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Robust approach for efficiency measurement of employee performance under profit sharing system

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Abstract

This study estimates the efficiency of employees' performances under profit sharing system using data envelopment analysis (DEA). This method is one of the most common methods used in efficiency measurement analysis. However, a robust approach is used to deal with the complexity of the traditional DEA estimators. Robust Data Envelopment Analysis (RDEA) is very useful when outliers contaminate the data. The sample includes five divisions which cover as many as 102 employees of a shipping company in Malaysia are analyzed by using R program. The results reveal that the initial DEA efficiency is an over-estimate of the true efficiency. RDEA provides better accuracy of the results. Further, the robust approach is appropriate to be used in the measurement of the efficiency of company divisions under profit sharing program.

Introduction

The company and its management keep investing a lot of money to improve employees' productivity to reach the ultimate goal by using the existing sources. Many researchers believe that one of the most effective ways to improve both performances and productivities of the employees isto provide some incentive plans, such as profit sharing. The system is believed to be able to encourage employees' morale and attitudes toward the company in a positive direction so that employees' satisfaction can be maintained. However, employees who are satisfied with the current work environment tend to give the best performances with the expectation of a direct reward of some company profits.

The system has grown rapidly in most of the European Union countries, USA, Canada, Taiwan, Japan, and so on. Estrin, Perotin, Robinson, & Wilson (1997) report profit sharing system show significant progress in industrial countries in the late 1980s and 1990s. However, France and the United Kingdom contribute the highest level of financial participation, especially profit sharing system, which 57 percent of workplaces in France offer the portion of company profits to its employees, while 40 percent of workplaces in UK provide profit sharing scheme. Generally, the growth of profit sharing system in those countries is supported by the government policy who promotes the system through tax concessions. Furthermore, in 1987 to 1991 the amount of profit sharing program has been implemented in the UK is increased from 145 to 2,049 plans. The participation to profit sharing program effects positively (or at least has neutral effect) to productivity (Perotin & Robinson, 2002). The study covers more than 20 countries involving thousands of reputable companies show very encouraging results. Profit sharing system has a positive impression to enhance the efforts of employees which increases their chances of getting a bigger share of the company's profit. Better effort from the employees leads to better productivity(Koskela & König, 2010).Jerger & Michaelis (2007) also analyze individual effort of employees under profit sharing system.

By knowing the efficiency performance of each employee, the company and its management can distribute the profit portion fairly based on their performances to maintain a sense of fairness among the employees. Efficiency measurement is first introduced by Farrell (1957) by using technical efficiency which describes firm ability to maximize the production of outputs with the existing inputs as well as a locative efficiency that reflects a firm to capitalize the available inputs optimally with the determined price levels. This study analyzes the employees' performance efficiency under profit sharing program by using DEA method. This method is very interesting because it allows to compare and rank records (companies, departments, employees, schools, universities, institutions' programs, et cetera) based on their features such as weight, revenue, salary, and size. The main advantage of DEA method relies on there is no need to build any prior

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assumptions. DEA is a nonparametric approach based on linear programming to measure a unit, an organization or a program, which is often called Decision Making Units (DMUs), with similar characteristics.

The method is introduced by Charnes, Cooper, & Rhodes (1978) so it is common to call this as CCR method. Later, the method is extended by Banker, Charnes, & Cooper (1984). There are studies done using DEA approach to assess employees' performances (see Golec & Kahya, 2007; Tao, 2012; Wu & Hou, 2010).Shirouyehzad, Lotfi, Aryanezhad, & Reza (2012) use DEA approach to evaluate employees' efficiency in a pipe company in Iran by using as many as 55 employees as the sample. The results reveal that the main factors that affect employees' efficiency performances are the conditions of physical working and a good commitment by the organization. Further, the result indicates there are ten employees have efficient performances. Whereas the group of employees who have the highest efficiency scores is those aged between 25-35 years, as well as the group of employees who have 5-10 years of work experiences. Evaluation of employees' performance by using DEA method is also used by Zbranek (2013), which uses three inputs and three outputs, while as many as 60 employees in the baking company are used as DMUs. The results indicate that there are 12 employees whoare fully efficient while the remaining employees have inefficient performances that need to improve their efforts to achieve efficient performances.

Although there are studies done on employees' performances using this method by applying profit sharing plans in the parameters of employees is very limited. However, nowadays there are a lot of companies offer its employees to participate in profit sharing plans because of its advantages for both of them. The measurement of employee performance efficiency should be doneto determine which division performs efficiently by using the existing resources. The company division with the best performance, which is identified by the highest efficiency score, can be used as a role model to other divisions to improve their performances. However, a robust approach is appliedto face the complexity as well as multidimensional nature of the traditional DEA estimators. The DEA method relies on the best unit identification which makes it sensitive to the existence of outliers which may reduce the accuracy of the analysis results. Cooper, Huang, Lelas, Li, & Olesen (1998) and Gstach (1998) use stochastic DEA to face these problems, which usually requires specification of statistical distribution. A study conducted by Wilson (1995) proposes a procedure for detecting outliers which are devoted to DEA methods whereas robust optimization is analyzed by Bertsimas & Sim (2003). However, this study implements bias-corrected technical efficiency scores by Simar & Wilson (1998) using robust approach.

This approach is a sampling procedure to produce new samples with replacement, which allows determining the accuracy steps of sample estimates, such as bias, variance, confidence intervals, prediction error, et cetera(Efron & Tibshirani, 1993). Gharakhani, Kazemi, & Haji (2011)measure the relative efficiency of Iranian high schools considering uncertainty on output parameters by using 35 high schools in Tehran as DMUs by applying the robust approach to DEA method. The results reveal that robust DEA approaches are better used for estimating the efficiency performance of Iranian High Schools. Testi, Fareed, Ozcan, & Tanfani (2013)apply a bias-corrected DEA model for assessing the physician performance diabetes using 96 family physicians. The results reveal that 35 practices perform efficiently based on the traditional DEA with the average of VRS scores is 0.86. Meanwhile, in the bias-corrected model, the average is 0.78. Data from shipping company is used to measure the employees' performance. The company engages in the delivery of goods from Malaysia to Indonesia in 2012. Five divisions of the company that cover as many as 102 employees that are received a share of the company profit are used as decision making units. The data is analyzed by using R program.

Research Method

This study applies data envelopment analysis for measuring the efficiency of employees' performances under profit sharing system. This method is very useful for facing the analysis problem with a lot of input and output variables. A DMU has efficient performance when the score of efficiency equal to one, which indicates that its efficiency performance is equal to 100 percent, otherwise when its efficiency score is less than one, then the DMU is declared inefficient. There are two models of DEA method, namely CRS (constant return to scale) model and VRS (variable return to scale) model. The first model is developed by Charnes et al. (1978) so it is also known as CCR model, while the other is introduced by Banker et al. (1984) and is also known as BCC model, which is a development of the first model. CCR model uses the assumption that ratio between the increasing input and output variables is similar. Other than that, this model assumes that each DMU performs at optimal scale. Whereas VRS model assumes that each DMU is not yet operating at optimal scale as well as the increasing of input and output variables is not similar.

This study uses the framework of DEA method where the naïve score is concerned following the structure developed by Charnes et al. (1978) as follows. Let x_n denote the observed of input where $n = 1,2,3, \dots, N$ to produce outputs y_m where $m = 1,2,3, \dots, M$ as $D = \{(x, y): x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\}$.Coelli, Rao, & Battese (1994) state that input set $P(y)$ contains inputs, which produce a number of outputs under D, so that $P(y) = \{(x): (x, y) \in D\}$. Then the mathematical model form of CRS input-oriented efficiency θ_k for a given DMU_k where $k = 1,2,3, \dots, K$can be written as follow (Charnes et al., 1978):

$$min_{\theta_k,\lambda}\theta_k \tag{1}$$

Subject to

$$-y_{mk} + \sum_{i=1}^{K} \lambda_i y_{mi} \geq 0 \tag{2}$$
$$\theta_k x_{nk} - \sum_{i=1}^{K} \lambda_i x_{ni} \geq 0 \tag{3}$$

and
$\lambda_i \geq 0$

This model assumes that $P(y)$ is strict convexity and strong disposability of input and output variables where the last assumption indicates that if $x \in P(y)$ and if $x' \geq x$ then $x' \in P(y)$. Then to impose CRS model to VRS model requires additional constraints of $\sum_{i=1}^{K} \lambda_i x_{ni} = 1$(Charnes et al., 1978). Due to this method is based on frontiers then data accuracy and preciseness are needed to produce acceptable results. Although the traditional DEA method is considered as one of the most powerful method for measuring efficiency performance, it is required precise and accurate data to provide unbiased efficiency scores for each DMU. However, it is very difficult to obtain real data accurately in the real world problems due to the uncertainty of input and output variables. The bootstrap method is a powerful statistical re-sampling method to approximate the estimator sampling distributions by using the empirical distribution. Basically, the bootstrap methods correct for the bias due to estimated boundary $\hat{P}^{\partial}(y)$ of the input variables may fail to incorporate the most efficient DMU. Then, for each DMU *i* bias $\theta_i = E(\hat{\theta}_i) - \theta_i = \widehat{\text{bias}\theta_i}$ similar to bias $\hat{\theta}_i^* = E(\hat{\theta}_i^*) - \hat{\theta}_i$. The procedure of this method is as follows (Simar and Wilson, 1998):

1) Estimate naive scores of DEA $\hat{\theta}_i = (\hat{\theta}_1, \hat{\theta}_2, \dots, \hat{\theta}_J)$ from the equation (2).
2) Repeat R times to produce K sets of bootstrap estimates $\{\hat{\theta}_{ir}^*\}_{r=1}^{R}$.
3) Calculate $\widehat{\text{bias}\hat{\theta}_i} = \frac{1}{R}\sum_{r=1}^{R} \hat{\theta}_{ir}^* - \hat{\theta}_i$for (x_{ir}^*, y_i)
4) Calculate bias-corrected score $\hat{\hat{\theta}}_i = \hat{\theta}_i - \widehat{\text{bias}\hat{\theta}_i}$

Therefore, according to Simar & Wilson (2007), the algorithm of input-oriented model of bias-corrected bootstrap DEA δ, the reciprocal of θ, is based on the fact that the input variables x_n do not depent on the environmental variables $\boldsymbol{z}_i$, which indicates the input variables that are not directly controlled by producers) are as follows (Simar & Wilson, 1998):

1) Estimate naive distance scores δ_i where $i = 1,2,3, \dots, J$.
2) Assume $\delta_i = \boldsymbol{z}_i\beta + \varepsilon_i \geq 1$, where ε_i are independent and identically distributed and independent from $\boldsymbol{z}_i$ while $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with left truncation at $(1 - \boldsymbol{z}_i\beta)$.
3) Calculate $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ by using observations for which $\delta_i > 1$.
4) Repeat R times to produce K sets of bootstrap estimates $\{\hat{\delta}_{ir}^*\}_{r=1}^{R}$ for (x_{ir}^*, y_i)
5) Calculate $\widehat{\text{bias}\hat{\delta}_i} = \frac{1}{R}\sum_{r=1}^{R} \hat{\delta}_{ir}^* - \hat{\delta}_i$.
6) Calculate bias-corrected score $\hat{\hat{\delta}}_i = \hat{\delta}_i - \widehat{\text{bias}\hat{\delta}_i}$.

To estimate the efficiency scores of each division under profit sharing program by using the existing sources (inputs and outputs), this study is based on the sampling variability of the VRS-DEA efficiency estimator introduced by Simar & Wilson (1998) with input-oriented model to estimate bias-corrected technical efficiency scores. Further, this study provides the confidence intervals around these efficiency scores of the company division under profit sharing program. The confidence intervals are estimated from the empirical sampling distribution, which is constructedform the observed DEA efficiencies.

Results and Discussion

This paper uses data from the shipping company that covers more than 540.000 goods from Malaysia to Indonesia in 2012. The company has as many as 250 employees, both full time and parttime. The data is from the annual data company which includes basic salary, the fraction of profit sharing, number of employees, working hours, the skills and expertise of the employees, as well as the background of the employees in general. After analysis using the selectivity method in the original data, then obtained as many as 102 employees that relevant to be sampled in this study. The average of employees' age is 35 years old with standard deviation is 18 years old, while the average of basic salary is RM 1,349.50 with standard deviation is RM 1,152.54. Monthly income has the average as many as RM 1,977.21 while the average of profit portion is RM 1,195. There are four directors, five managers, 14 head of divisions, and 79 staff who receive some of the company profits. Married employees are about 52 percent compare to single employees as many as 48 percent. Comparison of male employees and female employees is 84.3 percent to 15.7 percent. Further, there are 54.9 percent employees with high school degree get profit share, while the percentage of employees with a bachelor degree is 20.6 percent. Master degree employees have 22.5 percent, and Ph.D. employees have 2 percent.

However, this study uses five divisions in the company as DMUs to describe employee performance, i.e., Administration division, Finance Division, Customer Service division, Marketing division, and processing division. Whereas there are three inputs (basic wage, the number of employees, work experience) and two outputs (total job completed by the employees and total profit sharing earn by the employees) to measure the performance efficiency of these divisions. This study uses biased-corrected data envelopment analysis to estimate bias-correction of technical efficiency scores in input-oriented model based on Simar & Wilson (1998) using robust approach.

The estimations are conducted under a variable return to scale (VRS) model and input-oriented model where DEA minimizes the input variables to the given level of output variables. In other words, an inefficient unit needs to proportionally reduce its inputs proportions to achieve efficient unit while its outputs are held constant. It is used due to the departments have the most control over these input variables. Table 1 represents a descriptive statistics of the input and output variables.

Table 1. Descriptive Statistics

Variables	Min	Max	Mean	Std. Dev
Outputs				
y_1	174,040	210,100	192,294	13,598.265
y_2	84,900	134,100	96,240	21,213.628
Inputs				
x_1	135,000	256,800	169,920	50,036.906
x_2	10	38	20	10.738
x_3	33	74	51	17.813

Where y_1 represents the total job completed by the employees, y_2 represents the total portion of profit sharing earn by the employees, x_1 represents the basic wage, x_2 describes the number of employees, x_3 represents work experience. By using R program, table 2 shows the efficiency scores for both CRS and VRS models of each DMU by using the determined input and output variables.

Table 2. Efficiency Scores of CRS and VRS Models

DMUs	CRS Model	VRS Model
Administration	0.950	1.000
Finance	1.000	1.000
Customer Service	0.885	0.906
Marketing	1.000	1.000
Processing	0.819	1.000

Based on Table 2, the traditional DEA indicates that the averages of efficiency scores are 0.931 and 0.981 for CRS model and VRS model, respectively. It means that the average of CRS model efficiency score is 93.1 percent while VRS model is 98.1 percent. Further, for CRS model, the percentage division that performs efficiently is only 20 percent while the percentage of efficient division on VRS model reaches 80 percent. Moreover, there are two divisions that perform efficiently on both CRS and VRS models, i.e., Finance division and Marketing division (each division has perfect efficiency score of 100 percent). Whereas administration division and processing division perform efficiently on VRS model but has not efficient performance on CRS model, where the efficiency scores are 95 percent and 81.9 percent in the CRS models, respectively. Further, Customer Service division has inefficient performance on both models where the scores are 88.5 percent on CRS model, and it has efficiency score of 90.6 percent on VRS model.

Following the description of the discrimination phase introduced by Thanassoulis, Dyson, & Foster (1987) then it can be said that administration division should be able to support its activity by using only 95 percent of its sources in the CRS model. Therefore, to accomplish efficient performance, this division requires reducing input variables of 5 percent. Whereas processing division should be able to endorse its activity level by employing the existing input variables of 81.9 percent in the CRS model, which means that this division can reach efficient performance by reducing the input variables as many as 18.1 percent. Furthermore, customer service division should be able to support its activity level by using only 88.5 percent and 90.6 percent in the CRS and VRS models, respectively. This means that this division canperform efficiently by reducing the existing input variables as many as 11.5 percent and 9.4 percent in the CRS and VRS models, respectively.

However, we can safely conclude that VRS model produces better scores of division's efficiency under profit sharing system. Therefore, this study uses this model for estimating bootstrapped DEA efficiencies to deal with the biases in the estimation. Bootstrapping is used to correct the traditional DEA efficiencies for bias and then to estimate confidence intervals for them. Table 3, Table 4 and Table 5 show the results of bias-corrected DEA scores for the input-oriented model by using the number of bootstrap replications B= 500, 1000, 2000 while the size of the confidence interval for the bias-corrected DEA score is 0.01, 0.02 and 0.05.

Table 3. Efficiency Scores of the Biased-Corrected (B=500)

DMUs	alpha=0.01				alpha=0.02				alpha=0.05			
	theta	low	high	bias	theta	low	high	bias	theta	low	high	bias
D1	0.95	0.92	1.02	0.05	0.95	0.92	1.01	0.05	0.95	0.93	1.00	0.05
D2	0.95	0.92	1.06	0.05	0.95	0.91	1.03	0.05	0.95	0.91	1.02	0.05
D3	0.87	0.85	0.92	0.03	0.87	0.85	0.91	0.04	0.87	0.85	0.90	0.04
D4	0.95	0.91	1.02	0.05	0.95	0.91	1.04	0.05	0.95	0.92	1.02	0.05
D5	0.95	0.92	1.05	0.05	0.95	0.91	1.03	0.05	0.95	0.92	1.02	0.05

Table 4. Efficiency Scores of the Biased-Corrected (B=1000)

DMUs	alpha=0.01				alpha=0.02				alpha=0.05			
	theta	low	high	bias	theta	low	high	bias	theta	low	high	bias
D1	0.95	0.92	1.02	0.05	0.95	0.92	1.01	0.05	0.96	0.93	1.00	0.05
D2	0.95	0.91	1.03	0.05	0.95	0.91	1.03	0.05	0.95	0.91	1.01	0.05
D3	0.87	0.85	0.91	0.03	0.87	0.85	0.91	0.04	0.87	0.85	0.90	0.04
D4	0.95	0.91	1.04	0.05	0.95	0.91	1.03	0.05	0.95	0.91	1.01	0.05
D5	0.95	0.91	1.04	0.05	0.95	0.91	1.03	0.05	0.95	0.91	1.02	0.05

Table 5. Efficiency Scores of the Biased-Corrected (B=2000)

DMUs	alpha=0.01				alpha=0.02				alpha=0.05			
	theta	low	high	bias	theta	low	high	bias	theta	low	high	bias
D1	0.95	0.92	1.02	0.05	0.95	0.92	1.01	0.05	0.95	0.92	1.00	0.05
D2	0.95	0.91	1.05	0.05	0.95	0.92	1.03	0.05	0.95	0.91	1.01	0.05
D3	0.87	0.85	0.92	0.04	0.87	0.85	0.91	0.03	0.87	0.85	0.90	0.03
D4	0.95	0.91	1.04	0.05	0.95	0.91	1.03	0.05	0.95	0.91	1.01	0.05
D5	0.95	0.91	1.04	0.05	0.95	0.91	1.03	0.05	0.95	0.91	1.01	0.05

Where D1 represents administration division, D2 is financed division, D3 is customer service division, D4 is a division of marketing and D5 is a division of processing. Further, theta column indicates the vector of bias-corrected DEA score for each division, which is in the range of zero to one, while bias column shows the vector of bias for naive DEA score, and it is non-negative, and both of the low and high columns indicate the vector bounds of lower and upper confidence intervals for bias-corrected score.

From Table 3, by using 500 replications indicates that the confidence intervals of the efficiency scores of all DMUs are smaller when alpha is greater. Unless D4 (a division of marketing) which shows that the width of the confidence interval at alpha=0.02 is greater than at alpha=0.01, all DMUs show consistency interval shrinking. Overall, the results show a fairly narrow confidence interval for all DMUs where the average of its width is 0.112 with the maximum width is 0.147 when alpha is 0.01. Then the average width of the confidence intervals when alpha is 0.02 and 0.05 are 0.104 and 0.09, respectively. While the maximum widths are 0.132 and 0.107 when alpha are 0.02 and 0.05, respectively. The narrow interval indicates that there is a smaller chance of obtaining an observation within that interval, which means that the accuracy of the result is higher. Table 3 also indicates that valid conclusions can be made due to the bias estimates are fairly small.

Table 4 shows the results of bias-corrected scores using 1000 replications. It can be seen that the width of confidence interval decreases as the alpha value increases. The average and the maximum of width interval are 0.106 and 0.129 at alpha=0.01, respectively. While its values are 0.100 and 0.124 at alpha=0.02, respectively. Whereas the average and the maximum of width interval are 0.09 and 0.109 when alpha is 0.05, respectively. The results also indicate that the bias estimates are small enough so that valid conclusions canbe made.

Furthermore, Table 5 shows bias-corrected of efficiency scores by using 2000 replications. The interval widths of all DMUs show the same properties as the bias-corrected scores with replication as much as 1000 times, which go down when the alpha values go up. Further, any valid conclusions can be made due to the bias estimates are quite small. Summing it up, robust DEA scores of employees' efficiency performance under profit sharing program provides the narrow width of confidence intervals, which indicates that there is a smaller chance of obtaining an observation outside the interval. Generally, the narrower the interval tends to decrease the uncertainty of the results. In other words, there is a little risk of the results about missing the true value due to a narrower width of interval provides more precise results. Furthermore, the efficiency scores of robust DEA are always in the range of confidence interval, which the bias-corrected scores continually follow the scores of traditional DEA. Besides the empirical results reveal that the initial DEA score is close to the upper bound of the confidence interval, which indicates that the initial DEA efficiency is an over-estimate of the true efficiency. Overall, the bias estimates are quite small. Therefore, from the explanation above, the results of robust efficiency scores of the company's divisions under profit sharing program statistically significant, which provide more precise as well as more valid results. Because of that, it is possible to conclude that robust approach is appropriate to be used in the measurement of the efficiency of company divisions under profit sharing program.

Conclusion

This study uses data envelopment analysis to investigate the efficiency of employees' performances under profit sharing system. However, a robust approach is applied due to the complexity of the traditional DEA estimators. The results show that bias-corrected efficiency scores under robust approach provide more precise and valid conclusions in measuring employees' efficiency under profit sharing program.

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