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A Comparison of DEA and SFA Approaches: Application to the US Non-Life Insurance Market

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Abstract

Analyzing the efficiency of markets is essential for both business managers and policymakers. On the one hand, private companies need to be as efficient as possible, given that their competitiveness and their chance of survival depend on it. On the other hand, public enterprises declare to be committed to using public funds in the best possible way. To be competitive, firms need to improve their performance by incorporating the benchmark practices of their field in their management and studying efficiency levels may help identify potential areas for development. However, does the efficiency score depend on the method chosen to calculate it? In this paper, our aim is to compare the rate of agreement between two different approaches to measure efficiency, the parametric and the non-parametric. For the parametric procedure, we use stochastic frontier analysis (SFA), while in the case of the non-parametric, we use data envelopment analysis (DEA) and the dynamic approach of the DEA, the window DEA. To do so, we analyze 923 non-life (property/casualty) US insurance companies in the period 2007–2011. According to our results, comparable efficiency scores are found using SFA and DEA methodologies. More

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importantly, the two approaches rank companies in a similar order, mostly agreeing on which are the most and the least efficient firms. Therefore, we support that the approaches can be used complementarily.

Keywords: DEA, Window DEA, SFA, insurance market, efficiency

JEL Classification: C6, G14, G22

1. Introduction

Researching the best way to improve companies' efficiency is becoming an increasingly important managerial activity, given that competitiveness is growing. Both public and private organizations need to optimize the allocation of their resources to achieve the best performance possible. In this sense, it is interesting to analyze whether the methodology used to measure firms' efficiency influences the scores given to each firm. If the score given by different methods diverges, companies might search how to improve their efficiency based on decisions influenced by the methodology used to calculate the scores instead of their real needs. This research contributes to the previous literature, which focuses on comparing different approaches to measure efficiency. Similar to Dong et al. (2014), who analyze this issue in the banking sector, we study the insurance market.

The evaluation and analysis of business' efficiency are essential for any organization, public or private, as all they need is to optimize the allocation and management of their resources to achieve the best practices and better results. Furthermore, we should keep in mind that achieving a high-efficiency level is one of the main concern in any economic sector. The existence of an increasingly competitive environment, regulations, and specific standards explain why the analysis of efficiency is particularly interesting in the insurance industry and, therefore, the comparison of the different methodologies used for this purpose is equally relevant.

Typically, frontier models are used to measure firms' efficiency. In this context, two different approaches can be applied: parametric or non-parametric. The parametric approach is the Stochastic Frontier Analysis (SFA), and the non-parametric is the Data Envelopment Analysis (DEA). The principal difference between them is that DEA models do not require to define a priori the functional form of the efficient frontier.

Over the last few years, interest in the insurance market has grown notably. Recently, worldwide changes in regulation triggered merging and acquisition processes, which led businesses to continuously increase their competitiveness. Companies operate in a changing market where they need to get the best results given their available resources. The efficiency of the insurance market has been studied since the 90's. While new methodologies arise, so do the number of papers examining companies' efficient or inefficient performance. Most authors evaluate the efficiency of the different insurance markets using frontier models as their methodology. In these models, the efficiency of any decision-making unit (DMU) is assessed by comparing each company with those companies estimated as the most efficient ones, that is, the *benchmark*, whose behavior defines the efficient frontier.

By looking at the literature, both methods (SFA and DEA) have been widely used both to study the efficiency of insurance markets and compare countries, organizational forms, company sizes, or considering life and non-life insurers, for example. An extensive literature review on efficiency can be found in Eling and Luhnen (2010a) for the United States and European countries, or in Mose (2013) for African and some Asian countries. More recent papers using stochastic frontier analysis are those of Nawi et al. (2012) for the Malaysian market, Bhisma and Venkateswarlu (2014) for the Indian market, Yaisawarng et al. (2014) for the Thai non-life market, Alhassan and Biekpe (2016) for the South Africa insurance market, and Ferro and León (2017) for the non-life Argentinian insurance market. A remarkable paper is also that of Gaganis et al. (2013), in which, by employing SFA, the authors compare the efficiency of 52 countries during the period 2002 to 2008. Regarding manuscripts using DEA, we find Cummins and Xie (2013) for the U.S. insurance industry, Knezevic et al. (2015) for the Serbian market, Biener et al. (2016) for the Swiss insurance market, and Etugrul et al. (2016) focusing on the Turkish market, among others.

Several authors have jointly applied parametric and non-parametric methodologies to compare their outcomes. As Eling and Luhnen (2010b) noticed, although SFA efficiency scores are usually higher than those obtained by DEA, the information given by both methods is, overall, similar. In this sense, Cummins and Zi (1998) compare different stochastic approaches and a DEA-VRS model for life insurance firms in the U.S., finding that the correlation between average efficiencies obtained through each method is around 55 percent. Borger and Kerstens (1996) and, more recently, Eling and Luhnen (2010b), also find positive correlations at around 80 percent.

In this paper, we analyze the efficiency of the U.S. non-life insurance market during the period 2007 to 2011 using parametric and non-parametric approaches, namely, SFA, DEA, and

Window DEA. Our purpose is to compare efficiency scores obtained with each method to determine if their results are analogous. Moreover, we add to the literature by conducting a Window DEA to the insurance market. According to the extensive review of Kaffash et al. (2020), this methodology has never been applied to the insurance market before.

The paper is structured as follows; Section 2 describes the data sample and the variables used in the analysis, while Section 3 explains the different methodologies applied. Results are presented in Section 4, and, finally, Section 5 shows the main findings and conclusions.

2. Database

The dataset is obtained from Standard and Poor's "Global Credit Portal". It collects data of 923 Property/Casualty U.S. insurance companies from 2007 to 2011. Applying SFA and DEA modeling requires defining input and output variables. Numerous authors have debated the most appropriate definition of these inputs and outputs in different activities (see, for example, Cummins and Weiss, 2000 or Jarraya and Bouri, 2013). However, even though the selection of inputs and outputs plays a key role in estimating efficiency, there is no consensus on the optimal choice. Given that in the insurance industry, as part of the service sector, some quantities are intangible, implicit, or not available, this selection is even trickier.

To measure non-life insurers' outputs, we follow the value-added approach, the typical approach in the insurance market (see, for example, Cummins and Weiss, 2000; Mose, 2013, or Jaloudi et al., 2019) as it emphasizes the importance of outputs in the value creation process. According to this approach, any variable is considered an output when it provides a relevant added value basing on operating cost allocations. In this line, some authors use claims or net losses as outputs (Eling and Luhnen, 2010b; Alhassan and Biekpe, 2016; Ferro and León, 2017, Cummins and Weiss, 2000). Nevertheless, the use of claims as an output is controversial. It has been widely discussed that it violates the principle of "more output is preferable than less" (Diacon et al., 2002), given that insurance companies should try to minimize insurance claims. For example, holding inputs constant, an increase in losses due to catastrophic events, which do not imply better management, would rise estimated efficiency (BrocKett et al., 2005). Different solutions have been proposed, as smoothing the data or using expected losses to avoid the effect of large increases in losses (Cummins and Nini, 2002; Cummins and Xie, 2008, Leverty and Grace, 2008). To solve the problem of preferring a lower output rather than a bigger one when using claims, authors like

Klumpes (2005) propose the use of premiums paid plus investment income, or invested reserves minus claims minus changes in reserves. Nonetheless, using premiums as an output has also been criticized, since it represents price times output quantity (Zanghieri, 2009). Here, following Arrow (1971), we use a profit-oriented output, as in Mose (2013), Bhishma and Venkateswarlu (2014), Singh and Zahran (2013). Accordingly, the output is defined as premiums minus losses plus investment income. We understand that this definition avoids the disadvantages of using only losses, considering that the insurer is interested in maximizing its premiums. Simultaneously, the disadvantage of using only premiums is minimized, as they are combined with losses, which, to some extent, are also influenced by prices.

There is more consensus in the choice of inputs. In general, the main variables are labor and capital. Labor is usually proxied by commissions and underwriting expenses. Commissions relate to all payments made to labor, and underwriting expenses relate to administrative and physical expenses. Some authors like Cummins and Weiss (2000), Cummins et al. (1999) divide capital into physical debt and equity capital. Other authors introduce technical reserves separated from capital (Eling and Luhnen 2010b, Ennsfellner et al., 2004). Regardless of the measures used for capital or labor, most authors consider that these two variables are the most appropriate inputs. Accordingly, our inputs are labor, proxied by operating expenses, underwriting expenses, capital, and technical provisions. Both inputs and outputs have been deflated considering the evolution of the U.S. Consumer Price Index during the period of analysis. The main descriptive statistics of the database are provided in Table 1. Correlations between the selected variables, as it is customary (see, for example, Hemmasi et al., 2011), are positive in all cases[1].

Table 1. Descriptive statistics (unit: thousands of dollars)

	2007		2008		2009		2010		2011	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Output										
Net premiums	372.8	1,637.1	371.2	1,627.1	349.1	1,564.6	332.5	1,498.7	321.6	1,417.6
Net losses	245.9	1,174.5	269.0	1,291.6	246.8	1,215.8	240.7	1,177.7	248.5	1,149.0
Net invest. income	43.3	187.0	41.4	174.1	36.1	143.1	35.8	147.1	33.2	138.5

[1] For reasons of brevity, variable correlations have not been included in the table but are available upon request.

Inputs										
Commission expenses	46.2	178.1	45.5	181.6	42.6	175.3	41.2	166.5	39.9	157.4
Underwriting expenses	56.3	234.2	57.3	240.0	56.4	230.1	55.2	226.6	52.4	220.2
Capital	469.1	2,481.8	420.7	2,102.5	450.4	2,240.1	444.5	2,242.2	405.6	2,054.6
Technical reserves	558.5	2,139.6	569.0	2,179.3	553.0	2,133.7	540.5	2,102.6	514.2	1,976.9
Observations	923		923		923		923		923	

3. Methodology

In this paper, we use parametric and non-parametric techniques to estimate efficiency. First, we conduct a parametric analysis, the Stochastic Frontier Analysis (SFA), in which econometric theory is used to estimate a pre-specified functional form for the efficient frontier. Under this approach, inefficiency is modeled as an additional stochastic term. Second, we apply a non-parametric method, the Data Envelopment Analysis (DEA), which does not impose any functional form on the data given that it does not estimate a function. DEA is a very flexible method that uses linear programming to calculate an efficient deterministic frontier composed of efficient firms or *decision-making units* (DMU). These efficient DMU's are determined by comparing each DMU with the other DMUs in the database. DEA considers that the distance between each DMU and the efficient frontier is all due to inefficiency, while SFA allows it to be due to inefficiency jointly with an error term (Cummins and Zi, 1998).

3.1 Stochastic Frontier Analysis

Stochastic production frontier models were first introduced by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) (in Kumbhakar and Lovell, 2000). The SFA models a stochastic production (or cost) frontier for panel data where the disturbance term is a mixture of an inefficiency term and the idiosyncratic error. Both time-invariant and time-varying decay models were considered, but the time-varying decay model was finally chosen as it provides a better fit for our case of study. Specifically, we have:

$$y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + v_{it} - u_{it} \tag{1}$$

where y_{it} is the natural logarithm of the output, and x_{jit} is the natural logarithm of the inputs in the production function. The disturbance term is assumed to have two components. The inefficiency term, u_{it}, which is a time-varying panel-level effect, assumed to have a strictly non-negative distribution, and the idiosyncratic error, v_{it}, which is assumed to have a symmetric distribution. Following the Battese-Coelli (1992, 1995) parameterization of time effects, the inefficiency term is modeled as a truncated-normal random variable multiplied by a specific function of time. In the time-varying decay specification,

$$u_{it} = exp\{-\eta(t - T_i)\}\, u_i \tag{2}$$

where T_i is the last period in the ith panel, η is the decay parameter, $u_i \overset{iid}{\sim} N^+(\mu, \sigma_u^2)$, $v_{it} \overset{iid}{\sim} N(0, \sigma_v^2)$ and u_i and v_{it} are distributed independently of each other and the covariates in the model. When $\eta > 0$, the degree of inefficiency decreases over time; when $\eta < 0$, the degree of inefficiency increases over time. Because $t = T_i$ in the last period, the last period for firm i contains the base level of inefficiency for that firm. If $\eta > 0$, the level of inefficiency decays toward the base level. If $\eta < 0$, the level of inefficiency increases to the base level. When $\eta = 0$, the time-varying decay model reduces to the time-invariant model. The technical efficiency's estimations are calculated via $E\{\exp(-u_{it})\,|\epsilon_{it}\}$.

This method estimates the efficiency of each insurance company according to its function but does not imply specifying any *prior* specific distribution function. The functional form employed in the empirical analysis is the Translog production function, which is an extended version of the Cobb-Douglas production function, where the output of each DMU is the net premium earned minus the net losses incurred plus the net investment income, and the four inputs have been employed: commission expenses, underwriting expenses, capital, and the technical reserves. The model for a specific firm is the following:

$$\begin{aligned} \log y_{it} &= \log\beta_0 + \beta_1\log x_{1t} + \beta_2\log x_{2t} + \beta_3\log x_{3t} + \beta_4\log x_{4t} \\ &+\beta_{12}\log x_{1t}\log x_{2t} + \beta_{13}\log x_{1t}\log x_{3t} + \beta_{14}\log x_{1t}\log x_{4t} \\ &+\beta_{23}\log x_{2t}\log x_{3t} + \beta_{24}\log x_{2t}\log x_{4t} + \beta_{34}\log x_{3t}\log x_{4t} \\ &+\frac{1}{2}\beta_{11}\log {x_{1t}}^2 + \frac{1}{2}\beta_{22}\log {x_{2t}}^2 + \frac{1}{2}\beta_{33}\log {x_{3t}}^2 + \frac{1}{2}\beta_{44}\log {x_{4t}}^2 + v_{it} \\ &- u_{it} \\ & i = 1, \dots, K\,;\, t = 1, \dots, T \end{aligned} \tag{3}$$

Where y_{it} is the output of the i^{th} decision making unit (DMU) in the t^{th} time period, β_s is the vector of unknown parameters to be estimated, and the inputs are x_{1t} commission expenses, x_{2t} underwriting expenses, x_{3t} capital and x_{4t} technical reserves of the i^{th} company in the

t^{th} time period.

As in Bhishma Rao and Venkateswarlu (2014), the inefficiency effects are assumed to be independently distributed truncations with constant variance but the means are a linear function of observable firm-specific variables. We use the generalized likelihood-ratio test for testing that the inefficiency effects are not stochastic, that is, they depend on each company specific variables. The variance parameters are:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \tag{4}$$

Applying the maximum likelihood method, we estimate the parameters of the model and then predict the values of the technical efficiency for each company over time. The parameter γ must be in the range between 0 and 1 and is given by:

$$\gamma = \sigma_u^2 / \sigma^2 \tag{5}$$

The null hypothesis is $\gamma = 0$ specifies that there are no technical inefficiency effects, whereas the alternative hypothesis $\gamma > 0$ implies that there are technical inefficiency effects.

3.2 Data Envelopment Analysis (DEA)

According to Wise (2017), Data Envelopment Analysis (DEA) is the most common methodology used to study efficiency in the insurance market, followed by SFA. The DEA is an extension of the work done by Farrell (1957), consisting of a mathematical programming technique introduced by Charnes, Cooper, and Rhodes (1978). DEA uses linear programming techniques to build a production frontier, and to which we can refer to establish the efficiency or inefficiency of each one of the insurers from the sample. Output or input orientations can be used to classify firms. However, in the insurance industry, being part of the service sector, applying an output orientation is not suitable since the maximum output is, in fact, limited by the number of services that each DMU can provide (Cummins and Rubio-Misas, 2006; Badunenko et al., 2006). For an insurer, being efficient represents the ability to employ the minimum inputs to produce a given set of output (Diacon et al., 2002). According to the input orientation applied in this paper, efficient firms are placed over the production frontier. Any other firm that produces below this efficient production frontier will be classified as inefficient, measuring that inefficiency according to how far they are from the frontier. DEA allows considering the presence of different returns to scale: constant or variable. The model with constant returns, the DEA–CCR, was developed by Charnes, Cooper and Rhodes (1978), while the DEA–BBC, developed by Banker, Charnes and Cooper (1984) relaxes this assumption and allows variable returns to scale; this facilitates in showing scale inefficiency associated with the size of the company. The structure of the program would be:

$$Min\ \theta$$

$$s.t.: \sum_{j=1}^{N} y_{sj}\,\lambda_j \geq y_{si}, \qquad s = 1 \dots S$$

$$\sum_{j=1}^{N} x_{mj}\,\lambda_j \leq \theta x_{mi}, \qquad m = 1 \dots M$$

$$\sum_{j=1}^{N} \lambda_j = 1$$

$$\lambda_j \geq 0, \quad j = 1 \dots N$$

Where x_{mj} and y_{sj} represent the quantity, used by the company j, of the input m and the output s, respectively.

3.3 DEA Window

DEA Window analysis, as proposed by Charnes and Cooper (1985) and Charnes, et al. (1985), is a time-dependent variant of DEA capable of identifying efficiency trends of DMUs over time. It handles cross-sectional and time-varying data, providing a dynamic perspective of DEA analysis. Given that DEA Window describes a dynamic change of the efficiency of each DMU, which might be closer to SFA than the regular DEA, we find interesting to compare the results obtained through this method with that of SFA, offering a comparison with a non-parametric procedure which, as SFA, considers data in an intertemporal (panel) perspective.

Through the idea of moving averages, DEA Window treats each DMU in a different period of time as an entirely different one since the reference set for calculating the relative efficiency of each firm is different within each window. It makes possible to observe how each DMU performs in different periods, treating each firm as a different one within each window, and thus enabling the comparison of a DMU's efficiency in a particular period (or window) with its own behavior in other periods (e.g., Sueyoshi and Aoki, 2001; Halkos and Tzeremes, 2009; Yang and Chang, 2009; Zhang et al., 2011; Jia and Yuan, 2017).

Although there is no particular theory determining the ideal window width (Cullinane et al., 2004; Asmild et al., 2004), those who applied DEA Window analysis to the banking industry, point out that the width should be as small as possible to minimize the unfairness comparison over time, but large enough to have enough sample size. A smaller window would be preferable because all units within each window are measured against each other, thus presuming that there are no technical changes within each window (Zhang et al., 2011). Considering a set of N $(n = 1, \ldots N)$ DMUs in T $(t = 1, \ldots T)$ periods of time, the window starts at the time k $(1 \leq k \leq T)$, being the window width w $(1 \leq w \leq T)$. Based on the recommendations of Asmild et al. (2004), who suggest that a narrow window width must be used, in this paper, the width of the window is set to two years. Therefore, for the period 2007 to 2011 and the 923 firms, we have the following windows: 1^{st} window contains data from 2007–2008, 2^{nd} window from 2008–2009, 3^{rd} window from 2009–2010, and 4^{th} window from 2010–2011. The number of DMU under consideration within each window is 1846 $(n \times w)$.

4. Results

In this section, we provide the main results obtained from both the parametric and non-parametric analysis. First, we display the results drawn from the SFA (Stochastic Frontier Analysis). Second, the results of the DEA (Data Envelopment Analysis) and Window DEA are offered. In all cases, we included the mean of the efficiency scores obtained, its minimum, and its maximum values.

The results of the SFA are shown in Table 2. After fitting different model specifications, according to Akaike information criterion (AIC) and Bayesian information criterion (BIC), the Translog production function is the most adequate functional form for our model. Consequently, input and output variables have been transformed into logarithms. Following Battese and Coelli (1992), we implemented a stochastic frontier production function in which the technical inefficiency effects are assumed to be specific for each firm and vary over time (time-varying decay model). Time invariant models were also considered, but the hypothesis $\eta = 0$ was rejected. Given that *eta* is found to be significantly different from zero, specifically -0.164, the level of inefficiency increases to the base level. We reject the null hypothesis $\gamma = 0$, being *gamma* significantly different from zero, specifically 0.582.

Table 2. Stochastic Frontier Analysis results

Variable	Coefficient	Std. Err.
input1	0.434***	(0.061)

input2	0.516***	(0.076)
input3	0.699***	(0.094)
input4	-0.431***	(0.104)
½ input1 square	0.075***	(0.006)
½ input2 square	0.110***	(0.013)
½ input3 square	-0.058***	(0.018)
½ input4 square	0.010	(0.024)
input1*input2	-0.027***	(0.010)
input1*input3	-0.008	(0.013)
input2*input3	-0.065***	(0.012)
input1*input4	-0.045***	(0.013)
input2*input4	-0.018	(0.017)
input3*input4	0.085***	(0.017)
Constant	-0.334	(0.297)
mu	0.731***	(0.072)
eta	-0.164***	(0.016)
sigma2	0.208***	(0.015)
gamma	0.582***	(0.031)
Loglikelihood	-1605.623	
AIC	3249.246	
BIC	3371.385	
Observations	4575	
Number of i	923	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Output - net premium earned minus the net losses incurred plus the net investment income

Input 1 - commission expenses

Input 2 - underwriting expenses

Input 3 - capital

Input 4 - technical reserves

Once the SFA model is estimated, the predictions of the efficiency for each company and year are obtained. Average results of efficiency scores for each year are displayed in Table 3. We find a steadily declining trend in efficiency, which falls from its maximum average level of 0.6874 in 2007 to its minimum of 0.5014 in 2011.

Table 3. SFA efficiency levels

Year	2007	2008	2009	2010	2011
Efficiency	0.6874	0.6457	0.6000	0.5510	0.5014
Std. Dev.	0.1012	0.1105	0.1201	0.1290	0.1349
Min	0.3242	0.2656	0.2101	0.1596	0.1496
Max	0.9628	0.9564	0.9490	0.9405	0.9305
Observations	921	916	915	916	907

Afterward, we use the non-parametric approaches to calculate efficiency scores. Using an input-oriented DEA model with variable returns to scale, we obtain the level of efficiency of each firm. Similarly, we applied Window DEA to calculate efficiency in the four windows (2007–2008, 2008–2009, 2009–2010, and 2010–2011). Average efficiency obtained through DEA and the efficiency scores for each period in the different DEA windows are reported in Table 4.

Table 4. DEA and window DEA efficiency levels

Year	2007	2008	2009	2010	2011
Efficiency	0.5995	0.5896	0.5988	0.5753	0.4424
Std. Dev.	0.1822	0.1934	0.1841	0.1991	0.2156
Min	0.0125	0.0018	0.0025	0.0188	0.0030
Max	1	1	1	1	1
Observations	923	923	923	923	923
1st window	0.5599 (2007–2008)				
2nd window		0.5570 (2008–2009)			
3rd window			0.5613 (2009–2010)		
4th window				0.4537 (2010–2011)	

Given the figures in Table 4, the level of efficiency in the insurance market decreases from the period 2007 to 2011, both with the regular DEA and within the four frames of the DEA window. A similar outcome is obtained in SFA scores (Table 3). One possible explanation for these findings is the worldwide economic crisis that took place within the analyzed period. The lowest efficiency scores for the year 2011 could also be explained due to the fact that it was the costliest year because of the devastating earthquakes and storms that took place in the U.S. We find efficiency values from SFA slightly higher than those from DEA or window DEA. One potential reason for this result is that the non-parametric DEA measures all departures from the frontier as inefficiency, whereas the parametric SFA allows for a random error term (see Cummins and Weiss, 2000).

Additionally, it is worth analyzing whether parametric and non-parametric outcomes are similar. As Borger and Kerstens (1996), Cummins and Zi (1998), and Eling and Luhnen (2010b), we calculate the correlation between the efficiency scores of SFA and DEA/ Window DEA models[2]. The results of the Spearman's Rho and Kendall's Tau correlations for each year are presented in Table 5.

Table 5. Correlations between SFA and DEA scores

Year	2007	2008	2009	2010	2011
Spearman's rho	0.4960	0.6849	0.7536	0.7444	0.6668
Prob > |t|	0.0000	0.0000	0.0000	0.0000	0.0000
1st window	0.5101	0.6987			
Prob > |t|	0.0000	0.0000			
2nd window		0.7004	0.7320		
Prob > |t|		0.0000	0.0000		
3rd window			0.7556	0.7571	
Prob > |t|			0.0000	0.0000	
4th window				0.6763	0.6779
Prob > |t|				0.0000	0.0000
Kendall's tau-a	0.3568	0.5098	0.5815	0.5714	0.4993
Prob > |t|	0.0000	0.0000	0.0000	0.0000	0.0000
1st window	0.3692	0.5209			
Prob > |t|	0.0000	0.0000			
2nd window		0.5232	0.5645		
Prob > |t|		0.0000	0.0000		
3rd window			0.5816	0.5875	
Prob > |t|			0.0000	0.0000	
4th window				0.5082	0.5100
Prob > |t|				0.0000	0.0000
Observations	921	916	915	916	907

[2] Please, note that although window DEA calculates a single efficiency score for each window, since it treats the same firm in different years within each window as a totally different DMU, it also provides efficiency scores for each firm and year within the same window. Therefore, to compute correlations between SFA and window DEA efficiency, we use the scores for each DMU and year, resulting, in the case of the years in the middle windows (2008, 2009 and 2010), in two different scores, one for each window.

Spearman's Rho and Kendall's Tau correlations reveal a strong and positive association between SFA and DEA/ Window DEA scores (Borger and Kerstens, 1996; Cummins and Zi, 1998; Eling and Luhnen, 2010b). As in Eling and Ruo (2019), correlations in Spearman's Rho are bigger than that of Kendall's Tau. In any case, from Table 5, we can derive that efficiency levels obtained through DEA and SFA techniques provide similar results, being their outcomes positively related. The null hypothesis of independence between DEA and SFA scores is rejected in all cases.

Beyond resemblance in efficiency scores, it is also interesting to examine if parametric and non-parametric methods rank firms in a similar order. A comparable ranking would mean that, regardless of the precise value of the efficiency score obtained for each company, DEA and SFA methods point to the same firms as a benchmark or with the worst practices in their field. Hence, we get correlations between the ranking from the most to the least efficient firms obtained with SFA and drawn from DEA/window DEA. Results of the Spearman's Rho and Kendall's Tau between SFA and DEA rankings for each year of analysis are displayed in Table 6.

Table 6. Correlations between SFA and DEA rankings

Year	2007	2008	2009	2010	2011
Spearman's rho	0.5036	0.6898	0.7511	0.7640	0.6707
Prob > |*t*|	0.0000	0.0000	0.0000	0.0000	0.0000
1st window	0.5140	0.7002			
Prob > |*t*|	0.0000	0.0000			
2nd window		0.7025	0.7271		
Prob > |*t*|		0.0000	0.0000		
3rd window			0.7508	0.7540	
Prob > |*t*|			0.0000	0.0000	
4th window				0.6741	0.6787
Prob > |*t*|				0.0000	0.0000
Kendall's tau-a	0.3642	0.5167	0.5832	0.5754	0.5069
Prob > |*t*|	0.0000	0.0000	0.0000	0.0000	0.0000
1st window	0.3724	0.5242			
Prob > |*t*|	0.0000	0.0000			
2nd window		0.5267	0.5635		
Prob > |*t*|		0.0000	0.0000		
3rd window			0.5808	0.5867	

Prob > |*t*|			0.0000	0.0000	
4^{th} window				0.5084	0.5141
Prob > |*t*|				0.0000	0.0000
Observations	921	916	915	916	907

As it happens in correlations between the efficiency scores (Table 5), figures in Table 6 show that SFA and DEA/window DEA rankings are very similar. The correlation between the order of the DMUs derived from SFA and DEA procedures is strong and positive, proving that both methodologies complement each other, with their results being pretty much comparable.

To provide another insight into whether DEA and SFA provide analogous results ranking companies in roughly the same order, we contrast which firms are categorized as 20 percent more efficient and 20 percent more inefficient simultaneously by SFA and DEA / window DEA. To determine the pairwise agreement among both rankings, we calculate the proportion of firms considered efficient (and inefficient) by each approach. Table 7 displays the pairwise agreement on the most and least efficient firms by each method.

Table 7. Pairwise agreement on firms in most and least efficient 20 percent

Year	2007	2008	2009	2010	2011
Least efficient					
SFA - DEA	0.4108	0.5838	0.6486	0.6162	0.6054
SFA - WDEA1	0.4378	0.5514			
SFA - WDEA2		0.5784	0.6324		
SFA - WDEA3			0.6595	0.6216	
SFA - WDEA4				0.5676	0.6162
Most efficient					
SFA - DEA	0.5243	0.5568	0.6595	0.6324	0.5784
SFA - WDEA1	0.5081	0.5838			
SFA - WDEA2		0.5622	0.6378		
SFA - WDEA3			0.6486	0.6486	
SFA - WDEA4				0.5405	0.6054

Regarding the classification of the most efficient firms, the rate of agreement is over 50.81 percent up to almost 66 percent, whereas for the least efficient ones, it goes from 41.08 percent to

66 percent. In general, both SFA and DEA approaches rank companies in a similar order. Previous studies found that, in most cases, the most efficient firms are better identified than the least efficient ones (Cummins and Zi, 1998). In our case, this happens in 2007, 2009 and 2010. However, in 2008 and 2011, the agreement is higher in the least efficient companies. Therefore, we cannot reaffirm their conclusion in this regard.

5. Conclusions

In this article, the efficiency in the U.S. non-life insurance market is analyzed using both parametric (Stochastic Frontier Analysis, SFA) and non-parametric (Data Envelopment Analysis, DEA and Window DEA) approaches. Although these methods are the most applied procedures to calculate efficiency in previous literature (e.g., Wise, 2017), DEA Window procedure has not been applied before to the insurance market according to the review of Kaffash et al. (2020). By using these methodologies, we compare (1) DMU's efficiency scores, (2) how firms are ranked regarding their efficiency level, and (3) which are the most efficient ones. This provides a thorough insight into companies' performance. To do so, we use 923 firms from the Standard and Poor's "Global Credit Portal" database for the period 2007 to 2011.

Studying efficiency requires choosing the proper variables to measure firms' inputs and outputs. In the insurance market, as part of the service sector, this selection is not straightforward. Different authors have argued against and in favor of different inputs and outputs. After carefully revising the related literature, we decided to assess output with premiums minus losses plus investment income, following the value-added approach. As inputs, we use capital and technical provisions, and labor, proxied by operating expenses and underwriting expenses.

In the SFA time-varying decay model, we find an average efficiency score of 0.5971, larger than in Ferro and León (2017). There is a decreasing tendency during the analyzed period, with efficiency falling from its maximum in 2007 (0.6874) to its minimum in 2011 (0.5014). In the DEA with variable returns to scale, we obtain an average efficiency of 0.5611, lower than in Cummins and Xie (2013), but similar to Alhassan and Biekpe (2016). Using DEA window analysis, we get similar scores, between 0.45 for the last window (2010-2011) and around 0.56 for the others. In line with SFA, the level of efficiency decreases over the studied period, ranging from 0.5995 in 2007 to 0.4424 in 2011. The efficiency values from SFA are higher than those from DEA, which, as explained in Cummins and Zi (1998) and Cummins and Weiss (2000), could be because, while the non-parametric DEA considers all the distance from the frontier as inefficiency, the parametric SFA also allows it to be partially caused by random error term.

Our results are supportive of previous studies that find parametric and non-parametric approaches providing similar results (Cummins and Zi, 1998 or Eling and Luhnen, 2010b). To further investigate this, we calculate the correlation between efficiency scores received by SFA and DEA / window DEA models through Spearman's Rho and Kendalls' Tau coefficients, finding efficiency levels strong and positively related in all cases. Additionally, we examine the relation between DMU's efficiency rankings. An analogous ranking of DMUs would imply that both approaches report the same firms as the most and the least efficient ones, regardless of the efficiency score. As it happens in efficiency levels, DEA / window DEA and SFA rankings are similar, concluding that these methodologies locate DMU's in similar positions in the ranking. Lastly, we compare the companies categorized as the 20 percent more efficient and the 20 percent more inefficient to determine if efficient and inefficient insurers are properly identified. Pairwise agreement on firms most and least efficient drops optimistic results. For the most efficient companies, the agreement rate is between 50 and 66 percent, whereas for the least efficient, both methods agree in 40 to 65 percent of the cases.

Our results have significant policy implications for both business managers and policymakers. To compete efficiently in the insurance sector, as in any other market, private firms need to know how to analyze their current efficiency compared to that of their competitors, as well as their trend along the last years. Likewise, being committed to the best use of public resources, public insurance companies should also put their effort to incorporate in their management the best practices in the field. To this end, studying efficiency levels and recent trends might help to identify potential areas of improvement. In assessing the relative efficiency of a DMU, both DEA and SFA procedures rank DMUs in a pretty similar order, also offering comparable efficiency scores. Hence, we conclude that DEA and SFA approaches to quantify efficiency complement rather than substitute one another, and we recommend using both methods to assess efficiency, given that it would provide a broader vision of the performance and the situation of each DMU into its market.

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