EFFICIENCY DETERMINANTS AND CAPACITY ISSUES IN ANGOLAN INSURANCE COMPANIES

CARLOS PESTANA BARROS*, SILVESTRE DUMBO† AND PETER WANKE‡

Abstract
This paper describes a variety of approaches used to assess the efficiency of a sample of major insurance companies in Angola between 2003 and 2012. Starting out with the bootstrapping technique, several data envelopment analysis (DEA) estimates were generated, allowing the use of confidence intervals and bias correction in central estimates to test for significant differences in efficiency levels and input-decreasing/output-increasing potentials. Previous studies have focused on the measurement and explanation of the factors affecting the performance rather than the prediction. The use of neural networks combined with DEA results as part of an attempt to produce a model for insurance companies’ performance with effective predictive ability is investigated. The findings indicate that older insurance companies with Portuguese origin tend to be more efficient. Results also suggest that opportunities for accommodating future demand appear to be scarce.

JEL Classification: L, L8

Keywords: Insurance companies, DEA, bootstrap, Angola, neural networks

1. INTRODUCTION
This paper analyses the efficiency noted in Angolan insurance companies. Traditionally, there are two methods to estimate the production frontier using a productive efficiency analysis: the parametric model and the non-parametric model. While the former is based on econometric techniques and needs to specify a functional form for production technology, the latter is linked to the use of data envelopment analyses (DEAs), offering some advantages as it does not compel the a priori use of a functional form on production technology and is also capable of handling multiple outputs. However, it also shows some drawbacks, such as the vulnerability noted in its outcomes, resulting from deviant observations.

The driving forces leading this research are the following: first, there are no papers analysing insurance companies in Angola despite the increasing importance of this country in the world economy (Barros et al., 2014). Furthermore, this draws a distinction with other research carried out on insurance companies in other African countries (Munro and Snyman, 1995; Uche, 1999; Chourouk, 2003; Ibiwoye and Adeleke, 2008; Olaosebikan, 2012). Second, this paper includes all types of insurance companies, namely

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life and non-life companies that exist in the country analysed, since the number of insurance companies are limited. Third, the present research encompasses the period 2003-2012, enabling data to focus on the impact of deregulation in the insurance market.

2. CONTEXTUAL SETTING

2.1 Insurance in Angola

The insurance market in Angola comprises seven companies: ENSA – Empresa Nacional de Seguros de Angola, a public company owned by the government; AAA – Angola Agora e Amanhã, Pensões, a company with public and private local capital; Nossa Seguros, a private insurance company owned by local citizens; Global Alliance Seguros Angola, an English insurance company established in Angola and Mozambique; And Global Seguros, a private company owned by the citizens of Angola. The ownership of private companies, Mundial Seguros and Garantia, are in the hands of Portuguese and Angolan citizens.

The insurance market is small, representing 1.25% of the 2012 gross domestic product. However, the number of companies increased in the period, and new agencies are being opened in remote areas of the country. Table 1 presents some characteristics of the variables.

3. LITERATURE REVIEW

Two methods have been used to analyse productivity and efficiency in the insurance market: the parametric techniques (Cummins and Weiss, 1993; Fecher et al., 1993; Gardner and Grace, 1993; Ennsfellner et al., 2004; Fenn et al., 2008) and the non-parametric DEA (Cummins et al., 1996; Fukuyama, 1997; Cummins and Zi, 1998; Cummins et al., 1999; Diacon et al., 2002; Mahlberg and Ure, 2003; Cummins et al., 2004; Barros et al., 2005; Cummins and Xie, 2008; Barros et al., 2010; Mahlberg and Ure, 2010) method. Recent research on insurance efficiency includes the work of Bertoni and Croce (2011), who applied DEA to a panel of life insurance companies operating in five European countries (Germany, France, Italy, Spain and the UK) between 1997 and 2004 in order to estimate their productivity using a Malmquist efficiency model. Xie et al. (2011) examined the role of corporate governance in the demutualisation wave in the US life insurance industry during the 1990s and 2000s based on DEA. Hsu and Petchsakulwong (2010) examined the relationship between corporate governance and the efficiency performance of public non-life insurance companies in Thailand over the period 2000-2007 using the DEA model to estimate the efficiency performance of insurance companies that encompass their technical, allocation type, cost and revenue efficiency. A truncated bootstrapped regression is then adopted to test the relationship

Table 1. Mean values for the sample (2012)

<table>
<thead>
<tr>
<th>Number</th>
<th>Country</th>
<th>Company</th>
<th>Number of employees</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Angola</td>
<td>ENSA</td>
<td>24</td>
</tr>
<tr>
<td>2</td>
<td>Angola</td>
<td>AAA</td>
<td>18</td>
</tr>
<tr>
<td>3</td>
<td>Angola</td>
<td>Nassa</td>
<td>65</td>
</tr>
<tr>
<td>4</td>
<td>Angola</td>
<td>Global Alliance_Angola</td>
<td>25</td>
</tr>
<tr>
<td>5</td>
<td>Angola</td>
<td>Global</td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td>Angola</td>
<td>Mundial</td>
<td>629</td>
</tr>
<tr>
<td>7</td>
<td>Angola</td>
<td>Garantia</td>
<td>256</td>
</tr>
<tr>
<td>8</td>
<td>Angola</td>
<td>Universal</td>
<td>150</td>
</tr>
</tbody>
</table>
between efficiency performance and corporate governance. Eling and Luhnen (2010) presented a survey of efficiency and productivity models related to the insurance industry. Nektarios and Barros (2010) analysed the efficiency of Greek insurance companies throughout the period 1994-2003. Abdul Kader et al. (2010) studied the cost efficiency of non-life Takaful insurance firms operating in 10 Islamic countries. DEA are used to compute cost-efficiency scores, estimating at a second stage a logit model in order to test the influence that corporate characteristics have on these efficiencies. Mahlberg and Url (2010) analysed German insurance industry efficiency with a DEA that calculates the bootstrapped efficiency scores from 1991 through 2006 by applying a scale efficiency test based on bootstrapped statistics. Furthermore, a Malmquist index is also estimated. Luhnen (2009) analysed the efficiency in the German property-liability insurance industry covering the period 1995-2006 by using DEA, and at a second stage adopts a truncated regression and bootstrapping approach to analyse covariates that explain efficiency.

Research studies carried out on African insurance companies include Munro and Snyman (1995), Uche (1999), and Chourouk (2003). More recently, Ibiwoye and Adeleke (2008) applied a logistic regression to evaluate participation in the Nigeria National Health Insurance Scheme among employees in the formal sector, concluding that awareness was a major factor affecting participation in the scheme. Using a dynamic panel data model, Olaosebikan (2012) analysed the period 2004-2009 to examine the profitability of micro-life insurers in Nigeria. The outcome of the study indicates that the profitability of micro-life insurers is not influenced by factors such as ownership structure, leverage and the size of the firms. Profitability is found to be negatively related to the level of reinsurance.

4. METHODOLOGY

4.1 The Data
Secondary data regarding a sample of seven insurance companies from Angola, duly described in Section 2, were used. As regards the input/output variables, readers should recall that one of the aims of this paper is to assess the input slacks noted in these companies, as well as their output-increasing potentials. The four inputs collected from each insurance company were based on the following literature surveys: (i) operating costs (USD/year), (ii) number of employees, (iii) wages (USD/year) and (iv) capital (USD/year).

The outputs data were also based on a literature survey consisting of four variables collected: (i) claims paid (USD/year), (ii) profits paid (USD/year), (iii) premiums earned (USD/year) and (iv) ceded reinsurance (USD/year). Additional descriptive statistics for each input and output are presented in Table 2.

Contextual variables presented in Table 1 relate to the characteristics of the insurance company: age (in years), market share (in %) and the origin of the company (whether Portuguese or South African). A trend variable was also included.

4.2 DEA
(i) Background DEA is a non-parametric model that was first introduced by Charnes et al. (1978). Based on linear programming (LP), it is used to address the problem arising from calculating the relative efficiency for a group of decision-making units (DMUs) by
using multiple measures of inputs and outputs. With a given set of DMUs, inputs and outputs, the DEA model determines a measure of efficiency for each DMU, obtained as a ratio of weighted outputs to weighted inputs.

Consider a set of \( n \) observations on the DMUs. Each observation, \( \text{DMU}_j (j = 1, \ldots, n) \), uses \( m \) inputs \( x_{ij} (i = 1, \ldots, m) \) to produce \( s \) outputs \( y_{jr} (r = 1, \ldots, s) \). \( \text{DMU}_o \) represents one of the \( n \) DMUs under evaluation, and \( x_{io} \) and \( y_{ro} \) are the \( i \)th input and \( r \)th output for \( \text{DMU}_o \), respectively. Table 3 presents the envelopment model for the VRS frontier type, where \( \varepsilon \) is a non-Archimedean element, and \( s^- \) and \( s^+ \) account, respectively, for the input and output slack variables (Bazargan and Vasigh, 2003; Zhu, 2003; Cooper et al., 2007).

An output maximisation orientation was adopted here. Under these circumstances, decision makers should attempt to maximise production outputs for a given level of inputs, supposedly fixed in the short term. According to Borges et al. (2008), the choice of a model orientation, either input-oriented or output-oriented, depends on the characteristics of the market where the insurance companies operate. In competitive markets, as a general rule of thumb, DMUs are output-oriented, since it is assumed that inputs are under the control of the DMU, which aims to maximise its output subject to market demand (something that is outside the control of the DMU). On the other hand, in monopolistic markets, the units analysed (DMU) are input-oriented because in this market the output is endogenous while the input is exogenous. Taking into account that the main objective of insurance companies in Angola is to maximise revenues using the existing inputs within the context of a competitive market, the use of an output-oriented model is suitable to carry out this analysis, and is well aligned with previous studies (Jakšić and Rakočević, 2012).

| Table 2. Summary statistics for the sample (2003-2012) |
|-----------------|-----------------|-----------------|-----------------|
| Variables       | Min             | Max             | Mean            | SD              |
| Operating costs (I) | $2,180,760.00   | $874,896,099.00 | $117,677,226.94 | $211,307,698.46 |
| Number of employees (I) | $10.00         | $976.00         | $116.27        | $185.37         |
| Wages (I)       | $897,765.00     | $56,907,346.00  | $7,966,818.51  | $8,955,419.40   |
| Capital (I)     | $34,987.13      | $701,661,123.00 | $28,490,458.29 | $84,453,032.81  |
| Claims paid (O) | $369,443.12     | $701,543,200.00 | $21,189,753.07 | $83,576,608.50  |
| Profits earned (O) | $1,437,787.00   | $37,657,435.00  | $6,039,385.19  | $7,030,241.86   |
| Ceded reinsurance (O) | $753,238.85    | $95,643,212.00  | $9,097,859.52  | $13,140,263.40  |
| Age             | 10.00           | 35.00           | 13.57          | 8.81            |
| Market share    | 5%              | 61%             | 14%            | 12%             |
| Portuguese      | 1.00            | 0.87            | 0.34           |                 |
| South African   | 1.00            | 0.30            | 0.46           |                 |
| Trend           | 1.00            | 10.00           | 5.50           | 2.89            |
(ii) Data Reduction One of the frequent problems of DEA is a lack of differentiation between DMUs, which can be caused by an excessive number of input (output) variables related to the total number of DMUs observed in the respective analysis (Adler and Berechman, 2001). According to Cooper et al. (2001), the number of DMUs is a relevant issue when using DEA as the cornerstone methodology. More precisely, following Barros et al. (2012), the combination of the measured indicators should not only ensure adherence to the literature survey, but also to the DEA convention that the minimum number of DMU observations should be threefold greater than the number of inputs plus outputs.

However, it is deemed necessary to use a systematic statistical method to decide which of the original correlated variables can be omitted with the minimum loss of information, and which should be kept (Jenkins and Anderson, 2003). This issue is of the utmost importance as, traditionally, highly correlated variables have been omitted on an ad hoc basis, causing unpredictable impacts on DEA efficiency estimates (Jenkins and Anderson, 2003; Nadimi and Jolai, 2008).

Adler and Berechman (2001) developed a methodology based on the principal component analysis (PCA) in order to reduce the number of input (output) variables used in the DEA model into factors. PCA explains the variance structure of a matrix of data through a linear combination of variables, which usually describe 70-90% of the variance in the data. If most of the population variances can be attributed to the first few factors, then they can substitute the original variables without losing much information.

While comparing PCA and a variable reduction based on a partial covariance using a simulation based approach, Adler and Yazhemsky (2005) found that PCA provides a more powerful discrimination tool than variable reduction, consistently offering more accurate outcomes whenever the dimensionality course is present. However, one disadvantage is related to the fact that the targets and efficient peers obtained might reflect a substantial change in the current mix of input–output levels of the inefficient DMUs (Allen et al., 1997). As problems related to discrimination arise quite often, it becomes necessary to establish a trade-off between using all the DEA information and enhancing discrimination (Adler and Golany, 2007; Kordrostamia et al., 2011).

In this study, PCA was used to determine the most relevant inputs and outputs by extracting the factors. In other words, PCA allowed the identification of the most representative inputs and outputs within each factor by observing their factor loads.

(iii) Bootstrapping Non-parametric efficiency estimators, such as the DEA, typically rely on LP techniques to calculate estimates, which are often characterised as deterministic, seeming to suggest that the methods lack any statistical support (Simar and Wilson, 2004). Applied studies using these methods usually presented precise inefficiency estimates, without measuring or even discussing any uncertainty related to these estimates (Cesaro et al., 2009; Assaf et al., 2010).

The method applied in this research is not aligned to that presented by Simar and Wilson (2004), who adapted the bootstrap methodology to the case of DEA efficiency estimators, as it uses a Gaussian kernel density function for random data generation. All the calculations were carried out with Maple codes developed by the authors; 1,000 bootstrap replications were performed on models (1) and (2), following the discussion presented by Simar and Wilson (1998, 2004) and Curi et al. (2011) on deriving statistical properties for each DMU compared with a biased calculation, core correction trend and confidence intervals.
4.3 Predicting Efficiency Levels Using Neural Networks

It is noteworthy that most of the studies previously presented aimed to explain the factors affecting the efficiency, and no predictive analysis has been done. Whereas the prediction of performance of insurance companies is extremely important, a bad performance may lead to insolvency. Thus, conceiving a predictive model for the performance of insurance companies would be useful in avoiding or at least limiting such insolvency consequences to customers. Therefore, this study also proposes the use of contextual variables to predict insurance companies’ performance levels. More specifically, neural networks are trained to assess how the age, the market share and the company origin impact and could be used as predictors of efficiency levels in Angolan insurance companies.

Artificial neural networks are among the frequently used data mining models for prediction (Ledoter, 2013). An artificial neural network is inspired by the structure of biological neural networks where neurons are interconnected and learn from experience. Neural networks are composed of nodes (neurons) arranged in layers that are fully connected with the preceding layer via a system of weights (Gurney, 1997). Numerous different neural network architectures have been studied. However, the most successful applications of neural networks have been multilayer feed forward networks (Fausett, 1994). These are networks in which there is an input layer, one or more hidden layers, and an output layer. The next step is to apply a transfer function to this sum. The most popular transfer function is the logistic function. Finally, the output layer obtains input values from the hidden layer and the same transfer function is applied to create the output. Readers should refer to Shmueli et al. (2010) for more details.

5. RESULTS AND DISCUSSION

5.1 Main Analytical Components

An extraction was conducted on factors obtained from the transformation of the four input variables using the PCA with a varimax standardised rotation for data collected from eight insurance companies in Angola. According to Tabachnick and Fidell (2001), only factor loads greater than 0.50 deserve to be interpreted, and in these cases the variable is said to represent a good factor measure. Results are presented in Table 4 covering only auto-values greater than 1.

Two main factors represent the insurance company inputs, duly interpreted herein. Operating costs and the number of employees make up factor 1, interpreted as the operational scale index. This index shows the size of a given insurance company in terms (e.g. lower values would refer to smaller insurance companies,

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Factors</th>
<th>Capital</th>
<th>Outputs</th>
<th>Factors</th>
<th>Ceded reinsurance</th>
<th>Premiums earned</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating costs</td>
<td>0.91</td>
<td>−0.01</td>
<td>Claims paid</td>
<td>0.25</td>
<td>−0.54</td>
<td></td>
</tr>
<tr>
<td>Number of employees</td>
<td>0.91</td>
<td>0.01</td>
<td>Profits paid</td>
<td>−0.84</td>
<td>−0.06</td>
<td></td>
</tr>
<tr>
<td>Wages</td>
<td>−0.23</td>
<td>−0.74</td>
<td>Premiums earned</td>
<td>0.07</td>
<td>0.86</td>
<td></td>
</tr>
<tr>
<td>Capital</td>
<td>−0.23</td>
<td>0.74</td>
<td>Ceded reinsurance</td>
<td>0.58</td>
<td>−0.24</td>
<td></td>
</tr>
<tr>
<td>Kaiser–Meyer–Olkin measure of sampling adequacy</td>
<td>0.521</td>
<td></td>
<td>Kaiser–Meyer–Olkin measure of sampling adequacy</td>
<td>0.940</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bartlett’s test of sphericity</td>
<td>Approx. chi-square df</td>
<td>47.0294</td>
<td>Bartlett’s test of sphericity</td>
<td>Approx. chi-square df</td>
<td>2.821</td>
<td>6.00</td>
</tr>
<tr>
<td>Sig.</td>
<td>1.84600e-08</td>
<td>6</td>
<td>Sig.</td>
<td>0.830905</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent of variance explained by the factors</td>
<td>71.00%</td>
<td></td>
<td>Percent of variance explained by the factors</td>
<td>55.00%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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while higher values take into account the opposite). In turn, capital is the single variable that makes up factor 2, simply interpreted and named as capital.

On the other hand, four production output-related variables were reduced to two factors, both of them single variable factors with straightforward interpretations: premiums earned and ceded reinsurance.

5.2 DEA Original and Bootstrapped Estimates

The initial efficiency estimates and their bootstrapped correction are presented in Table 5, as well as the respective dual values. As one would expect, the CCR model yields lower average efficiency estimates than the BCC model, amounting to values of 0.59 and 0.86, respectively, where an index value of 1.00 is equivalent to a maximum efficiency. This result is not surprising, as the CCR model fits a linear production technology, whereas the BCC model features variable returns to scale, which are more flexible and reflect managerial efficiency, as well as purely technical limits. As a matter of fact, the CCR and BCC scores will only be equal if there is no scale inefficiency.

With regard to the initial and bootstrapped estimates comparison on efficiency measurements, it is important to acknowledge that initial DEA estimates tend to show an upward bias. According to Bogetoft and Otto (2010), if no measurement errors exist, then all the observations in the sample belong to the technology frontier. As expected, the bootstrap correction bias led to lower estimates in BCC and CCR frontiers. According to Wanke (2012), results like these suggest that the DEA convexity assumption is applicable to the entire efficient frontier.

In addition to providing efficiency measures, DEA also provides other relevant information. According to Thanassoulis (2001), the virtual input and output levels reflect the extent to which the efficiency rating of a Pareto-efficient DMU is underscored by each one of its inputs and output levels. On average, insurance companies in the sample rely mostly on their capital (75.7%) to obtain their virtual inputs efficiency rating, and on the ceded reinsurances (66.7%), as regards their virtual outputs. However, it is important to note that the existence of multiple good solutions for the model does not necessarily mean that the specific DMU cannot find a high virtual level for its inputs or outputs in any of the best solutions available for the model.

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Results on the input and output slack corrected-bias for the insurance industry in Angola are presented in detail in Fig. 1. More precisely, available input-decreasing and output-increasing potentials were calculated in percentage terms, dividing each corrected slack by the respective input/output index. One can easily appreciate that available capital slacks to meet future demand growth have substantially decreased over the last four years. Capital is the most relevant virtual input in the production frontier of the Angolan insurance companies. On the other hand, when corrected-bias estimates for the output-increasing potentials are put into perspective, a similar conclusion emerges with respect to ceded reinsurance, the most relevant virtual output of the production frontier.

However, the inference of using future strategic actions based on the conclusions of a slack analysis should be conducted with care, and are inserted in the orientation model chosen. Essentially, as discussed in Coelli (1996), the DEA model orientation should be selected according to the type of quantities (inputs or outputs) decision makers have most control over.

More precisely, according to Wanke et al. (2011), the basic idea behind the selection of an input-oriented model is that the output-increasing potential should be interpreted with more care, unless a demand for it exists. Furthermore, when selecting an input orientation, decision makers are focusing on “stressing” production inputs for a given level of output that may not necessarily be maximal, as discussed in Odeck and Alkadi (2001). On the other hand, some insurance company inputs tend to be fixed, as they may reflect long-term investments and well-trained staff that are difficult to demobilise in the medium/short term, as stated in Cullinane et al. (2006). Thus, in cases showing similarities with this research, decision makers should focus on maximising outputs for a given level of production inputs (preferably, an output orientation decision).

Therefore, the overall picture calls for a capacity expansion, as the current level of the most relevant virtual input (scale variables in an output-oriented model) according to Thanassoulis (2001) does not seem to accommodate future demand growth in several DMUs.

Besides capacity expansion, there are, however, short-/middle-term actions that could be taken in order to increase insurance companies’ production outputs, and therefore efficiency, given a certain level of inputs. Insurance companies could benefit, for instance, from specific policies implemented in accordance with their major characteristics. These results are discussed next.

5.3 Predicting Efficiency Levels
This final step was performed on the bias corrected bootstrapped efficiency scores, affected by the contextual variables presented in Section 4. All these variables were normalised before using it to train a neural network – with one hidden layer and 20 perceptrons – in order to correctly predict the efficiency levels. This neural network reported a pseudo R-squared of 99.25% after iterating for a hundred times before finding the best result. All the steps taken followed those presented in Faraway (2006), and Fig. 2 presents the sensitivity analysis on the efficiency scores. One may perceive that efficiency levels tend to increase with the age of the company and its Portuguese origin. The remainder variables – trend, South Africa and market share – did not reveal a clear impact on performance, mostly oscillating around the mean, although they help in accurately predicting the efficiency levels of Angolan insurance companies. These results suggest that efficiency in Angolan insurance companies is driven most by cultural and relational

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Figure 1. Slack analysis – industry means
Figure 2. Sensitivity analysis of a trained neural network for values of the efficiency scores.
aspects with their former metropolis rather than based on scale (market share), or either are presenting a clear evolution over the course of time.

6. CONCLUSIONS

The findings presented herein suggest that there is a capacity shortfall in the insurance industry in Angola. Their output-increasing potentials are severely constrained, particularly in terms of the ceded reinsurance-increasing potentials. Our findings may assist the decision-making process by setting priorities related to capacity expansion. In comparison with other alternative research carried out on the insurance industry, this paper offers, for the first time, an innovative analytical approach on insurance companies in Angola by using neural networks to predict efficiency levels based on contextual variables. Further research is required to confirm these results.

The ruling implications expressed in this paper are that, on the basis of these conclusions, insurance companies in Angola should adopt a benchmark procedure to evaluate their efficiency throughout the year and follow the same best practice procedures used by more efficient companies. This exercise could be employed by the association of insurance companies in order to facilitate the adoption of procedures empowering them to achieve an efficiency increase.

More precisely, since most insurance companies are still relatively small, when compared with their peers in foreign developed countries, mergers and acquisitions appear to be the natural path to achieve gains in efficiency and mitigate capacity shortfalls. It follows, then, that mergers and acquisitions in the Angolan insurance industry could increase in the near future, as the measures delivered in this paper may help determine the best match with respect to the companies’ profile in terms of age, origin and market share.

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