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Corporate Performance Measurement Using an Integrated Approach: A Mongolian Case

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ABSTRACT

The main goal of the study is to calculate the relevant efficiency scores of companies listed on the Mongolian Stock Exchange based on their efficiency scores. We apply an integrated principal component analysis (PCA) and data envelopment analysis (DEA) model to estimate corporate efficiency. The objective of using this integrated method to reduce the dimensionality of the dataset analysed and to evaluate companies' efficiencies reliably. The number of variables using in the DEA model affects the results directly because of the DEA method is sensitive to the number of input and output variables. The PCA method can reduce the number of variables so that the information loss would be the smallest. The research uses one hundred publicly-listed Mongolian companies' financial statements of 2015. Initially, DEA is applied conventionally using seven input and four output variables. Then, PCA is applied with the same variables to determine Principal Component (PC) scores, which are used for DEA as variables to improve its discrimination power. The results of the conventional DEA and the PCA-DEA models are compared to evaluate the consistency. The results of the input-oriented DEA model (under variable return to scale) determined 54 efficient companies, and the average efficiency scores were 0.73. However, PCA-DEA method diagnosed only five efficient companies, and the average efficiency was 0.65. Based on the results, we can state that the PCA-DEA method provides a more accurate picture of the real performance of the analysed companies.

INTRODUCTION

Performance evaluation plays a vital role in every type of business; used for revealing their deficiencies and comparing current business activities with that of their peers. Evaluating performance using separate financial ratios does not provide satisfactory results to judge the companies examined. Therefore, there is a need for a complex measurement method that can give it with one indicator, an efficiency score. One such method is Data Envelopment Analysis (DEA), which can use many input and output variables and transform them into a relative efficiency indicator. However, the importance of performance measurement is underestimated within Mongolian companies. Data Envelopment Analysis (DEA) has been used in many business sectors to evaluate performances; however, the level of research focused on Mongolian business sectors is limited. Currently, there is no published research - on performance measurement applied DEA and Principal Component Analysis (PCA) - targeting Mongolian companies. This study uses PCA and DEA to reduce the dimensionality of the dataset and to evaluate companies' input efficiencies using the *R statistical program*. DEA is a widely used non-parametric approach - to measure the efficiency of Decision-Making Units (DMUs) - based on multiple inputs and outputs. The main applications of DEA are benchmarking of firms and determining the level inefficiencies within them.

Although DEA has many advantages, the discrimination power declines (and possibly proves the majority of DMUs as efficient) when the number of inputs and outputs is relatively high, to overcome the *'curse of dimensionality'* in DEA, the PCA can be combined with it. PCA is a multivariate technique capable of reducing the dimensionality of a multivariate dataset while accounting for much of the variation present in the original dataset. Though both DEA and PCA are widely used as separate methods, the number of studies that combined the two is not so many. During the research, two main goals were formulated. On the one hand, to examine the performance of Mongolian listed companies using the DEA method and to form an opinion on the performance of Mongolian companies for the year investigated. On the other hand, to examine whether the combination of DEA and PCA methods can improve performance measurement, and it provides a better valuation. The remainder of the paper is organised as follows: section two reviews the literature on performance measurement, DEA, and PCA. Section three presents the data set and variables used during the analysis. Part four consists of empirical results. Finally, conclusions are presented in section five.

1. LITERATURE REVIEW

1.1 Performance Measurement

Performance can be explained in many ways, such as the fulfilment of an obligation, the accomplishment of a task, or (from a financial or customer point of view) having a high firm value or brand value (Takacs, 2014) etc. Corporate performance measurement is used to reveal firm deficiencies and to improve competitiveness compared with their peers. The business performance consists of two components: efficiency and effectiveness. Effectiveness is the extent to which customers' requirements are met. The efficiency is a measure of how economically the firm's resources are utilised when providing a given level of customer satisfaction (Takacs, 2015). This research concerns efficiency analysis only. The fundamental idea of efficiency analysis is to separate production units that perform well from those that perform poorly. Economic efficiency encompasses technical efficiency and allocative efficiency. This research considered technical efficiency only since economic efficiency and allocative efficiency require price information in addition to the input and output data (Bharti and Chitnis, 2016). Efficiency has two orientations:

- *Input orientation:* A DMU is inefficient if it is possible to reduce its inputs without augmenting its other inputs and without reducing its outputs.
- *Output orientation:* A DMU is inefficient if it is possible to augment its outputs without increasing its inputs and without decreasing its other outputs (Cooper et al., 2011).

Both input and output efficiency take a score of *'1.0'* for efficient companies. The difference between a firm's efficiency score and 1.0 determines the inefficiency. Therefore, the smaller the inefficiency is, the better the firm's performance (Cooper et al., 2011).

1.2 Data Envelopment Analysis

Data envelopment analysis is a linear programming-based technique to measure the relative performance of organizational units. DEA is a data-oriented approach for evaluating the performance of a set of peer entities, which converts multiple inputs into multiple outputs (Cooper et al., 2011). In the DEA method, both input and output efficiency take a score of 1 for the efficient companies, which means one-unit marginal input results in the one-unit marginal output. Once the efficiency frontier is determined, inefficient DMUs can improve their performance to reach the efficiency frontier; by decreasing their current input levels, or increasing their current output levels. DEA encompasses four models: variable return to scale (VRS) and constant return to scale (CRS), as well as increasing return to scale (IRS) and decreasing return to scale (DRS). The assumption is that if any production combination is possible there, it can scale up or down in an arbitrary measure. In this research, the VRS model of DEA was used (Färe and Grosskopf, 2004).

Classical DEA models often identify too many DMUs as efficient. This case also occurs when the number of DMUs under evaluation is not large enough, concerning the total number of inputs and outputs (Omrani et al., 2015). The higher the number of variables included, the lower the level of discrimination. Furthermore, because DEA methods calculate a ratio among inputs and outputs for each DMU (via a weighting method) when inputs or outputs of a given DMU are strongly correlated. Therefore, efficiency estimates of a DMU are biased when a slack variable analysis of DEA is applied. To deal with these problems, the integration of DEA with PCA method can be used to obtain more stable estimations, a contrast to traditional methods (Hsin-Pin and Jia-Ruey, 2013).

There are a considerable number of studies applying DEA in different fields. For example, Nikoomaram et al. (2010) analyzed the relationships between financial ratios and efficiency results of DEAs, conducted among 24 companies, for six years, with 144 observations. The results of the test showed significant relationships between three variables (Return on Sales, Earnings per Share, and Operating Cash Flow) and the efficiency results of the DEA. There is also occurred a particular application of the DEA method in the literature; for example, Suhanyi and Suhanyiova (2014) used this method as an investment decision-making tool to support decision-making in local regions.

1.3 Principal Component Analysis

The results of the conventional DEA model and the PCA-DEA model demonstrated that the PCA-DEA is a more powerful tool for corporate performance ranking. They also stated that principal components (PCs) could be used to change either all the inputs and outputs or groups of variables with a common factor. The PCs are used as input and output variables for the DEA analysis, reducing the data used in the DEA model. Using PCs instead of original data does not impact the features of the DEA model. Adler and Golany (2002) mentioned that the use of PCs could noticeably improve the strength of DEA models.

PCA method is a multivariate statistical method that converts a correlated number of p variables into an uncorrelated number of k variables where $p \geq k$. That is, PCA is a multivariate method to reduce the dimensionality of a multidimensional dataset. However, it takes into account for as much as possible of the variance present in the original dataset. The variable reduction is achieved by transforming to a new set of variables, the PCs have uncorrelated principal components, and ordered so that the first few accounts for most of the variation in all the original variables (Everitt and Hothorn, 2011). The first principal component possesses the highest variance in the sample data; the second one has the second-highest variance, and so on (Ahmadvand et al., 2011). The principal components (PCs) can be used as surrogates for the initially large number of variables and consequently provide a more straightforward basis for graphing or summarizing the data, and also perhaps when performing further multivariate analyses of the data (Everitt and Hothorn, 2011). The PCs are estimated as the projections on the eigenvectors of the covariance or correlation matrix of the dataset. The variance of a dataset is an indicator of how dispersed the data is. The larger the deviation, the more information included (Hsin-Pin and Jia-Ruey, 2013). There are two main central ideas of PCA. First, it is a useful data analyzing tool to identify and express patterns in the dataset. Second, it highlights the data's similarities and differences. The result of a PCA is a smaller number of new variables than the originals (Omrani et al., 2015).

Principal components analysis is useful when:

- The number of explanatory variables is relatively high to the number of observations.
- The explanatory variables are highly correlated (Everitt and Hothorn, 2011).
- The most common procedures for deciding the number of components to retain are:
- Retain just enough components to explain some specified, large percentage of the total variance of the original variables.
- Values between 70% and 90% are usually suggested.
- Exclude those PCs whose eigenvalues are less than 1.0 (Everitt and Hothorn, 2011).

The uses of less than full information will lead to a loss of some of the explanatory ability of the data but will improve the discriminatory power of the model. The only other methodology for reducing dimensionality is to abandon specific variables. However, by doing so, all information derived from those variables is automatically lost. Contrarily, if certain PCs are removed, the information content of these variables does not vanish unless the PC weight is placed entirely on that variable (with a zero weighting in all other PC combinations) (Adler and Golany, 2002). This is the reason why some researchers use PC scores as input and output data for DEA models, including among others Serrano 1Cinca and Mar Molinero (2004). Unlike previous authors, Vargas and Bricker (2000) combined the DEA method with the factor analysis using a similar approach that was presented in the case of PCA.

As with the DEA, there is plenty of research relating to the application of PCA in business studies. For example, Azadeh et al. (2007) examined an integrated framework for the assessment and ranking of manufacturing systems - based on management and organizational performance indicators - for the Iranian telecommunications sector. Ahmadvand et al. (2011) applied PCA to implement a DEA model to improve discrimination and variables dependency. Jakaitiene et al. (2018) proposed a methodology of PCA-DEA to evaluate the performance of the European education system. Tavakoli and Shirouyehzad (2013) used PCA-DEA to evaluate the performance of Foolad Technic Company based on its human capital management. Hsin-Pin et al. (2013) concluded in their research work that, by combining PCA and DEA in evaluating the performance of energy projects, the evaluation was improved compared to that who has only used the simple DEA method. Ahmadvand et al. (2011) proposed PCA-DEA approach, to filter out the undesirable input and output variables simultaneously in the case of road safety evaluation in Iran. Additionally, the following researches also used PCA-DEA: Põldaru and Roots (2014) in quality of life, Adler and Golany (2001) in hub-and-spoke networks, Liang et al. (2009) in ecology performance, Faed et al. (2016) in the intelligent analysis of customer complaints, Andrejic (2013) in the distribution centres, and Shanmugam and Johnson (2007) in medical examples, etc. Jothimani et al. (2017) used financial ratios as input and output parameters of performance evaluation by PCA-DEA in an Indian stock market study, similar to this. The primary purpose of this study is to assess the effectiveness of PCA-DEA over DEA alone, in the calculation efficiency. Accordingly, the following objectives are relevant:

- Determination of companies' efficiency based on conventional DEA.
- Determination of companies' efficiency based on the integration of PCA and DEA models.
- Comparison of the efficiency results of the conventional DEA and PCA-DEA models.
- Evaluation of the consistency of the conventional DEA and PCA-DEA models.

2. DATA AND RESEARCH METHODOLOGY

2.1 Data And Variables

Mongolian companies are constituted in one of two ways; as public or non-public entities. Since public companies' financial reports are required to be audited, their data are more reliable than those of non-public companies' ones, and they are publicly available. In this research, one hundred public companies' financial statements (of 2015) was obtained from the MSE and used as data. By the end of 2015, there had been 235 public companies listed on the MSE. The 100 selected companies were chosen because their data accounted for about 42.6% of those registered, while the other 135 companies (57.4%) were excluded due to their low level (or absence) of activities. In this paper, seven input variables from the cash flow statement are used, and four outputs, i.e., revenue, gross profit, pre-tax profit, and net cash flow. Descriptive statistics on input and output variables are presented in Table 1. Table 1 illustrates the descriptive statistics of the four input and seven output variables, and it is clear from the high standard deviations that the variables have large ranges. Since the variables are expressed in monetary values - which vary according to the size of the company - input and output variables are normalized (separately) for further research. Table 2 shows that every output-variable correlated strongly with each other, except for the net profit. Cash paid for wages, and cash paid for insurance are strongly correlated (0.99), too, which is evident since the amount of social insurance depends on the amount of salary. Investment cash flow correlates negatively with every other variable, showing that companies that spent much more on operating and financing activities tended to invest less. From table 2, one can conclude that net profit has the weakest effect among the output variables, while revenue is the strongest, based on the correlation coefficients. Moderate and robust correlations are written in italics in the table. The PCA can reduce the number of the correlated indicators - through a linear transformation - while minimising information loss.

Table 1. Descriptive statistics of variables using in DEA and PCA (thousand tugriks)

Variables	*Minimum*	*Maximum*	*Mean*	*Standard Deviation*
Revenue	0	240,637	15,315	41,855
Gross Profit	-1,990	116,431	4,498	15,732
Pre-tax profit	-3,497	41,612	1,048	5,375
Net profit	-16,099	18,736	1	2,627
Cash paid for operations	0	279,464	14,891	41,790
Cash paid for wages	0	29,653	1,584	4,347
Cash paid for insurance	0	7,866	405	1,094
Cash paid for inventory purchases	0	118,219	5,523	16,301
Cash paid for administrative expenses	0	13,392	551	2,106
Investing cash flow	-41,396	551	-1,420	5,580
Financing cash flow	0	49,294	2,424	7,703

Source: Authors' calculation by SPSS statistical program

Table 2. Pearson's correlation coefficients of the variables

Variables		*y1*	*y2*	*y4*	*x1*	*x1*	*x2*	*x3*	*x4*
Revenue	y1								
Gross Profit	y2	0.84							
Pre-tax profit	y3	0.78	0.95						
Net profit	y4	0.34	0.46	0.48					
Cash paid for operations	x1	0.97	0.78	0.72	0.17				
Cash paid for wages	x2	0.87	0.60	0.54	0.31	0.79			
Cash paid for insurance	x3	0.87	0.56	0.49	0.29	0.80	0.99		
Cash paid for inventory purchases	x4	0.79	0.48	0.41	-0.06	0.87	0.67	0.70	
Cash for operating expenses	x5	0.60	0.76	0.64	0.41	0.51	0.53	0.49	0.29
Investing cash flow	x6	-0.76	-0.73	-0.70	-0.29	-0.68	-0.70	-0.70	-0.38
Financing cash flow	x7	0.82	0.87	0.75	0.38	0.76	0.63	0.60	0.64

Source: Authors' calculation in SPSS

2.2 Research Methodology

This research aims to integrate DEA and PCA. The procedures for the analysis are as follows:

1. PCA is applied to input and output variables separately, to calculate PC scores. The PC scores are obtained only at the end of PCA, which makes it is difficult to use them as direct inputs to the DEA. Therefore, the PC scores are extracted from the PCA. Then, using the PC scores, the DEA is completed separately and sequentially using the programming possibilities of the R statistical system.

$$X_i = PC_i + b > 0 \qquad i = 1, \dots, p,\ p \le m \qquad (1)$$

where, X_i = new DEA inputs; using eigenvalue greater-than-one rule;
PC_i = PCs of the input variables.

2. Calculation of eigenvalues and eigenvectors. Selection of the number of PCs, application of the eigenvalue greater-than-one rule and scree plot diagram.
3. The data of the DEA model must be positive, but some of the PC scores can be negative. Therefore, negative scores must be converted into positive values (Tavakoli and Shirouyehzad, 2013). The PC scores were raised by the minimum negative value in the case of both input and output PC data (Adler and Yazhemsky, 2010), that is the following is done to eliminate the negative values of the PC scores:

$$b_i = PC_i + \min(PC) \qquad (2)$$

where, b_i = adjusted PC scores

4. The input-oriented PCA-DEA VRS model is applied. In the PCA-DEA model, the input and output variables of the conventional DEA model are replaced by PC scores of the input and output variables.
5. The input-oriented conventional DEA VRS model is applied using (initially) the chosen seven input and four output variables.
6. The results of conventional DEA and PCA-DEA models are compared.

The procedures for the efficiency analysis of the integrated PCA-DEA model can be seen in Figure 1.

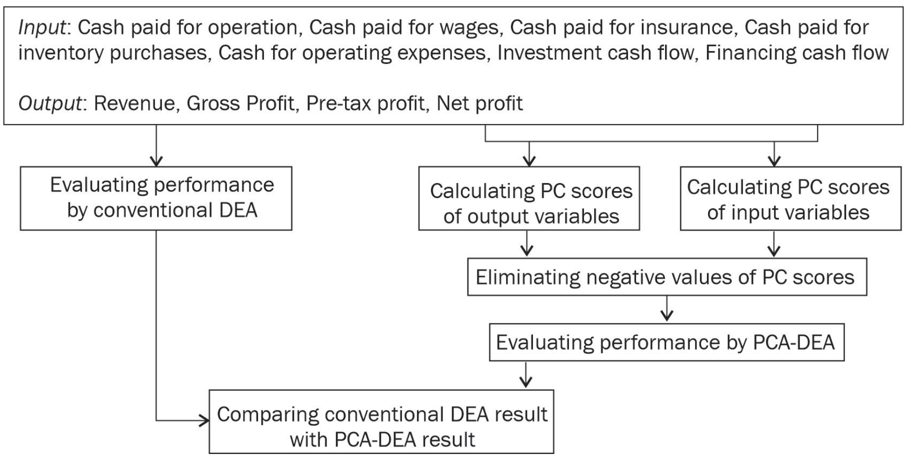

Figure 1. Flowchart of the research stages

Source: Authors' compilation

3. ANALYSIS AND RESULTS

For the calculation of efficiency scores, there was chosen the VRS type of the DEA model. The VRS type of model has no proportional change for input and output variables, and it is based on increasing or decreasing returns to scale. Contrarily, the CRS model has a proportional change for input and output variables and based on constant input or output variables. However, the heterogeneity of our data shows that there are big differences among the companies (DMUs). Therefore, it was the reason to choose the VRS type of DEA model. The PCA was executed on the *'psych'* package of R statistical program. The PCA was applied separately to both the input and output variables. The PCA results of seven input variables are shown in Table 3. There are different criteria for determining the number of principal components, which should be abandoned, such as eigenvalues greater than one, or if the PCs include at least an 80% of the total variance of variables.

From Table 3, one can see that only the eigenvalue of the first component has a value above one, which can explain 70.59% of the total variance. The second component can explain 12.94% of the total variance, and the cumulative proportion of this level is 83.54%; however, its eigenvalue is less than one.

Table 3. PCA results of input variables

Principal components (PC)	Eigenvalues	Proportion (%)	Cumulative proportion %
PC1	2.22	70.59	70.59
PC2	0.95	12.94	83.54
PC3	0.81	9.43	92.97
PC4	0.58	4.83	97.80
PC5	0.30	1.34	99.15
PC6	0.22	0.75	99.90
PC7	0.08	0.09	100.00

Source: Own calculation by R statistical program

The sum of the eigenvalues (variance of the PCs) equals the sum of the variances of the original variables. Since the analysis uses standardized values, the sum of the component variances equals the number of variables. The PCA results of input variables are presented in Figure 2. The Kaiser criterion (eigenvalue above 1.0) is not the only way to decide the number of components abandoned. One of the other common ways is to see the scree plot (‘*elbow diagram*’) of PCA results, as shown in Figure 2. There is a clear break between components 1 and 2, and slight decreases until component 5. The first five components explain almost all of the variances (99.15%). Since values between 70% until 90% is usually suggested, the first component is used for further analysis as an input variable.

It is also possible to see from Figure 3, which variables contribute more to the components. Figure 3 describes the contribution of variables for the first component, which is chosen for further analysis. The first PC score is used as an input variable for the PCA-DEA model. Figure 3 indicates that cash which was paid for operations (17.48%), for wages (16.87%), and social insurance (16.69%) play essential roles in the first PC, which will be the input variable of DEA model. Based on the contributions to the first PC, the cash paid for administrative expenses is the least essential indicator (9.76%). Eigenvalue analysis of output variables is provided in Table 4. According to the eigenvalue greater-than-one rule, the first PC is chosen for further analysis, which explains 74.86% of the total variance. The second PC explains 18.43% of the total variance, followed by PC3 (5.54%) and PC4 (1.16%).

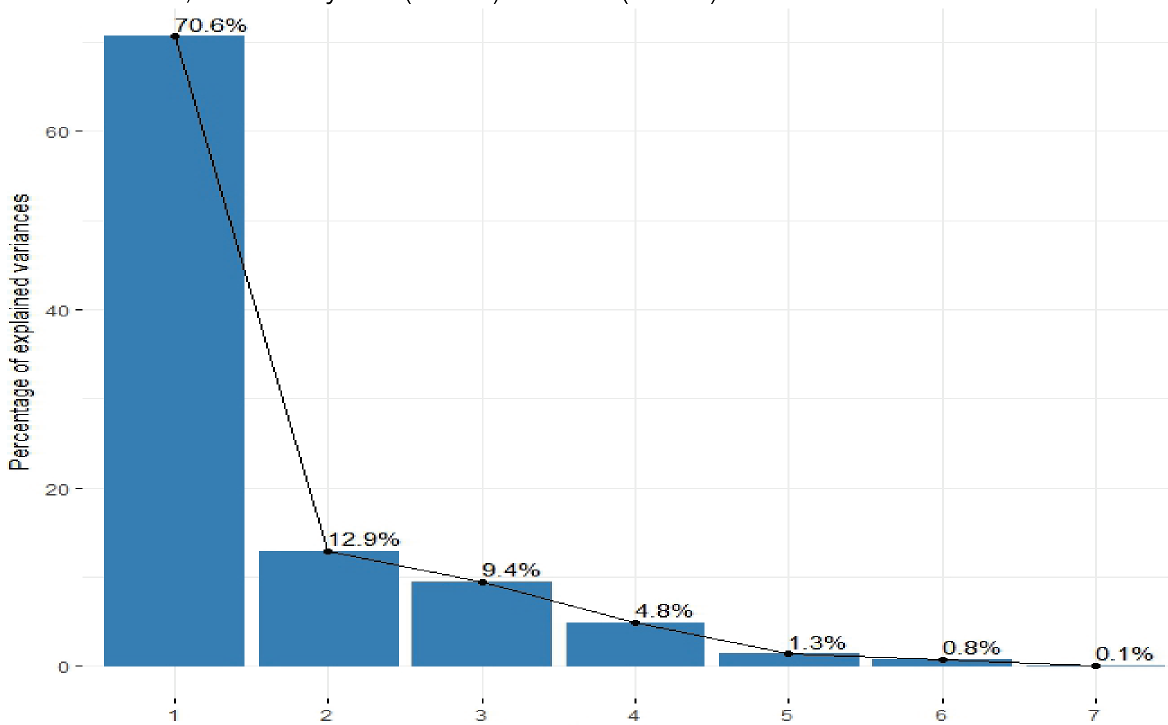

Figure 2. Scree plot of input variables PCA results

Source: Authors’ creation by R statistical program

The labels of bars in Figure 2:

1st bar (1): First PC   2nd bar (2): Second PC   3rd bar (3): Third PC
4th bar (4): Fourth PC   5th bar (5): Fifth PC   6th bar (6): Sixth PC
7th bar (7): Seventh PC

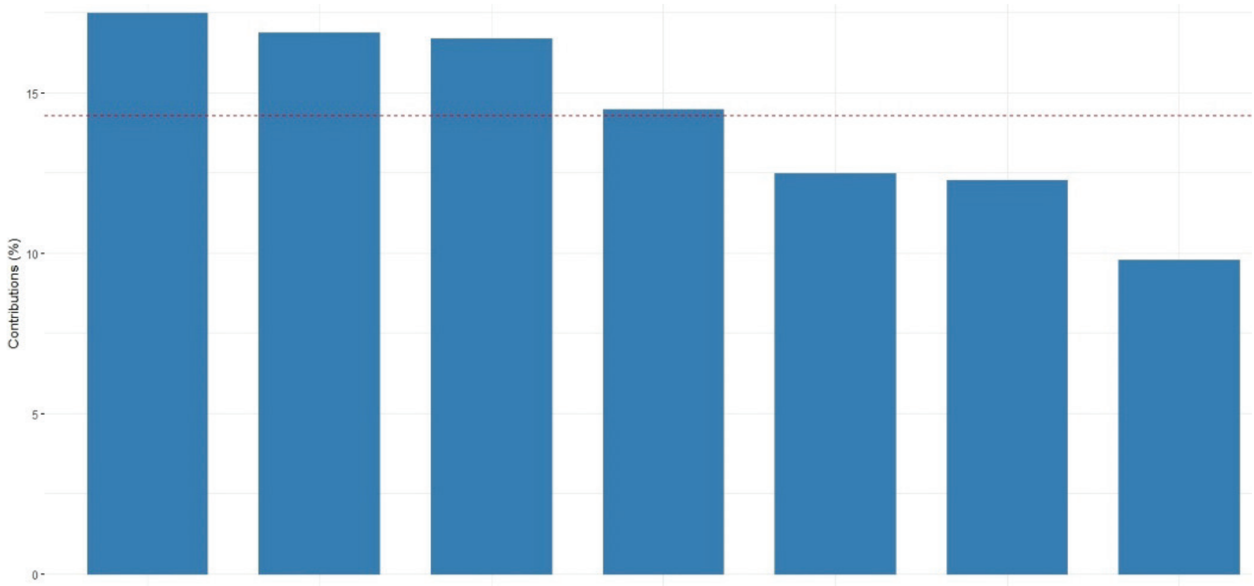

Figure 3. The contribution of variables to the first component

Source: Authors' creation by R statistical program

The labels of bars in Figure 3:

1st bar (X_1): Cash paid for operations   2nd bar (X_2): Cash paid for wages
3rd bar (X_3): Cash paid for social insurance   4th bar (X_7): Financing cash flow
5th bar (X_4): Cash paid for inventory purchases   6th bar (X_6): Investing cash flow
7th bar (X_5): Cash paid for operating expenses

Eigenvalue-analysis of output variables is provided in Table 4. According to the eigenvalue greater-than-one rule, the first PC is chosen for further analysis, which explains 74.86% of the total variance. The second PC explains 18.43% of the total variance, followed by PC3 (5.54%) and PC4 (1.16%).

Table 4. PCA results of output variables

Principal components (PC)	*Eigenvalues*	*Proportion (%)*	*Cumulative percentage (%)*
PC1	*1.730*	*74.86*	*74.86*
PC2	0.858	18.43	93.29
PC3	0.470	5.54	98.83
PC4	0.216	1.16	100.00

Source: Authors' calculation by R statistical program

As shown in Table 4, 74.86% of the total variance determined by the variables used for the investigation was possessed by the first PC. We can express the four primary variables through the first PC within the range of a loss of 25.1%. Accordingly, regarding the first PC, the net profit variable was the least important, while the gross profit variable was the most important. Figure 4 shows that the contribution of the first component to the total variance is approximately 75%, whereas the second one contributes 18.4% to the total variance.

After determining the PCs of the input and output variables separately, the first PC of inputs (explains 70.6%) and the first PC of outputs (explains 74.9%) are selected as variables for the input-oriented PCA-DEA VRS model.

Table 5 presents the efficiency scores of conventional DEA and PCA-DEA models, along with their descriptive statistics. In the traditional DEA model, efficiency scores were calculated using the original data (seven input and four output variables). In contrast, the PCA-DEA model used the first PCs of the initial input and output variables. In the case of the conventional DEA, 54 companies out of 100 (54%) were determined as efficient, while the PCA-DEA model indicated only five efficient companies. However, the number of companies in the efficiency range of 0.0-0.4 (strongly inefficient) was almost identical for conventional DEA (21) and PCA-DEA (23) models. The relative standard deviation of the PCA-DEA values (52.05%) is less than that of the conventional DEA model (44.62%). These values show that the reduction of dimensions has a considerable effect on the efficiency classification. The difference between the mean and median is noteworthy, which is 0.27 in the case of the conventional DEA model, while in the case of PCA-DEA model is only 0.03. These differences indicate that the efficiency results of PCA-DEA are closer to normal distribution compared with conventional DEA efficiency results.

It can also be stated taking into account the averages and medians in Table 5 that the larger difference for the traditional DEA also means that this model is very likely to overestimate the efficiency scores of the companies examined. In the conventional DEA model, the median achieves the value of 1, which means that more than half part of companies are efficient while the average is only 0.73. In the PCA-DEA model, the proximity of the mean and the median confirms the assumption that this method provides values that are closer to reality. It can also be seen from Table 5 that despite the above differences, the average of the efficiency indicators of the two methods is very close to each other, the difference is only (0.73 - 0.65 =) 0.08. The PCA-DEA model has a relatively high number of near-efficient companies (efficiency score > = 0.8 and <1.0), which is 36 companies.

The efficiency results of the conventional DEA model and the PCA-DEA model - to analyze consistency - are illustrated in Figure 5. From Figure 5, we can see that to compare the two models, the distribution of performance scores shows significant differences. The companies were classified either as 'too efficient' or 'too inefficient' considering the results of the conventional DEA model. Figure 5 also shows that the efficiency scores of the PCA-DEA mixed model present a more balanced performance, which - knowing the Mongolian concrete economic situation - are likely closer to reality.

Table 5. Efficiency results of two models

Efficiency ranges	Simple DEA	PCA-DEA	Statistical indicators	Simple DEA	PCA-DEA
0.0 - 0.4	21	23	Minimum	0.00	0.05
0.4 - 0.5	2	8	1st quartile	0.56	0.42
0.5 - 0.6	4	11	Standard deviation	0.38	0.29
0.6 - 0.7	3	11	Variance	0.14	0.08
0.7 - 0.8	5	6	Median	1.00	0.68
0.8 - 0.9	7	10	Mean	0.73	0.65
0.9 - 1.0	4	26	3rd quartile	1.00	0.92
Efficient	54	5	Maximum	1.00	1.00

Source: Authors' calculation by R statistical program

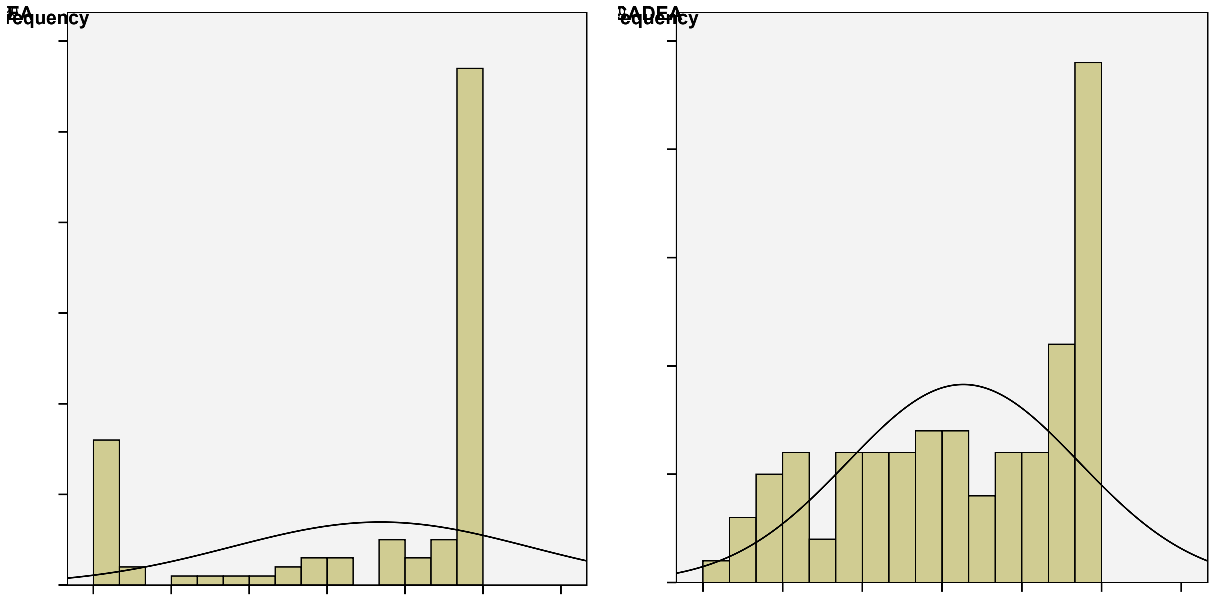

Figure 4. Comparison of the distributions of DEA and PCA-DEA efficiency scores

Source: Own calculation by SPSS statistical program

In Table 6, the efficacy results obtained were divided into four efficacy groups. The table shows that in the combined model only about one-tenth the number of efficient companies compared to the simple DEA model. Still, it can be stated that the number of companies that can be considered as nearly efficient is high in the combined model.

Table 6. Efficiency groups of the two models

Efficiency range	*Level of efficiency*	*Simple DEA model*	*Mixed PCA-DEA model*
>= 0.0 and < 0.4	inefficient	21	23
>= 0.4 and < 0.8	moderately efficient	14	36
>= 0.8 and < 1.0	nearly efficient	11	36
= 1	efficient	54	5

Source: Authors' calculation

CONCLUSIONS

The DEA method is a non-parametric, deterministic special optimisation method. The non-parametric assumption can lead to the conclusion that there are no prerequisites to use DEA. However, it is important to note that there are prerequisites such as the ratio of the number of input and output variables to the number of DMUs, the large number of input and output variables, sensitivity to outliers, etc. In this study, we had dealt with a way to reduce input and output variables.

Using the principal component analysis and factor analysis is a possibility to reduce variables in the DEA model. We chose principal component analysis because it has been used before us in some cases, and in contrast to factor analysis, principal component analysis performs a reversible transformation.

The application of the method aimed to analyse the performance of the examined companies more precisely through their efficiency indicators.

Analysis by conventional DEA and combined PCA-DEA models resulted in a meaningful difference in the results. Traditional DEA analysis provided a much better result in the number of efficient companies than the combined model. However, the results also show that in the case of the efficiency scores of the 100 companies, there is a minimal difference between the average efficiency indicators of the two methods. Also, by examining the relative standard deviation and distribution of the two methods' efficiency scores, it can be concluded that the results obtained with the PCA-DEA model show a smaller standard deviation and a closer approximation to the normal distribution. However, the comparison of the frequency values of the efficiency results of the two models shows that the number of highly inefficient firms is not significantly different.

Overall, the combined method gives a better efficiency rating for Mongolian listed companies. The results of the combined model can be found to be better, considering the practical experience.

Finally, it should be noted that the research has limitations since the analysis performed is only relevant for the group of companies involved in the investigation. In the future, it would be expedient to extend the analysis to a broader range of companies and also to apply stochastic frontier analysis (SFA).

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