \geq 0$ (r=1,2,…..,n) and (i=1,2,……,m). This mathematical representation can be clarified as finding the appropriate values for u and w that maximise the efficiency level of the observed firm subject to all efficiency scores being less than or equal to 1. To avoid infinite solutions (Coelli et al. 2005) and obtain a linear programming model, the Charnes-Cooper transformation can be used as follows:

$$Max \sum_{r=1}^{n} \mu_r Y_{r0}$$

subject to:

$$\sum_{i=1}^{m} w_i X_{i0} = 1$$

and

$$\left(\sum_{r=1}^{n} \mu_r Y_{rj} - \sum_{i=1}^{m} w_{ir} X_{ij}\right) \leq 0$$

whereas μ and $w_i \geq 0$ (r=1,2,…..,n) and (i=1,2,……,m). As a result of these linear programming iterations, the efficiency level of the observed DMU – DMU_0 in this case – is equal to 100% if and only if:
i. = 1
ii. = 0 for all (i=1,2,……,m) and (r=1,2,…..,n).
If we return to the debate between Farell and Koopmans, proposition (i) is a necessary condition for Farell for efficiency; however, Koopmans states that full efficiency necessitates both (i) and (ii). Figure 1 illustrates DEA in a very generic representation, which allows for a straightforward discussion of Farell and Koopmans's efficiency approaches. For Farell, all the points on the isoquant curve can be considered as efficient combinations of input-1 and input-2. However, Koopmans reveals the fact that points on the isoquant curve with slack usage of inputs (like A, F, I) can't be shown as an efficient combination of inputs.

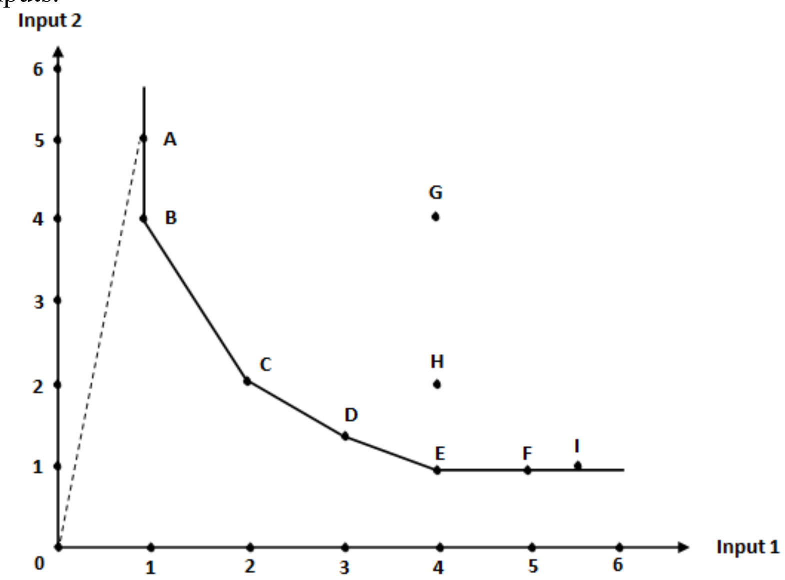

Figure 1: General representation of DEA
Source: Erkoc (2012)

DEA CRS and VRS Models

The analysis up to this point has assumed that DMUs operate at constant return to scale (CRS), as put forward by Charnes, Cooper and Rhodes (1978), where t times increase in inputs will result in t times increase in output:

$$tY = tf\{X\}$$

On the other hand, in many sectors, due to "imperfect competition, government regulations and constraints on finance", firms can't be run at optimal scale (Coelli et al. 2005). Therefore, scale efficiency, which has an impact on the technical efficiency of a firm, arises in these circumstances. So as to capture the magnitude of "scale effect", Färe, Grosskopf and Logan (1983) and Banker, Charnes and Cooper (1984) developed a variable returns to scale (VRS) in which CRS assumption is relaxed. Figure 2 illustrates the divergence of VRS models from CRS models in a quite generic way. For instance, the efficiency of point B is calculated as the ratio of O_1/O_2 regarding the VRS frontier, whereas is equal to O_1/O_3 if the CRS frontier is taken as the reference point. Eventually, it is apparent that the VRS frontier takes the magnitude of scale efficiency into account while measuring the total efficiency.

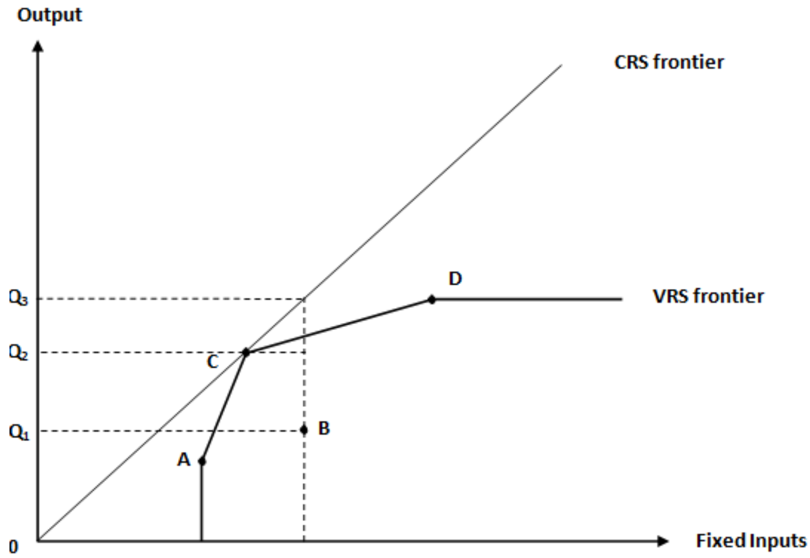

Figure 2: DEA CRS and VRS models
Source: Coelli et al.(1998)

The linear programming model of VRS is quite similar to the CRS model as indicated in the previously discussed formulas. The only difference is the addition of a convexity constraint to the system:

$$\sum_{j=1}^{k} \lambda_j = 1, for\ j = 1,2 \dots, k$$

for j= 1, for j=1,2,….,k.
The mathematical relationship between VRS and CRS efficiency measurements can be illustrated as (Coelli et al. 2005):

$$TE_{CRS} = TE_{VRS} * SE$$

where SE denotes scale efficiency, which means that the CRS technical efficiency of a firm can be decoupled into pure technical efficiency and scale efficiency (SE). Even though an analytical association exists among CRS and VRS models, input and output efficiency scores are different in VRS models unlike in CRS models (Emrouznejad 2000).

Analysis and Result Discussion

The pivotal role in the Baltic banking and, as a result, pension fund marketplace belongs to players of Nordic origin, while local companies with mixed shareholding structures provide some diversification to the market, even though not all major Nordic market players are present in the Baltic countries. In particular, when the market share is based on total assets, the two largest banks in Denmark – *Danske Bank* and *Nordea* – manage 67% of the total market (European Banking Federation 2012). Swedish commercial banks are divided into three categories. Universal banks: banks that are represented in a large part of the financial market and offer all kinds of financial services are categorised as universal banks. Among the Swedish universal banks, we find the 'big four' banks: *Nordea*, *Swedbank*, *Svenska Handelsbanken* and *SEB*. Together they have a strong position on the Swedish market, although the market shares vary in different niche markets. There is also *DNB*, domiciled in Norway, which is also represented in each Baltic country. The Baltic marketplace is mainly occupied by such Nordic financial groups as *Swedbank*, *SEB*, *Nordea*, *DNB* and to some extent *Danske Bank*. The Baltic countries in the given research are defined as Estonia, Latvia and Lithuania, and certain local market players are also present in these countries. Twenty pension fund management companies are included in the research and are listed in Table 1 (the last two capital letters stand for Estonia in the case of EE, Latvia in the case of LV and Lithuania in the case of LT).
The cluster analysis is performed by using the single linkage method (Lee 2015). Clusters which constitute a special scientific interest are numbers one, two and four. The first cluster represents small to medium-size pension fund management companies (i.e. assets do not exceed EUR 400 mio) with a low to non-existent share of non-pension fund management income (i.e. typically 0-15%). The second one is comprised of big companies (i.e. assets range from EUR 400-930 mio) with low to non-existent

non-pension fund management income (i.e. up to 9%). Number four is comprised of big companies (i.e. assets range from EUR 500-950 mio) with moderate exposure to non-pension fund business (i.e. 14-34%).

Table 1

Summary of the cluster analysis of pension fund management companies

Cluster	Item	2014	2013	2012	2011	2010	2009
1.	Companies	Danske Capital LT, Nordea LV, MP Pension Funds Baltic LT, DNB LV, Nordea EE, Danske Capital EE, DNB Nord LT, Finasta LV	DNB LV, LHV EE, Danske Capital EE, DNB LT, Finasta LV, Nordea LV, Nordea EE, MP Funds LT, Ergo Funds EE, Danske Capital LT	DNB LV, LHV EE, Danske Capital EE, DNB LT, Finasta LV, Nordea LV, Nordea EE, MP Funds LT, Ergo Funds EE, Danske Capital LT	DNB LV, LHV EE, Norvik LV, Danske Capital EE, DNB LT, Finasta LV, Nordea LV, Nordea EE, MP Funds LT, Ergo Funds EE, Danske Capital LT	DNB LV, DNB LT, LHV EE, Norvik LV, Finasta LV, Danske Capital EE, Nordea LV, Ergo Funds EE, MP Funds LT, Danske Capital LT, Nordea EE	Norvik LV, Finasta LV, Ergo EE, Nordea LV, Danske Capital LT, MP Pension Funds Baltic LT, Danske Capital EE, Nordea EE, DNB LV, LHV EE, DNB Nord LT
	AuM range, millions of euros	45-323	43-374	39-252	31-219	8-143	6-97
	Non-pension share range	0-9%	0-11%	0-14%	0-23%	0-36%	0-18%
2.	Companies	Swedbank LV, SEB LV, Swedbank LT, SEB LT	Swedbank LV, Swedbank LT	Swedbank LV, Swedbank LT	Swedbank LV, Swedbank LT	Swedbank LV, Swedbank LT	Swedbank LV, Swedbank LT
	AuM range, millions of euros	653-930	548-737	524-628	445-512	426-497	379-411
	Non-pension share range	0-9%	0%	1-2%	0-2%	0-3%	1-4%
3.	Companies	-	-	Hipo Fondi LV, Finasta LT	CBL LV, Hipo Fondi LV, Finasta LT	CBL LV, Hipo Fondi LV, Finasta LT	CBL LV, Hipo Fondi LV, SEB EE
	AuM range, millions of euros	-	-	114-166	92-368	104-435	235-441
	Non-pension share range	-	-	50-55%	51-55%	25-55%	44-61%

4.	Companies	CBL LV, LHV EE	SEB LV, SEB LT	SEB LV, SEB LT	SEB LV, SEB LT	SEB LV, Swedbank EE, SEB LT	SEB LV, SEB LT
	AuM range, millions of euros	504-594	770-780	524-754	616-633	608-953	556-580
	Non-pension share range	15-22%	14-18%	15-16%	17-24%	20-34%	17-19%
5.	Companies	Norvik LV, Ergo EE	-	-	-	-	-
	AuM range, millions of euros	65-250	-	-	-	-	-
	Non-pension share range	19-22%	-	-	-	-	-
Outliers	Companies	SEB EE, Finasta LT, Swedbank EE	Norvik LV, CBL LV, Swedbank EE, SEB EE, Finasta LT	Norvik LV, CBL LV, Swedbank EE, SEB EE	Swedbank EE, SEB EE	SEB EE	Swedbank EE, Finasta LT
	AuM range, millions of euros	139-1100	124-1,284	155-1,473	846-1,300	1,980	52-882
	Non-pension share range	19-40%	27-55%	29-43%	34-47%	47%	31-46%

Source: authors' calculations based on company data.

Companies classified as outliers will occasionally appear in the top quartile of the most efficient companies, which will be demonstrated by the analysis below.

Cost and Capital Efficiency DEA CRS and VRS Models

Cost and capital efficiency DEA CRS and VRS models are implemented in the following sections. The models can be viewed as consisting of two cost types: actual costs and implied capital costs. The actual cost part of the models comprises administration and commission costs as input variables. The capital cost part of the models, which is also an input variable, comprises implied cost of capital defined as a required pre-tax return on equity, which is multiplied by average equity in a specific year. Three scenarios are used for calculating the implied cost of capital: pre-tax ROE of 11%, 15% and 19%. The choice of these figures is based on analysis of ROE developments in the banking and asset management field. The output variable of the models is commission fees generated in a specific year. Therefore, the whole cost and capital efficiency model has three input variables (i.e. costs) and one output variable (revenue). The model has three scenarios depending on the pre-tax ROE discussed above. The results for Hipo Funds LV, which sold its pension fund management operations to SEB LV in 2012, are not included in the results for 2014 and 2013. Therefore, there are 118 observations in total, which are made up of 20 companies for the period of 2009 -2014 except the results for Hipo Funds in 2014 and 2013.

The DEA CRS Model – General Results

A regression analysis was run to examine whether bigger assets under management and a bigger share of non-pension fund income increase the cost and capital efficiency of pension fund management companies. Because the dependent variable cost efficiency is expressed in a range from 0 to 1 and share of non-pension fund management revenue is also expressed in a range from 0 to 1 while assets under management are expressed in millions of euro, assets under management figures were normalised for each year of the research by using the following formula:

$$x_{Norm} = \frac{(X - x_{Min})}{(x_{Max} - x_{Min})}$$

where X stands for actual variable, x_{Min} is the least variable, x_{Max} is the largest variable and x_{Norm} is a normalized variable.

The regression equation is expressed in the following manner:

$$CE = \beta_1 * NormAuM + \beta_2 * ShareNonPensInc + \alpha$$

where CE is cost efficiency score, NormAuM is a figure of normalised assets under management obtained by using the formula stated above, ShareNonPensInc is a share of non-pension fund revenue and α stands for intercept.

The regression analysis for all three pre-tax return on equity scenarios proved that there is no correlation between efficiency score and assets under management and share of non-pension fund management revenue. Table 5 summarises the main findings of the regression analysis run for three scenarios of pre-tax return on equity.

Table 2

Statistical findings of the regression analysis

No.	Parameter	11%	15%	19%
1.	Adjusted R-squared	0.03	0.03	0.05
2.	Significance F	0.06	0.05	0.02
3.	Observations	118	118	118

Source: authors' calculations based on company data.

Very low values of adjusted coefficients of determination (referred to as R-squared in Table 5) clearly demonstrate that there is no empirical evidence that pension fund management companies with bigger assets under management and a bigger share of non-pension fund management revenue tend to be more efficient than the average company on the market. The findings of the regression analysis are considered to be significant because significance figures range from 0.02 to 0.06.

The DEA CRS model – cluster efficiencies

The goal of this section is to assess the efficiency of each cluster in different pre-tax ROE scenarios with a particular focus on the first cluster of small to medium-size non-diversified pension fund management companies and big non-diversified as well as moderately diversified pension fund management companies. Efficiency ranks are calculated for the three pre-tax return on equity scenarios described in the section above. The first cluster of small to medium-size non-diversified pension fund management companies comprises the greatest scientific interest. In particular, the efficiency of companies belonging to this cluster is pivotal for the paper. The cluster is the biggest one in terms of the number of its members, even though this figure tends to decrease from eleven in 2009 to just eight in 2014. To begin with, the capital-light (pre-tax ROE=11%) scenario is considered first (see Figure 3). With the exception of 2010 and 2011, where the cluster hosts only two top quartile performers, typically three out of five top quartile performers are found in this cluster. This is very strong evidence that the cluster hosts competitive companies from the top quartile.

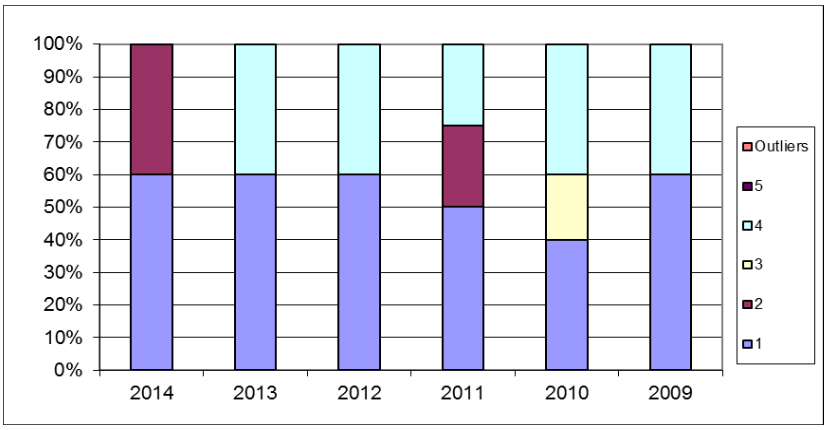

Figure 3: Clusters of the top quartile performers (ROE=11%)
Source: prepared by the authors

The next scenario, which assumes ROE of 15%, reveals nearly the same findings (see Figure 4). In particular, clusters one and four are the most often represented in the top quartile of efficiency ranks, even though cluster one is represented by three companies only in two years while in the previous scenario three companies of the cluster were included in the top quartile four times. Another obvious difference compared to the previous ROE scenario is that cluster number two appears four times as opposed to two appearances in the capital-light scenario. Given the fact that cluster two represents a big pension fund management company with low to non-existent exposure to non-pension fund management business, this finding is considered to be valuable from the perspective of the efficiency analysis of small to medium-size pension fund companies compared to big pension fund management companies.

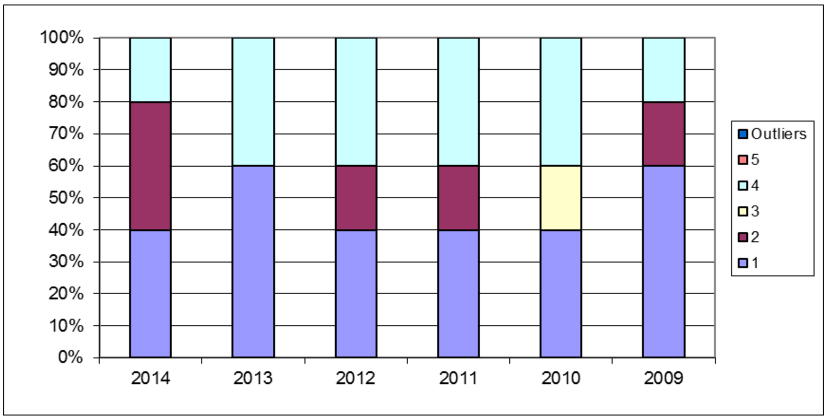

Figure 4: Clusters of the top quartile performers (ROE=15%)
Source: prepared by the authors

Cluster number three appears only once; thus, it can be disregarded. Other clusters, including outliers, do not appear in the scenario of ROE equal to 15% at all. Finally, the most capital-intensive scenario, which assumes ROE of 19%, is examined. The most apparent finding is that the first cluster is not represented in 2009 at all. However, it is represented in all other years, typically nominating two of its companies for the top quartile members. The fourth cluster of companies is represented in each single year and most often these are two companies of the cluster, except 2014. It should be noted that the fourth cluster primarily consists of two companies, except for 2010, when it had three members. Thus, such a result should be considered very strong from a probabilistic perspective.

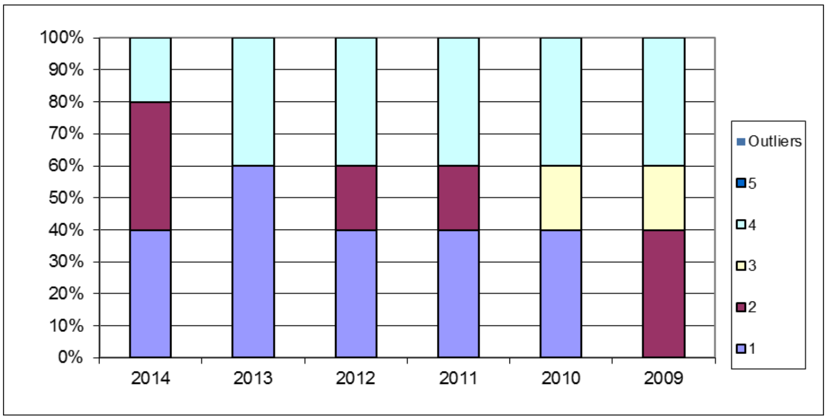

Figure 5: Clusters of the top quartile performers (ROE=19%)
Source: prepared by the authors

Cluster number two is represented four times, which is very similar to the previous scenario. However, it should be noted that in 2014, two companies which originally constituted cluster number four joined cluster number two and contributed to the high efficiency figures of the cluster. Cluster number three occupied a place in the top quartile twice out of six years of observation, which is still not sufficient to make any positive conclusions about the efficiency of companies in the cluster.

To summarize the efficiency result discussion, members of cluster one demonstrated top efficiency in all three scenarios of return on equity because the cluster was included in the top quartile of efficiency rankings in any single year except 2009, which was precisely the so-called bottom of the financial crisis. The members of cluster number four clearly enjoy the probabilistic advantage of being included in the top quartile of the efficiency ranking. These are big pension fund management companies with low to moderate exposure to non-pension fund management business. It is noteworthy that more intensive capital scenarios led to more frequent appearances of the big pension fund management companies with non-existent to low non-pension fund management revenue, represented by cluster number two, in the top quartile of the efficiency ranking. The same observation, to a lesser extent, is valid for the abovementioned cluster number two. Therefore, this section provided evidence that more intensive capital scenarios increase the relative efficiency of big pension fund management companies with both non-existent to low and low to moderate non-pension fund management income. Moreover, such companies also enjoy the probabilistic advantage of occupying the top quartile of the efficiency ranking compared to small to medium-size pension fund management companies with non-existent to low non-pension fund management income. Big companies with low to moderate non-pension fund management income tend to outperform those with non-existent to low non-pension fund management income, however.

The DEA VRS Model – General Results

A regression analysis was run in the same way as in the DEA CRS section of the article to examine whether bigger assets under management and a bigger share of non-pension fund income increase the cost and capital efficiency of pension fund management companies.

The regression analysis for all three pre-tax return on equity scenarios proved that there is a weak correlation between efficiency score and assets under management and share of non-pension fund management revenue. Table 6 summarises the main findings of the regression analysis run for three scenarios of pre-tax return on equity.

Table 3

Statistical findings of the regression analysis

No.	Parameter	11%	15%	19%
1.	Adjusted R-squared	0.1956	0.1718	0.1496
2.	Significance F	0.00	0.00	0.00
3.	Observations	118	118	118

Source: authors' calculations based on company data.

Even though the values of adjusted coefficients of determination (referred to as R-squared in the table) are higher than those obtained for the DEA CRS model, they are still considered to be too low to provide empirical evidence that pension fund management companies with bigger assets under management and a bigger share of non-pension fund management revenue tend to be more efficient than the average company on the market. The regression equation is significant provided that substantial significance values do not exceed 0.00003.

The DEA VRS model – Cluster Efficiencies

The DEA VRS model findings are assessed through the cluster perspective in this section of the paper. The most attention is paid to the 1st cluster of the small to medium-size pension fund management companies with non-existent to low exposure to non-pension fund management revenue. The top quartile efficiency ranks are presented in Figure 6.

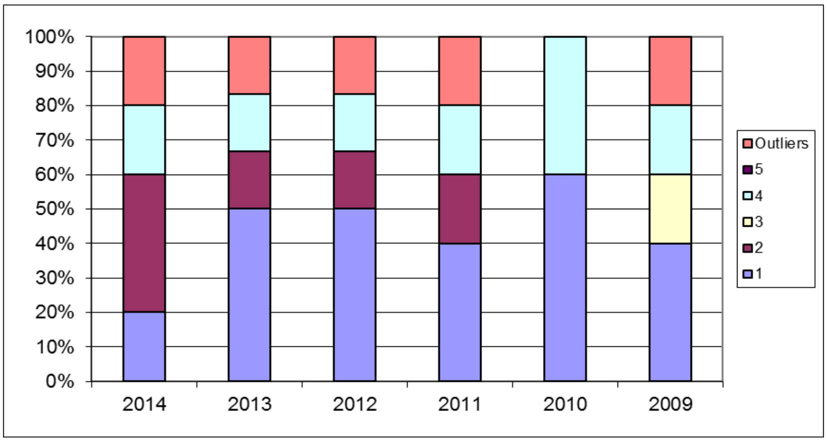

Figure 6: Clusters of the top quartile performers (ROE=11%)

Source: prepared by the authors

The findings suggest that companies from cluster number one are the most often represented in the top quartile given the capital-light scenario (i.e. ROE=11%). In particular, there are typically two to three companies originating from the given cluster out of five to six companies in the top quartile. Consistently, cluster number four is a permanent resident of the top quartile, also being represented in any single year. Consistently with findings from the previous section of the paper, given the small number of companies forming cluster number four, there is a clear probabilistic advantage for the cluster members to get into the top quartile. The appearance of cluster two, which is supposed to host big companies with non-existent to low exposure to non-pension fund management business, is also quite consistent with the findings of the previous section. However, the DEA VRS model reveals valuable findings in relation to the so-called outliers. Quite unexpectedly companies classified as outliers appear in any single year except 2010. Certainly, it is worth mentioning that the variable return to scale model can mean increasing, decreasing or a combination of increasing and decreasing returns to scale. Given the clear contrast to the DEA CRS model, inclusion of outliers as well as more frequent appearances of big pension fund management companies in the top efficiency quartile in accordance with the DEA VRS model speaks in favour of decreasing returns to scale.

The scenario with average capital intensity, assuming pre-tax return on equity of 15% per annum, demonstrates fairly similar findings as the capital-light scenario described above. The findings are shown in Figure 7.

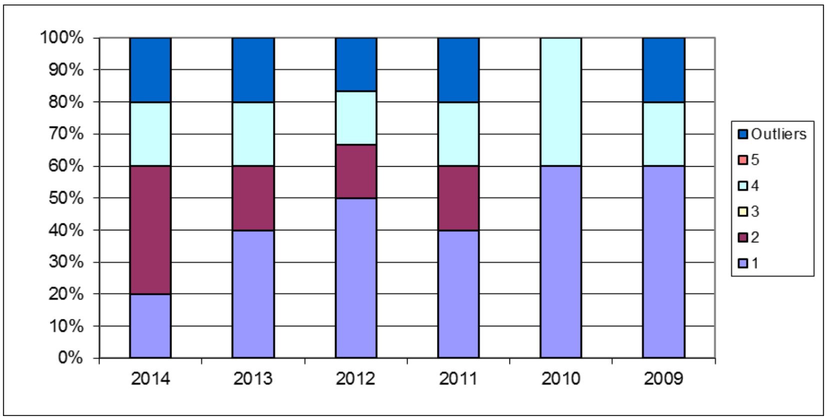

Figure 7: Clusters of the top quartile performers (ROE=15%)
Source: prepared by the authors

Typically, almost half of top quartile companies have a first cluster origin while the rest are distributed among the fourth cluster, second cluster and outliers.
The capital-intensive scenario, which assumes ROE of 19%, clearly ensures a more favourable environment for the second cluster of pension fund management companies (i.e. big companies with non-existent to low non-pension fund management income), while the conditions for outliers and companies belonging to cluster number four are nearly the same as for the two capital scenarios described above (see Figure 8). Logically, the second cluster companies are benefiting at the expense of the first cluster companies, which is clearly represented less often in this scenario of capital intensity – typically not more than two companies out of five.

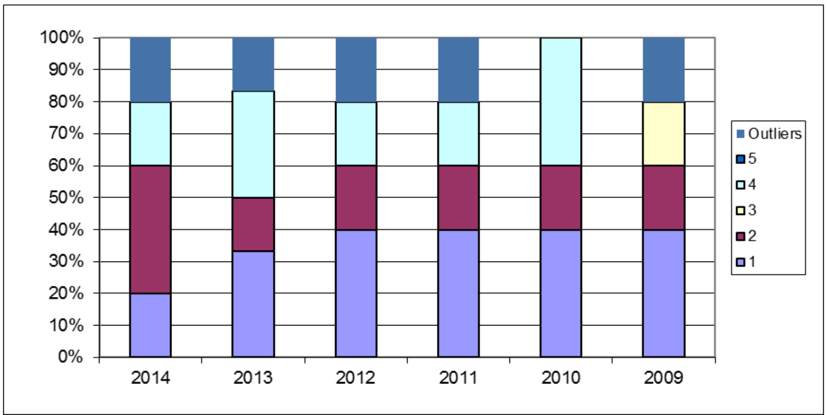

Figure 8: Clusters of the top quartile performers (ROE=19%)
Source: prepared by the authors

To summarize the efficiency result discussion, members of cluster one demonstrated top efficiency in all three scenarios of return on equity because the cluster was included in the top quartile of efficiency rankings in any single year. However, this cluster was closely followed by cluster number four and outliers as well as occasionally by cluster number two companies. It is noteworthy that more intensive capital scenarios increase the relative efficiency of big pension fund management companies with both non-existent to low and low to moderate non-pension fund management income. Moreover, such companies also enjoy the probabilistic advantage of occupying the top quartile of the efficiency ranking compared to small to medium-size pension fund management companies with non-existent to low non-pension fund management income. Big companies with low to moderate non-pension fund management income are represented less often than those with non-existent to low non-pension fund management income, however.

CONCLUSIONS

The regression analysis revealed that pension fund management companies with bigger assets under management and a bigger share of non-pension fund management income do not demonstrate higher operational efficiency ratings. The findings of the DEA CRS analysis from the cluster perspective demonstrated that the top quartile of clusters consists of small to medium-size pension fund management companies with a non-existent to low share of non-pension fund management income and big companies with non-existent to low non-pension fund management income as well as those with moderate exposure to non-pension fund business. The DEA VRS analysis revealed a similar pattern with one key distinction in relation to outliers which managed to earn their place in the top quartile. In particular, outliers penetrated the top quartile mostly at the expense of the big pension fund management companies with moderate exposure to non-pension fund management business, which might have increased the correlation between efficiency ratings and assets under management and share of non-pension fund income. Thus, evidence has been obtained that small and medium-size pension fund management companies are capable of achieving competitive efficiency compared to their peers with bigger assets under management, which may be non-diversified or more diversified companies.
Management of small and medium-size companies should pursue efficiency improvements, if needed, by benchmarking against top performers within their own cluster. Empirical evidence suggests that pursuing much bigger assets under management (i.e. typical for other clusters) and/or greater business diversification to non-pension fund management activities will not necessarily improve the efficiency of such companies because no general correlation has been found between efficiency and assets under management and share of non-pension fund management income. The strategy of pursuing much greater diversification to non-pension fund management income resulted in inefficiency (i.e. outliers typically have great exposure to non-pension fund management business) rather than efficiency improvement. The DEA VRS findings might challenge the latter statement and thus it might need further investigation.

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