The efficiency assessment of food safety in China's agriculture: a case study of the rice sector

Hodnocení efektivnosti potravinové bezpečnosti čínského zemědělství: případová studie odvětví produkce rýže

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Abstract: Rice is the main food in China's home consumption and plays an important role in its food security. But, how is the status of food safety and environmental efficiency in China's agriculture? Obviously, an incorrect manner of pesticide application will hold negative effects on human health and environment. In this article, we develop an analytical framework based on the Luenberger DEA method to calculate the output technical efficiency and input environmental efficiency simultaneously. In the second-stage analysis, the stochastic frontier model is used to estimate the impact of explanatory variables and managerial efficiency on efficiency. We apply the methodology in the empirical case study of China's rice production for measuring the food safety performance of China's rice sector.

Key words: food safety, environmental performance, Luenberger DEA, Distance output Technical Efficiency (DTE), Distance input Environmental Efficiency (DEE), stochastic frontier model, managerial efficiency, rice

Abstrakt: Rýže je základní složkou domácí spotřeby potravin v Číně a hraje tedy významnou roli v rámci její potravinové bezpečnosti. Jaká je ale úroveň potravinové bezpečnosti a dopadů na životní prostředí ze strany čínského zemědělství? Je zřejmé, že nesprávné využívání pesticidů má negativní důsledky na lidské zdraví a životní prostředí. V článku je předložen analytický přístup, založený na Luenbergerově DEA metodě k současnému výpočtu technologické efektivnosti outputu a environmentální efektivnosti inputu. Ve druhém kroku analýzy je použito stochastického mezního modelu k odhadu vlivu explanatorních proměnných a manažerské efektivnosti na celkovou efektivnost. Tuto metodologii jsme aplikovali na empirickou případovou studii produkce rýže v Číně k měření míry potravinové bezpečnosti čínského odvětví produkce rýže.

Klíčová slova: potravinová bezpečnost, dopady na životní prostředí, Luenbergerova DEA, Distance Technical Efficiency (DTE) outputu, Distance Environmental Efficiency (DEE) inputu, stochastický mezní model, manažerská efektivnost, rýže

Although rice is the main food consumed traditionally in China, after China's entry to the WTO, China's rice is directly confronted with the competition of foreign agricultural products. Because consumers increasingly consider the information on the safety of food in making their purchasing decisions, China's government and farmers are now becoming concerned with the food safety in the agricultural sector. With such increasing awareness of health problems, the policy to improve the health performance in the agricultural production is essential.

On the other hand, China is the largest grain consumer in the world and its future food balance is especially significant for the world grain production (Huang et. al. 1999). As a result, Chinese farmers and government have to consider both the food sanitation and the food yield in order to meet the food demand in China.

However, most of the sanitary and environmental assessment methods are only built on estimating the impact of agricultural activities on the environment and do not consider both the output and the environmental performance at the same time. Although there have been some studies focusing on estimating the environmental performance of the Chinese agricultural sector (Zhang Tao et al. 2005; Zhang Tao 2008), no one measures the technical-environmental efficiency crediting both the increase in output (productivity) and the decrease in chemical inputs (sanitary and environmental performance) simultaneously. Therefore, some technical-environmental indicator should be developed and used to identify both the sanitary and environmental performance and productivity simultaneously in farming operations.

In this paper, the Luenberger DEA method is used to calculate the environmental and technical efficiencies simultaneously in the Chinese rice production. At the same time, pursuing environmental efficiency in the crop sector may further enhance the sector's capacity to reduce costs, while contributing to a good sanitary and environmental performance. The efficiency associated with pesticide inputs is estimated through a linear programming method. In addition, the case study of rice production can provide some implications for the understanding of the environmental and productivity performance in the whole China's plant production.

MATERIAL AND METHODS

Methodology, the Luenberger DEA

Most of the environmental efficiency assessments using the Luenberger DEA (such as Chung et al. 1997 and Boussemart et al. 2003) allow for the possibility of crediting the observations for both the reduction of bad outputs (environmentally detrimental outputs) and the increase of good outputs (desired outputs) simultaneously. However, when applying it in Chinese planting operations, it is easier and more applicable to minimize the pesticide inputs instead of bad outputs because of the farmers' excessive use of pesticides. In addition, most of the available studies focus on evaluating the potential impact of the pesticide residues and find the fact that Chinese farmers apply excessive pesticides in planting, but they cannot provide a precise measure to direct farmers in reducing the pesticide use. The results from this method minimizing pesticide inputs while increasing or sustaining outputs can provide a direction to the policy-makers or farmers for reducing the pesticide use and improving their environmental performance.

We start from the observations of K units that use N good inputs $x = (x_1, ..., x_N) \in R_+^N$ and W bad inputs (here, it is only the pesticide input which is applied excessively in China.) $b = (b_1, ..., b_w) \in R_+^w$ to produce outputs $y \in R_+^M$. In these inputs, W bad inputs are the environmentally detrimental inputs. As a definition of the environmental efficiency (EE), we use the following reference technology S which is similar to the definition of Banker et al. (1984) and Ball et al. (1994).

$$S = \{(x,b,y): \sum_{k=1}^{K} z^k x_n^k \leq x_n,\ n = 1,...,N$$
$$\sum_{k=1}^{K} z^k b_w^k \leq b_w,\ w = 1,...,W$$
$$\sum_{k=1}^{K} z^k y_m^k \geq y_m,\ m = 1,...,M$$
$$\sum z^k = 1,\ k = 1,...,K$$
$$z^k \geq 0,\ k = 1,..., K\} \qquad (1)$$

Three sets of constraints indicating the vector of outputs y are produced by the vector of good inputs x and bad inputs b, based on the reference technology S.

Based on the above production set, the Farrell output measurement of technical efficiency (Farrell 1957) can be defined as

$$1/TE = (D_o(x,b,y))^{-1} = \sup\{\theta : (x,b,\theta y) \in S\} \qquad (2)$$

In this function, TE is based upon the maximum expansion of the output vector using the given set of inputs. The reciprocal of the function (2) is the Shephard output distance function (Shephard 1970; Fare et al. 1994).

According to Banker et al. (1984) and Ball et al. (1994), a bad input-oriented efficiency index can be described as:

$$EE = (D_i(x,b,y))^{-1} = \inf\{\theta : (x,\theta b,y) \in S\} \qquad (3)$$

Function (3) can be directly treated as the definition of EE. Here, EE is environmental efficiency, which is equal to θ. If $\theta < 1$, the sample is not lying on the frontier of the production set, and an improvement of environmental performance is possible for this sample. If $\theta = 1$, it indicates that, in the current status of technology reflected by the frontier of the production set, no significant improvements in the sanitary and environmental performance could be made for the sample.

Although the above functions can provide the traditional Farrell output technical efficiency and input environmental efficiency, these two indices are calculated separately. Thus, the calculated scores of the above methods only can credit the maximum expansion of outputs with the given inputs or credit the maximum contraction of bad inputs with the given outputs. In order to allow for the possibility of crediting observations for the reduction of bad inputs and the increase of outputs simultaneously, the Luenberger directional distance function instead of the Shephard distance function should be used. The Luenberger directional distance function for calculating the output technical efficiency (directional output technical efficiency) and the input environmental efficiency (directional input environmental efficiency) simultaneously can be expressed as

$$\vec{D}_o(x,b,y;g) = \sup\left\{\beta : (x, y+\beta g_y, b-\beta g_b) \in S\right\} \qquad (4)$$

where "g" is the vector of "directions" in which outputs are scaled. Here we assume that $g_y = y$ and $g_b = b$. β is the expansion of the outputs and the contraction of the bad inputs when the expansion and contraction are identical proportions for the given level of other inputs. The above directional distance functions can be expressed as solutions to the linear programming problems as follows:

$$\vec{D}_o(x,b,y;g) = Max\beta$$

$$\sum_{k=1}^{K} z^k x_n^k \le x_n,\ n = 1,\dots,N$$

$$\sum_{k=1}^{K} z^k b_w^k \le (1-\beta) b_w,\ w = 1,\dots,W$$

$$\sum_{k=1}^{K} z^k y_m^k \ge (1+\beta) y_m,\ m = 1,\dots,M$$

$$\sum z^k = 1,\ k = 1,\dots,K$$

$$z^k \ge 0,\ k = 1,\dots,K \qquad (5)$$

Then, the direct distance functions can be expressed as:

$$\vec{D}_o(x,b,y;g) = \sup\left\{\beta : (y+\beta g_y) \in S\right\} = (1/TE) - 1 \qquad (6)$$

and

$$\vec{D}_i(x,b,y;g) = \sup\left\{\beta : (b-\beta g_b) \in S\right\} = 1 - EE \qquad (7)$$

Thus, we can calculate the directional output technical efficiency (DTE) and the directional input environmental efficiency (DEE) using the following functions:

$$\vec{D}_o(x,b,y;g) = \sup\left\{\beta : (y+\beta g_y, b-\beta g_b) \in S\right\} =$$

$$= (1/DTE) - 1 = 1 - DEE \qquad (8)$$

The relationship can be rewritten as DTE = 1/(1 + β) and DEE = 1 – β.

Data for the analysis

The Luenberger DEA model was calculated based on the linear program problems established with the statistically representative samples of farms in China. A set of the cross-sectional farm level data were used to estimate the production frontier and efficiency. We collected the input and output data covering 168 farms in the Zhejiang, Jiangsu, Shaanxi, and Hebei provinces of China in 2002. In this paper, we chose the pesticide input as the environmentally detrimental input in the China's rice production.

The data set was based on the same land unit which was 1 mu (about 677 square meters). Therefore, the land input was not included in our model. We chose six important input variables (labour, seed, pesticides, fertilizers, irrigation, and machinery). The unit of labour is the work days inputted in production. The output, seed input, pesticide, and fertilizer were all measured by the total quantity of inputs. The irrigation and machine inputs were measured by the total expenditures on them. The pesticide input was treated as the main environmentally detrimental input which had the most important impact on the environment and human health.

Table 1 lists the summary statistics of the sample data used in the DTE and DEE estimates. The quantity of rice output of the individual farms ranged from 485.36 (unit: 500 gram) to 1 229.5 per mu with the average of 869.75 per mu. Labour input varied widely

Table 1. Summary statistics of data

	Output (500 g)	Labor (days)	Seed (500 g)	Fertilizer (500 g)	Pesticides (1 000 g)	Irrigation (RMB: Yuan)	Machinery (RMB: Yuan)
Mean	869.75	18.00	12.53	43.11	1.12	19.92	19.04
Median	852.59	16.65	10.20	40.79	1.04	18.87	17.15
Maximum	1 229.5	38.61	47.39	99.9	4.28	63.58	77.64
Minimum	485.36	7.22	1.92	16.74	0.17	7.59	0.58
Std. Dev.	149.37	6.19	8.49	13.94	2.03	14.28	14.86

from the minimum of 7.22 work days to the maximum of 38.61 work days per mu per season. The quantity of fertilizer input (per mu) ranged from 16.74 to 99.9 per mu with the average of 43.11 per mu. The input of pesticides also varied widely from the minimum of 0.17 kg to the maximum of 4.28 kg per mu per season. Such large input gaps in pesticides would result in a big difference in the environmental performance.

RESULTS AND DISCUSSION

The Luenberger DEA results

Following the methodology described in Section 2, we have computed the DTE and DEE indices as well as the traditional Farrell output technical efficiency index for each of the 168 farms in the sample.

Table 2 depicts some statistical characteristics of calculated results from the model. The estimated scores of directional output technical efficiency (DTE) ranged from 0.62 to 1 with an average of 0.88. The calculated scores of directional input environmental efficiency (DEE) ranged from 0.38 to 1 with the average of 0.84. The scores of the traditional Farrell output technical efficiency (TE) varied from 0.37 to 1 with the average of 0.83.

Table 2. Summary statistics of results

	DTE	DEE	TE
Mean	0.88	0.84	0.83
Median	0.87	0.85	0.82
Maximum	1	1	1
Minimum	0.62	0.38	0.37
Std. Dev.	0.099	0.14	0.14

DTE = Distance output Technical Efficiency
DEE = Distance input Environmental Efficiency
TE = Technical Efficiency

Table 3. The distribution of efficiency scores

Efficiency range	Number of observations		
	DTE	DEE	TE
1	30	30	30
0.9	32	29	27
0.8	73	47	36
0.7	26	34	43
0.6	7	18	18
0.5	0	6	11
0.4	0	3	2
0.3	0	1	1
0.2	0	0	0

The result of the TE shows that, as for the average score of the TE, the output of the whole rice sector in China has the potential to be increased by 17% while all the inputs are constant. The average scores of the DTE and DEE indicate that we can improve the rice output by 12% and reduce the pesticide inputs by about 16% simultaneously while making other inputs constant. Obviously, if we only want to increase the output, the scenario of the TE result should be used. If we concern output and food safety, the scenario of the DTE/DEE results should be chosen.

Table 3 depicts the frequency distribution of the DTE, DEE, and TE for rice farms in China. From Table 3, the numbers of the full DTE, DEE, and TE scores are all 30, indicating that for these farms, there is no potential to increase their outputs and to reduce the pesticide inputs. But most of the efficiency scores of the DTE, DEE, and TE range from 0.7 to 0.9, representing that there still exists some potential to increase the rice outputs while reducing the pesticide inputs in plant operation. From Table 3, it also can be discovered that some efficiency scores of rice farms are lower than 70% or even 50%, indicating that for these farms both the outputs and the sanitary performance can be greatly improved. In Table 3, it is clear that for the whole rice sample, the DEE score of pesticide inputs in Chinese rice sector is lower than the DTE "score", which suggests that the environmental performance in Chinese agricultural sector is worse than its productivity performance.

The lowest scores of the DTE and DEE for the same farm are 0.62 and 0.38, representing that the output of this farm can be increased by about 38% and its pesticide inputs can be decreased by 62% simultaneously while making other inputs constant.

The second-stage analysis and results

In the second-stage analysis, we use the stochastic frontier model to regress the calculated DTE and DEE scores against the observed explanatory variables. This method was first proposed by Fried et al. (2002) in the second-stage regression for technical efficiency and Reinhard et al. (2002) in the second-stage regression for environmental efficiency. According to this method, the variation in the estimated environmental efficiency or technical efficiency can be apportioned to three sources: (1) the impacts of the exogenously explanatory variables in the deterministic part; (2)

the impact of the random error and other sources of statistical noise; and (3) an unexplained shortfall of efficiency beneath the best practice observed in the sample (in Fried et al. (2002) this is called managerial inefficiency; and in Reinhard et al. (2002) this is called the conditional environmental efficiency). Therefore, there will be two useful types of information from the second stage regression. One is the relationship between the explanatory variables and the estimated DTE and DEE. This information can be derived from the estimated coefficients of the stochastic frontier function. The other is the evidence about the producer's ability in pursing efficiency, which can be called managerial inefficiency. This information comes from the inefficiency component of stochastic frontier model.

The stochastic frontier regression models specified for cross-sectional data can be interpreted in the following way. According to Aigner et al. (1977) and Meeusen and van den Broeck (1977), the stochastic frontier model could be written as: $Yi = \mathrm{F}(Xi, \hat{A})\cdot\exp\{Vi - Ui\}$. In this function, Y is the dependent variable, X is a vector of explanatory variables, $\hat{A}$ is the parameter vector, Vi is the error term that is assumed to be independently and identically distributed, and Ui is the nonnegative component used to capture inefficiency. The Ui is assumed to be independently distributed and thus obtained by the half-normal distribution. Therefore, the efficiency score could be defined as: Efficiency = $Yi/[\mathrm{F}(Xi, \hat{A})\cdot\exp\{Vi\}]$ or Efficiency = $\exp\{-Ui\}$.

We use the Cobb-Douglas functional form in the regression. The variables of cross-sectional data set for the second-stage regression include the dependent variables of the calculated DTE and DEE scores from the first stage measurement, and the explanatory variables: average educational years of farmers, transportation expenditure, local labour price, and regional dummies. There are three regional dummies incorporated into regression functions, separately representing the Zhejiang, Shaanxi and Hebei provinces. The regional dummy of the Jiangsu province is dropped.

The estimated results of the stochastic frontier model are listed in Table 4. A significant issue that arises in this context is whether the specific managerial inefficiency component can be captured. In order to know if such specific inefficiency component can be captured in the cross-sectional data, the Likelihood-ratio test is performed on the stochastic frontier model. The null hypothesis is that all managerial inefficiencies are zero. The χ^2-statistic of this test is equal to 3.5 for the DTE model and 36.4 for the DEE model, indicating that the null hypothesis can be significantly rejected at 5% level. This test result suggests that managerial efficiencies are different across producers. Another Chi square test is applied to test if all slopes of the functions are

Table 4. Estimated results of DTE and DEE model (168 observations)

Variables	DTE regression				DEE regression			
	Coef.	Std. Err.	$\|Z\|$ stat.	$P > \|Z\|$	Coef.	Std. Err.	$\|Z\|$ stat.	$P > \|Z\|$
Average educational years	0.028	0.006	5.05	0.000	0.0029	1.2e–06	2 410.6	0.000
Labor price	–0.024	0.005	5.3	0.000	–0.004	1.0e–06	3 954.2	0.000
Transportation expenditure	–0.001	0.0004	2.76	0.006	–0.0003	1.6e–07	1 794.6	0.000
Regional dummy for								
Shaanxi	0.124	0.023	5.6	0.000	0.0247	7.2e–06	3 432.1	0.000
Hebei	0.038	0.021	1.79	0.076	–0.0069	0.00001	635.3	0.000
Zhejiang	0.065	0.023	2.75	0.006	–0.0026	3.9e–06	666.03	0.000
Const.	1.03	0.042	24.35	0.000	1.04	6.6e–06	3 289.2	0.000
Σu	0.101				0.209			
Σv	0.055				5.8e–9			
Chi^2 (H_0: all inefficiencies 0)	3.54 (0.03)				36.4 (0.000)			
Wald Chi^2(H_0: all slopes 0)	73.6 (0.000)				2.87e+9 (0.000)			
Log likelihood	184.1				141.2			

zero. The χ^2-statistic of this test is 73.6 for the DTE model and 2.87e+9 for the DEE model, indicating that the null hypothesis that all slopes are zero can be significantly rejected at 1% level. From estimated results in Table 4, Σu (the standard deviation of the inefficiency components for each producer) is equal to 0.1 for the DTE model and 0.21 for the DEE model, which are largely higher than the standard deviation of noise components Σv.

From the estimated results of the DTE model in Table 4, except the regional dummy of the Hebei, all other Z-statistics of estimated parameters are higher than 2. Thus, except for this parameter, all others are statistically significant at the level of 5%. As for the DTE model, all the regional dummies hold the positive relationship with the DTE. Except for the variable of the average educational years, all the other explanatory variables (labour price and transportation expenditure) have the negative relationship with the DTE, which suggests that they put the downward pressure on the DTE. The positive relationship between the average educational years and the DTE shows that a higher education level will result in a higher technical efficiency and thus a higher output.

As for the estimated results of the DEE model in Table 4, all the Z-statistics of the estimated parameters are higher than 600, indicating that all parameters are statistically significant at the level of 0.1%. For DEE model, the explanatory variables of labour price and transportation expenditure also have the negative relationship with the DEE. Again, the positive relationship between the average educational years and the DEE shows that a higher education level will result in a higher environmental efficiency and therefore a better sanitary and environmental performance. This may result from the fact that better educated farmers will use pesticides more efficiently and scientifically. In addition, except the regional dummy of the Shaanxi, all the other regional dummies (Zhejiang and Hebei) have the negative relationship with the DEE.

Table 5. Summary statistics of managerial efficiency

	Managerial efficiency of	
	DTE	DEE
Mean	0.92	0.86
Median	0.93	0.86
Maximum	0.98	1
Minimum	0.76	0.53
Std. Dev.	0.042	0.108

The summary statistics of the Managerial efficiencies of the DTE and DEE are depicted in Table 5. From Table 5, the estimated scores of managerial efficiency for the DTE ranged from 0.76 to 0.98 with the average of 0.92. The estimated managerial efficiency scores for the DEE ranged from 0.53 to 1 with the average of 0.86. The mean of the DEE managerial efficiency scores shows that, for the whole sample, the managerial level and some other factors may influence the DEE. These factors include some unexplained components which have potential impacts on the DEE, and they can be reflected in the U_i of the stochastic frontier function. In other words, this means that there exist some factors which can influence the DEE but are not clearly incorporated into the deterministic part of the stochastic frontier function as explanatory variables, such as the managerial level and water.

Although there are managerial efficiencies influencing the DTE, the influence of them on the DTE is not great because the average score of them is high up to 0.92. In addition, this indicates that most of the factors influencing the DTE can be found in the deterministic part of the stochastic frontier function as explanatory variables. But for the managerial efficiencies of the DEE, their impacts on the DEE are greater for their relatively lower scores. This suggests that there exist more influential factors which are not considered as the explanatory variables.

The distribution histograms of managerial efficiencies for the DTE and DEE are graphed in Figure 1 and 2. It can be easily discovered from these figures that managerial efficiencies of the DEE are distributed more dispersedly ranging widely from 0.5 to 1. As for managerial efficiencies of the DTE, most scores of them only range from 0.8 to 1. This status further indicates that the managerial efficiency influences the DEE more strongly than it does the DTE. Another interesting issue is that there are some full managerial efficiency scores for the DEE, indicating that these farms are operated in the most favourable circumstances with the highest managerial level for the sanitary and environmental performance. In addition, this represents that, for these full managerial efficiency observations, their inefficiencies in the sanitary and environmental performance can be all attributed to the existing explanatory variables in the function.

The magnitude of managerial efficiencies gives some implications of the problems confronted by the farmers or governors in improving the sanitary and environmental performance. However, the explanatory variables are not available to clarify this part of the DTE or DEE. It should be noted here that, besides the managerial level, some other factors also

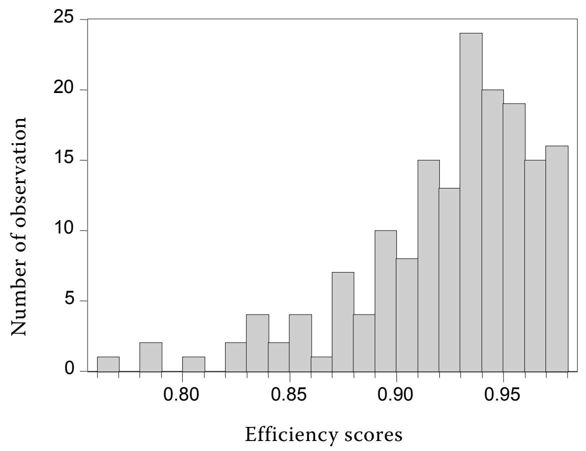

Figure 1. Histogram for managerial efficiency of DTE

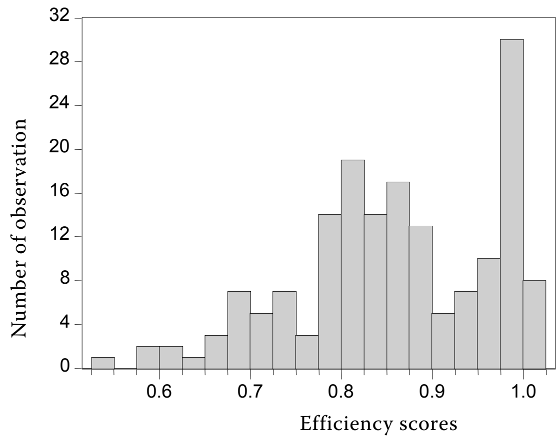

Figure 2. Histogram for managerial efficiency of DEE

might influence it, such as the local temperature, water and so on.

CONCLUSIONS

In this paper, based on the Luenberger DEA method, we develop an analytical framework to calculate the distance output technical efficiency and the distance input environmental efficiency simultaneously. In addition, the stochastic frontier model is applied to estimate the impact of explanatory variables and the managerial efficiency on the DTE and DEE in the second-stage analysis. The analytical framework used to measuring the DTE and DEE simultaneously differs from other methods found in the literature. Although there are some available studies to measure the input environmental efficiency, they cannot provide the information crediting both technical efficiency and environmental efficiency simultaneously. In addition, the existing literature using the Luenberger DEA method to measure environmental performance focuses on calculating the output environmental distance function and the relative indexes while ignoring the input environmental performance and the efficiency scores. There are nearly no studies calculating the environmental efficiency directly using the Luenberger DEA method in the empirical analysis of the China's agricultural sector. This paper can partially fill such gap by developing an analytical framework and providing an empirical analysis.

From the results of the Luenberger DEA model, the average scores of the DTE and DEE indicate that we can improve the rice output by 12% and reduce the pesticide inputs by about 16% simultaneously while making other inputs constant.

From the estimated results of the stochastic frontier model, the mean managerial efficiencies of the DTE and DEE are all higher than the mean scores of the DTE and DEE, suggesting that a part of the DTE and DEE can be explained by the explanatory variables in the second-stage regression. An interesting result is that the impact of managerial efficiencies on the DEE is stronger than that on the DTE. Another interesting result shows that some observations have the full DEE managerial efficiency, indicating that their inefficiencies in the sanitary and environmental performance can be all attributed to the existing explanatory variables in the function.

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