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豬流行性下痢對肉豬市場生產效率之影響 – 資料包絡分析法之應用

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摘　要 本研究欲探討豬流行性下痢(PED)對台灣肉豬市場生產效率之影響，於 2014 年三月期間總共收集 96 筆有效養豬戶個體資料，本研究透過資料包絡分析法(DEA)估計在豬流行性下痢影響前與影響後之台灣肉豬產業生產效率變化。實證結果顯示豬流行性下痢影響台灣肉豬產業之生產效率降低達 8.6%。規模較大、場齡較老以及位於中部的養豬戶受到較大的影響，同時本研究也發現政府部門當時所公布的豬隻存量的影響變化與本研究所預估之生產效率的影響變化相當接近，亦也間接支持本研究生產效率估計之結果。

關鍵字：資料包絡分析法、肉豬、豬流行性下痢、生產效率

Understanding the Production Efficiency Change from Porcine Epidemic Diarrhea via the Data Envelopment Analysis Approach

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ABSTRACT This article focuses on understanding how the Porcine Epidemic Diarrhea (PED) virus influenced the production efficiency of the swine industry in Taiwan. A total of 96 valid sample data were collected during March of 2014. The Data Envelopment Analysis (DEA) was adopted to evaluate production efficiency before, and after, the PED events. Results show that the PED events in Taiwan had weakened overall technical efficiency about 8.6%. Large scale farms, older farms, and farms in the Central area appeared to be the most heavily impacted. Lastly, the percentage change in production efficiency in the DEA estimation are very close to the percentage changes in inventory on farms reported by government. This supports our estimation of efficiency lost by the DEA practically.

Keywords: Data Envelopment Analysis (DEA), Pigs, Porcine Epidemic Diarrhea (PED), Production Efficiency

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Ⅰ. INTRODUCTION

Porcine Epidemic Diarrhea (PED) is a highly contagious disease impacting hogs. In the 1970's, PED broke out in Europe, was first found in the US in 2013, and struck Asian countries such as China, Japan, Korea and Taiwan in more recent years (Snelson, 2014). PED-infected hogs typically show symptoms of diarrhea, vomiting and poor appetite. Mortality can be as high as 40% and tends to have a greater impact on baby pigs. PED is a production disease, and Taiwan is no exception. Data provided by Council of Agricultural (COA, 2015) Executive Yuan suggest that PED led to a decrease of about 5% (300,000 head) in total hog numbers and 6.8% (600 hog farms) in total hog inventory. Since January 2014, hog prices have been hovering around $70NT/kg. The existence of PED around the world in recent years also has the potential to bring about a structural change in Taiwan's hog industry.

The spread of PED in Taiwan started in October 2013. At that time, there were no vaccines to prevent, or cure, the disease. The high mortality rate, especially in baby pigs, represented a major shock to hog production, and led to extremely high hog prices in auction markets. The impact was felt across all scales of hog farms in Taiwan. However, no analysis was conducted to estimate the impact of PED on production efficiency in the hog industry. As a result, the objective of this article will focus on the effects of PED on production efficiency declines in the Taiwan hog industry to examine how the hog farms, government and academia dealt with the problems differently.

In this article, the data envelopment analysis (DEA) method is used to estimate the impact of DEA on production efficiency in the hog industry. DEA is a non-linear programming model originated by Charnes et al. (1978) and is also called the CCR model, which is a multi-input and multi-output model used to estimate the production efficiency among firms. The CCR model was discussed and well developed in literature. Recently, DEA has been applied to measure a firm's efficiency in different industries and issues, such as the banking system (Sherman and Gold, 1985; Vassiloglou and Giokas, 1990; Yue, 1992; GrifellTatje and Lovell, 1997), hospitals (Fixler et al., 2014), energy and environmental issues (Fried et al., 2002). Many studies have also used DEA to measure the production efficiency in the hog industry. Rowland et al. (1998) used data from hog farms in Kansas to examine the impacts of hog farm and farmer characteristics on production efficiency. Somwaru et al. (2003) used data from 2,500 individual hog farms and applied DEA to measure production efficiency and scale elasticity in China. Their results showed that large scale hog farms are most efficient in production and middle size hog farms, with increasing returns to scale, are the most profitable. Yang et al. (2008) adapted the DEA method with undesirable output and examined hog production efficiency in Taiwan while also taking hog waste into consideration. They found that 60% of the hog farms in Taiwan exhibited diminishing marginal returns and that large hog farms were more efficient than the small ones.

The objectives of this article are (1) to estimate the production efficiency of the hog industry before the impacts of PED; (2) to estimate the production efficiency of hog industry after the impacts of PED events; (3) to examine production efficiency changes resulting from PED such as differences in farm size, manger's age, and farm location. The last section will provide empirical discussion and implications for related sectors.

II. METHODOLOGY AND DATA

The literature suggests that the DEA method can not only be used to estimate a firm's production efficiency (including technical efficiency and scale efficiency) but also the change of production efficiency. Chang et al. (1995) used the DEA method to examine the development and efficiency change of 23 different districts in Taiwan. Their results and policy applications have implications for the urban planning division. Sufian (2004) examines the efficiency change of commercial banks in Malaysia before and after mergers. These results show that mergers benefit small and medium sized banks through economies of scale and that large commercial banks should decrease their scale in order to improve efficiency. This study uses a concept of efficiency change, similar to Sufian (2004), to examine efficiency changes from PED in Taiwan.

Wang and Wang (2005) combined the application of DEA method and the heuristic technique to analyze the efficiency change of 22 integrated circuit (IC) design companies in Taiwan before and after a merger. Results suggested the most efficient scenarios among the possible merging alternatives. Hashimoto and Haneda (2008) studied Japanese medical companies' R&D efficiency change during 1983-1992 and showed that the R&D efficiency decreased by 50% during that time. Lakner and Breustedt (2017) used DEA to estimate that organic farms could be 27% more efficient than conventional farms.

One challenge of using DEA method to estimate productivity changes is that is requires Taiwanese hog farmers to share their production records. Typically, producers are reluctant to do that. According to the concept of input and output variables in Salehirad and Sowlati (2005), the DEA method can adopt the variables based on the volume of input material used and the volume of output quantity produced. An advantage of this approach is that is only requires hog farmers to provide less sensitive information, such as number of pigs, number of sows, number of laborers, number of PED-affected pigs, etc. This is much easier than attempting to get actual costs and return information. Thus, the concept of DEA estimation in this study is based on changes in the number of pigs. As hog inventory increases, so does hog sales. Due to differences in production efficiency on each farm, all farms with the same output would not necessarily have the same number of hogs.

Theoretical Model

Production efficiency in the DEA method is defined from Farrell (1957) and is estimated through mathematical programming to obtain the efficiency frontier. The DEA method has developed from single output to multiple-inputs and multiple-outputs, and general mathematical models have been built. In this article, we use the traditional CCR model and BBC model (Banker et al., 1984) to estimate technical efficiency (TE) first, and then derive pure technical efficiency (PTE), scale efficiency (SE) and the distribution of returns to scale[4].

The difference between the CCR and BCC models is the setting of returns to scale. The CCR model calculates technical efficiency of all decision making units under the assumption of constant returns to scale (CRS). However, not all of the decision making units are of the same scale and different scales could be the reason for technical inefficiency. The BCC model then was developed under the assumption of variable returns to scale (VRS) to estimate the technical efficiency of different decision making units. In the BBC model, technical efficiency is the product of pure technical and scale efficiency. To obtain the scale efficiency of different decision making units, we divide the technical efficiency estimated in the CCR model by the pure technical efficiency calculated in the BCC model.

There are two ways to measure efficiency in the DEA method, input-orientation and output-

[4] We focus on the overall production efficiency change before and after PED. If you are interested in the distribution of returns to scale, please contact corresponding author.

orientation. In this article, since the impacts of PED on outputs of hog farms are different and inputs for hog farms would not change much in the short term, we chose output orientation mode to calculate the production efficiency. This means that given the input level, an increase in outputs will increase production efficiency. The empirical model is as follows:

The Evaluation of Technical Efficiency

Given the input prices, we assume the hog farm will minimize costs to produce hogs, which means allocation efficiency will be equal to 1 and technical efficiency will be equal to production efficiency. The TE in the CCR model under output-orientation mode would be equal to equation (1).

$$Max\ \mathrm{TE}_k = \theta_k + \varepsilon\left(\sum_{i=1}^{m} s_i^+ + \sum_{r=1}^{s} s_r^-\right) \quad [1]$$

$$s.t.\ \sum_{j=1}^{n} x_{ij}\lambda_j - x_{ik} + S_i^+ = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - \theta_k y_{rk} - s_r^- = 0$$

$$\lambda_j, s_i^+, s_r^- \geq 0$$

$$i=1,\ldots,m,\ r=1,\ldots,s,\ j=1,\ldots,n$$

where TE_k: technical efficiency of the hog farm *k*;

x_{ik}: *i* th input of the hog farm *k*;

x_{ij}: *i* th input of the hog farm *j*;

y_{rk}: *r* th output of the hog farm *k*;

y_{rj}: *r* th output of the hog farm *j*;

θ_k, λ_j: lagrange multiplier;

ε: non-archimedean number and assumed to be 10^{-6}.

S_r^- and S_i^+ are Slack variables in equation (1). The DEA searches among feasible solution sets of the decision making units and solves the multipliers to maximize the efficiency. In the model, TE will be equal to the product of PTE and SE. PTE measures the capability to allocate technical resources used by decision making units. SE measures the efficiency of decision making units' scale. When the product of PTE and SE is equal to 1, it means that the decision making unit achieves relative efficiency not only in technical efficiency but also in scale efficiency. When the product of PTE and SE is less than 1, it means that the decision making unit is relatively inefficient either in technical efficiency or scale efficiency.

The CCR model assumes that all firms are under constant returns to scale to measure the production efficiency. The BCC model relaxes this assumption and allows for variable returns to scale but all decision units must be under the same returns to scale. The pure technical efficiency in the BBC model could be written as the following.

$$Min\ \mathrm{PTE}_k = \theta_k + \varepsilon\left(\sum_{i=1}^{m} s_i^+ + \sum_{r=1}^{s} s_r^-\right) \quad [2]$$

$$s.t.\ \sum_{j=1}^{n} x_{ij}\lambda_j - x_{ik} + S_i^+ = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - \theta_k y_{rk} - s_r^- = 0$$

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

$$\lambda_j, s_i^+, s_r^- \geq 0$$

$$i=1,\ldots,m,\ r=1,\ldots,s,\ j=1,\ldots,n$$

where PTE_k is the hog farm *k*' s pure technical efficiency and other variables are specified as in equation (1).

The Evaluation of Pure Technical Efficiency

Each decision making unit' s SE can be calculated as TE/PTE. The value of SE will be between 0 and 1 and can be used to estimate the returns to scale of firms. When SE is equal to 1, it means that the decision making unit is under CRS and is achieving its best scale efficiency. When SE is less than 1, it means that the decision making unit is under decreasing returns to scale, or increasing returns to scale, and should either decrease or increase its production to achieve optimal scale efficiency.

In empirical DEA studies, there is a two-stage process to analyze factors affecting production efficiency. In the first stage, the PE values of each decision making unit are estimated. In the second stage, the estimated PE's are set as dependent variables and regressed against explanatory variables to estimate the marginal effects. The estimated PE values are between 0 and 1, and therefore are limited variables. If ordinary least squares were used, the estimation would be biased or asymptotic to zero (Greene, 1981). To deal with the censored variable, we use the Tobit censored regression model in the second stage through STATA 13.0 to calculate efficiencies for each hog farm and marginal effects of each factor.

The change of production efficiencies before, and after PED, can be estimated by kernel density estimation, which is a non-parametric method to estimate the density function of the continuous random variables. The function estimated in this article is $\hat{f}_{\lambda}(x)=\frac{hv}{n\lambda}\sum_{i=1}^{n}K_0(\frac{x-x_i}{\lambda})$, where $K_0(\cdot)$ is the kernel density function, λ is the bandwidth, n is the number of observations, x_i is the i th observation, and v is a vertical scale factor defined as the following:

$$v=\begin{cases} n \rightarrow v\ Scale = frequency \\ 100 \rightarrow v\ Scale = percentage \\ 1 \rightarrow v\ Scale = proportion \end{cases}.$$

In this article, frequency scale is used to present results from the kernel density estimation, which are illustrated in Figure 1. The figure shows that frequency is highest in the range from -5 to 0 and the kernel density curve is also at a higher level. This is useful to exhibit the distribution of efficiencies and how the efficiencies changed after PED.

Relative DEA Variables

Based on the volume of input material used and the volume of output quantity produced in Salehirad and Sowlati (2005), the variables adopted in this study are different from the traditional types of variables used in the DEA method. Two important indicators are often used to evaluate the productivity of the swine industry: one is litters per sow per year (LSY), and the other is litter size at weaning (LSW). Following the LSY calculation from Yen (2001), LSY is about 2.4 liters per year, but the average LSY in Taiwan is less than 2.4 litters. According to the estimation of LSY from Lo and Chen (2008), Huang et al., (1998), Huang (2009), and Huang (2012) the productivity (LSY) of a commercial hog operation should be around 2 liters per year or 1 liter every six months, and the LSW is about 8.7-8.85 head in Taiwan.

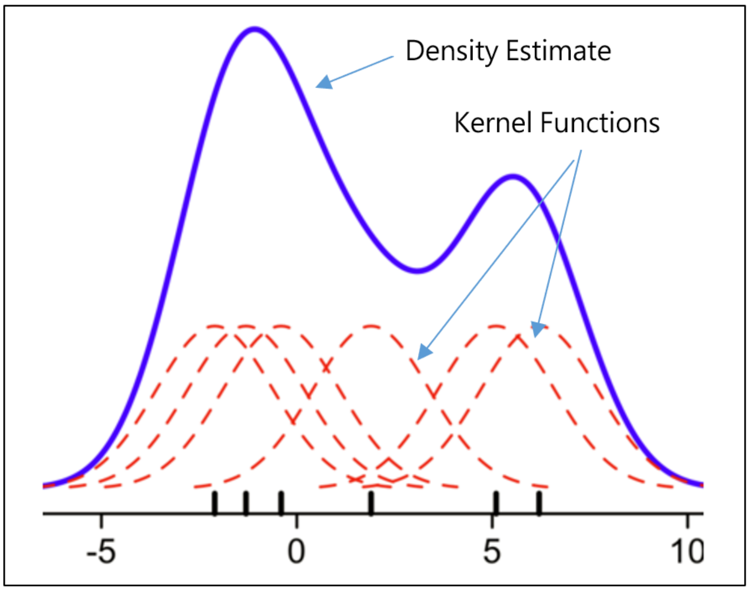

Fig. 1 The illustration of kernel density estimation

Source: http://cdn.spiderfinancial.com/sites/all/files/KDE-Tutorial-101.pdf

This article attempts to apply the DEA method to evaluate technical efficiency with two different stages: Before PED and after PED. The fundamental calculation for technical efficiency uses pig numbers in input and output for each hog farm. The input number refers to how many pigs were produced during a certain time period, which relates directly to sow numbers. The output number measures how many pigs were sent to markets during a certain period and is expressed as monthly output for each farm. Therefore, the production efficiency estimated by the DEA method can purely represent the productivity of hog operators at a given point in time. Since pig numbers for input and output are different for every hog farm, the concept of using pig numbers in the DEA method allows us to determine if technical efficiency differences exist among farms due to size, age of operator, or region.

The input and output variables used in this article are shown in Table 1. In order to calculate a consistent period for input and output, each variable is set to a half year base period. The output before PED (O_{11}) is set to be the number of pigs sold per half year, which is simply six times the average monthly pigs sold. The output after PED (O_{21}) includes death loss from PED for the six month period. The inputs are set to be sow numbers and laborers per half year and this is assumed to be the same before and after the PED events. Technical efficiency can be calculated from each input / output set, so two different technical efficiency estimates can be made before and after PED. In order to further understand the changes in technical efficiency with regard to different factors, a simple *t* test was applied to test for differences by farm size, farmer age, and farm region.

Data Source and Sample Distribution

Common research sampling and implementation challenges include questionnaire quality, ethnic issues, representation issues, matches with respondents’ interest, etc. Even response time has been found to result in lost interest if surveys are too long (Dillman, 2007). Farmer respondents in particular need an extra patient person to fully explain the potential benefits of the research that is being conducted. Thus, the best sampling strategy for farmer respondents is typically conducted in a very time sensitive manner.

Table 1 Variables Setting in Two Different Estimations

	Variables		Unit	Description
BEFORE PED	Output	O_{11}	head per six months	average monthly pigs sold*6
	Input	I_{11}	head per six months	sow number; an indication of pig inventory input for half year
		I_{12}	persons per six months	average monthly laborers*6
AFTER PED	Output	O_{21}	head per six months	average monthly pigs sold*6 (removing the accumulated pig deaths from PED already)
	Input	I_{21}	head per six months	sow number; an indication of pig inventory input for half year
		I_{22}	persons per six months	average monthly laborers*6

The sampling method in Chen et al. (2009) and Chen (2012) utilized the bookkeeping records of the management system from Animal Technology Laboratories in Taiwan which allowed them to use every cost and benefit to evaluate technical efficiency via the DEA method. However, information about costs and benefits are often in short supply, inaccurate, and difficult to obtain. Therefore, this article attempts to utilize hog inventory input and output to evaluate technical efficiency in order to overcome data challenges, but still measure the impact of PED. With this method of hog input and output numbers, only a few questions were needed in the questionnaire: average monthly farm laborers, sow numbers, average number of pigs sold per month, and the total number of confirmed deaths from PED. These questions are typically easier for farmers to answer since hog farmers tend to focus on mortalities during PED scares.

Implementing a survey during a PED event was challenging because hog farmers had been quarantined and were unlikely to welcome unfamiliar faces on their farm. Since many Taiwanese hog farmers, especially the second generation, were involved with a closed group through Facebook, this allowed them to share and discuss hog production issues. This Facebook closed group also became a feasible way to collect the necessary information. Since many hog farmers expressed difficulty in dealing with PED during the outbreak in spring of 2014, a survey was implemented to collect information to be shared with those farmers. The web-based survey was only open from March 7, 2014 to March 21, 2014. With this web-based survey method, many hog farmers were self-motivated to respond to this questionnaire.

A total of 96 hog farmers responded to the survey during the two-week period. The sample distribution is shown in table 2. A total of 67 hog farmers confirmed that they were dealing with PED. The average PED occurrence period was about two months (the shortest period was 10 days, and the longest period was about five months) among these 67 hog farmers. The average efficiency changes per farm from PED were about 650 head. Regarding farm size, about 48% of respondents were managing less than 1,999 head, about 30% managed 2,000-4,999 head, approximately 12% managed 5,000-9,999 head, and about 10% managed over 10,000 head. Regarding the age of the farm operator, about 10% of respondents had been operating for less than 10 years, about 19% had been in operation for 10-19 years, about 35% had been in operation for 20-29 years, and approximately 36% had been in production over 30 years. Regarding farm region, about 57% of respondents were from the central area, about 34% were from the south area, and approximately 9% were from the rest of regions.

The sample distribution for average sow numbers per farm was about 457 head. The minimum number of sows was 75 head, and the maximum number of sows was 2,250 head. Therefore, the sample distribution covers all of Taiwanese hog farm scales. On average, each farm sold 402 hogs per month and employed five laborers. According to the 2014 hog report from Council of Agriculture, Executive Yuan, there were 8137 hog farms, and most were located in the central (37%) and southern (39%) regions of Taiwan. It was determined that the collected sample in this study appropriately represented the Taiwanese swine industry.

Table 2 Variable Definitions and Summary Statistics (*N* = 96)

Variables	Definition and Variable Description	Mean	Std. Dev.	Min.	Max.
Sow number	Continuous variable; respondents' sow numbers on farm	457	567	75	2250
Laborers	Continuous variable; respondents' laborers on farm	4.81	2.91	2	12
Head sold per month	Continuous variable; respondents' head sold per month	402	394	25	1450
TE	Continuous variable; average technical efficiency before PED	0.56	0.24	0.04	1
PTE	Continuous variable; average pure technical efficiency before PED	0.78	0.23	0.33	1
SCALE	Continuous variable; average scale efficiency before PED events	0.73	0.23	0.08	1
Total days with PED	Continuous variable; respondent reported total days of PED occurrence on their farm	63.52	26.69	10	150
Total head loss	Continuous variable; respondent reported total head loss from PED	642.6	882.4	50	4000
Farm tenure 10-19 years	Binary variable=1 if respondent's farm tenure is within 10-19 years	0.19	0.40	0	1
Farm tenure 20-29 years	Binary variable=1 if respondent's farm tenure is within 20-29 years	0.35	0.48	0	1
Farm tenure over 30 years	Binary variable=1 if respondent's farm tenure is over 30 years	0.36	0.48	0	1
Scale 2000-4999 head	Binary variable=1 if respondent's farm scale is between 2,000-4,999 head	0.30	0.46	0	1
Scale 5000-9999 head	Binary variable=1 if respondent's farm scale is between 5,000-9,999 head	0.12	0.33	0	1
Scale over 10000 head	Binary variable=1 if respondent's farm scale is over 10,000 head	0.10	0.30	0	1
Central	Binary variable=1 if respondent's farm locates at central area in Taiwan	0.57	0.49	0	1
South	Binary variable=1 if respondent's farm locates at south area in Taiwan	0.34	0.47	0	1

III. EMPIRICAL RESULTS

This article estimates the impact of PED on the Taiwanese swine industry. With the survey sampling method, a DEA method is further adopted to evaluate the TE, PTE, and SE which is shown in table 3. On average, the TE before PED was about 0.56, the PTE was about 0.78, and the SE was about 0.73. The impacts of PED are directly related to mortality so the number of pigs sold per month decreases. As expected, values for TE, PTE, and SE are, in general, decreased after PED. After PED, TE decreased 8.6%, PTE decreased 6.6%, and SE declined about 2.8%. T tests confirmed that the changes in TE and PTE were significant at the 5% level in explaining that the PED significantly influenced the production efficiency of the swine industry.

The distribution for the values of TE, PTE, and SE can be illustrated via the kernel density lines, as shown as in figures 2, 3, and 4. Figure 2 shows two distributions, which are based on before (solid line) and after (dashed line) PED, for the TE values of the sampled hog farms. As mentioned previously, TE declined 8.6%, which can be observed via the movement of the distribution lines. Therefore, the peak of the distribution line also moves upward and to the left. Furthermore, this outcome also corresponds to previous outcomes as is shown in table 3.

Figure 3 illustrates the distribution of PTE values for all sampled hog farms. Note the distributions of the PTE values have two different peaks which imply that Taiwanese hog farms may not have a consistent PTE. Also note that after PED, the left curve of the distribution lines expands, meaning that most farms saw a decrease in PTE. It is interesting that so much reproduction differences exist in Taiwan. This also implies that farms with low reproduction rate should work to improve management skills and adopt new techniques to improve reproductive rates. Figure 4 demonstrates the distributions for the SE values for all sampled hog farms. Note the distribution line shifts to the left following PED, but is also clear that most Taiwanese hog farms have higher scale efficiencies.

This article also attempts to explain changes in TE, PTE, and SE resulting from farm scale, farm age, and region by using *t* tests to determine if differences are significant. In table 3, changes in TE reveal significant decreases of 13% for the 2,000-4,999 head scale and 9% for those over 10,000 head. Changes in PTE suggest a statistically significant decrease of 21% for operations over 10,000 head and a significant decrease of 8% for those between 2,000-4,999 head. This finding suggests that larger scale farms are likely to face higher mortality rates as a result of PED. Changes in SE values reveal a significant decrease of about 5% for 2,000-4,999 head operations and a 15% increase for those over 10,000 head. The decrease associated with farms between 2,000-4,999 head was expected, but the increase for larger operations was not. This could be due to lower densities after loss of hogs to PED. Therefore, the SE values have increased for the larger scale farms after the PED event.

The problem solving ability of a hog operation is likely to be correlated with experience, so it is worthwhile to consider farm experience when examining changes in TE, PTE, and SE. In table 3, changes in TE reveals a significant decrease of about 18% for farms in existence between 10-19 years and an 11% decrease for farms in production over 30 years. However, the changes in PTE show a significant decrease of about 10% for farm tenure between 10-19 years and farm tenure over 30 years. As for regional differences, changes in TE values exhibit a significant decrease of about 12% in the central area and changes in PTE suggested a significant 10% decrease. This suggests that some areas in Taiwan may potentially face greater challenges resulting from PED.

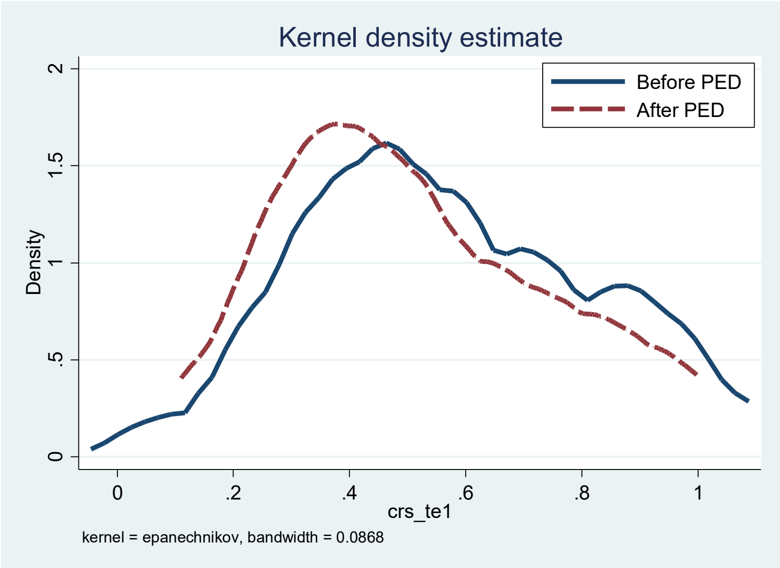

Fig. 2 The illustration for the movement of technical efficiency before and after PED

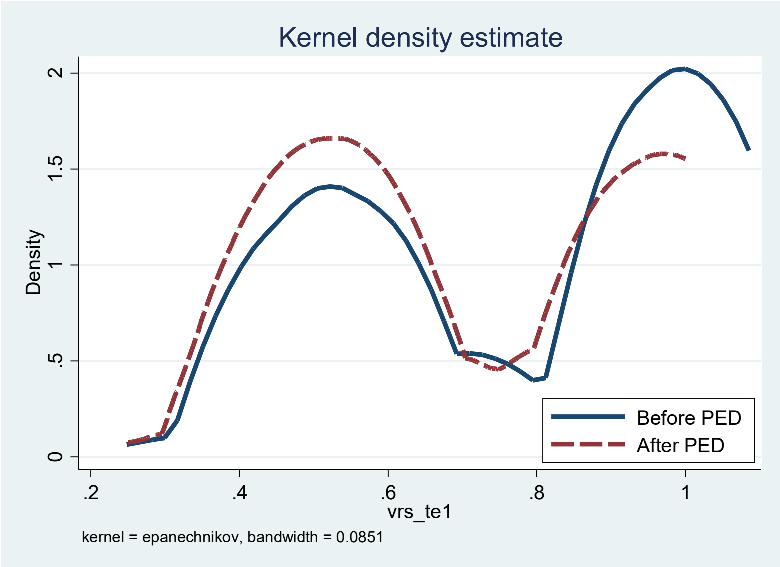

Fig. 3 The illustration for the movement of pure technical efficiency before and after PED

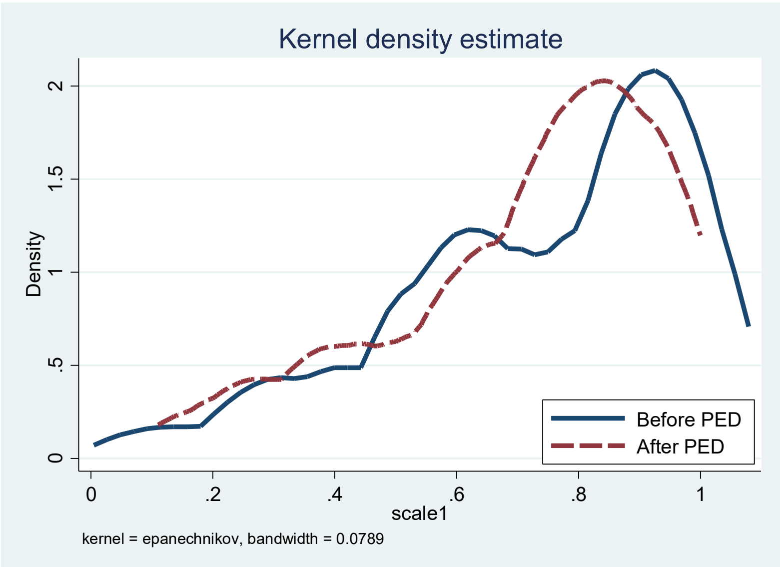

Fig. 4 The illustration for the movement of scale efficiency before and after PED

Table 3: The Value of TE, PTE, SE with Comparison under Different Circumstances and *t* Test

		TE				PTE				SE			
		Before PED	After PED	% Change	*t*-test	Before PED	After PED	% Change	*t*-test	Before PED	After PED	% Change	*t*-test
Average Total Efficiency		0.567	0.519	-8.6%	**	0.782	0.731	-6.6%	**	0.738	0.717	-2.8%	-
Farm scale	Below 1999 head	0.533	0.494	-7%	-	0.843	0.820	-3%	-	0.634	0.589	-7%	-
	2000~4999 head	0.565	0.494	-13%	**	0.627	0.579	-8%	*	0.897	0.849	-5%	**
	5000~9999 head	0.710	0.702	-1%	-	0.821	0.762	-7%	-	0.844	0.883	5%	-
	Over 10000 head	0.553	0.502	-9%	*	0.911	0.720	-21%	***	0.613	0.706	15%	***
Farm tenure	Below 9 years	0.569	0.531	-7%	-	0.874	0.839	-4%	-	0.665	0.666	0%	-
	10 to 19 years	0.579	0.473	-18%	*	0.797	0.720	-10%	*	0.751	0.690	-8%	-
	20 to 29 years	0.543	0.538	-1%	-	0.734	0.728	-1%	-	0.746	0.734	-2%	-
	Over 30 years	0.582	0.518	-11%	*	0.799	0.720	-10%	*	0.738	0.721	-2%	-
Farm region	Rest of area	0.620	0.558	-10%	-	0.765	0.771	1%	-	0.780	0.681	-13%	*
	Central area	0.547	0.483	-12%	*	0.784	0.702	-10%	**	0.710	0.700	-1%	-
	South area	0.587	0.549	-6%	-	0.783	0.757	-3%	-	0.772	0.741	-4%	-

Notes: Asterisks indicate levels of significance: * = 0.10, ** = 0.05, and *** = 0.01.

Table 4: The Outcomes of Tobit Censored Regression for Regarding Factors

Dependent Variable	△TE	△PTE	△SCALE
Total days with PED	0.0031	0.001	0.00049
	(0.0024)	(0.000)	(0.004)
Total head loss	0.00084***	0.0017***	0.00019
	(0.00011)	(0.00012)	(0.002)
Farm tenure 10-19 years	-0.043	-0.043	-0.030
	(0.028)	(0.054)	(0.030)
Farm tenure 20-29 years	-0.041	-0.077	0.004
	(0.027)	(0.053)	(0.028)
Farm tenure over 30 years	-0.065**	-0.082	-0.017
	(0.024)	(0.056)	(0.028)
Scale 2000-4999 head	-0.014	0.044	-0.009
	(0.015)	(0.027)	(0.025)
Scale 5000-9999 head	-0.067***	-0.019	-0.050*
	(0.022)	(0.035)	(0.029)
Scale over 10000 head	-0.182***	-0.084**	-0.217***
	(0.035)	(0.041)	(0.071)
Central	-0.0038	-0.100**	0.034
	(0.013)	(0.043)	(0.038)
South	0.003	-0.048	-0.000
	(0.011)	(0.043)	(0.037)
Constant	0.078***	-0.014	0.059
	(0.025)	(0.067)	(0.045)
sigma	0.045***	0.060***	0.073***
	(0.006)	(0.007)	(0.008)
Observations	64	67	64
Adjusted R^2	-0.298	2.087	-0.393
Log-Likelihood	89.88	20.05	46.65

Notes: Asterisks indicate levels of significance: * = 0.10, ** = 0.05, and *** = 0.01.
△ signs mean the changes of TE, PTE and Scale.

While *t* tests provide a good level of understanding about PED impacts with regard to different factors, it is still worthwhile to examine how these factors jointly affect the changes of TE, PTE, and SE values individually via a Tobit censored regression model. The outcomes of Tobit censored regression are shown in table 4. The overall examination is consistent and robust. Three different dependent variables are individually examined to determine any impact from independent variables such as Total days with PED, Total head loss, farm tenure, farm scale, and region. Results reveal that the changes in TE values are impacted by mortality rate, the farm tenure, and farm scale. Farms that experienced higher hog mortality had greater TE and PTE values. Farms that had been operating over 30 years were more likely to experience a decrease in PTE than farms that had been operating less than 9 years. Overall, larger scale farms (5000 head and larger) were more likely to see negative impacts on TE, PTE, and SE than were smaller scale farms (less than 1,999 head). Respondents from the central area were more likely to experience negative impacts on PTE than respondents from the northern and eastern regions. In summary, large scale farms, farms that had been in operation longer, those with greater mortality losses, and farms in the central area experienced more negative impacts on TE, PTE, and SE.

From the above discussed results, the impacts of PED on mortality are clear. Many experts were trying to estimate the welfare loss as a result of a PED outbreak (Paarlberg, 2014; Schulz and Tonsor, 2015; Sasaki et al., 2019). Their studies show that the total welfare loss from PED ranged from $900 million to $1.8 billion US dollar in the US, and $339,107 thousand Japanese Yen in Japan. If the total efficiency change can be estimated earlier, it would raise enough attention for government to react. The Taiwanese COA (2015) reports total inventory of hogs on farms annually and estimated about 5,806,237 head[5] at the end of 2013. Their estimate on total hog inventory was 5,422,399 head in April, 2014. This period represented a time when PED severely impacted the Taiwanese hog sector.

With the advantages of the DEA method, the production efficiency regarding each hog farm is able to be calculated before and after the PED. On a percentage basis, the mortality loss suffered during this period was a 6.6%[6]. It is noteworthy that the sampling period used in this article was very similar to the COA reporting period, and the percentage of efficiency change at 6.6% is very close to the 8.6% decrease in TE found in this article. This result seems to suggest that the DEA method may be a reasonable approach to estimate efficiency changes from PED. However, for this to be true, there are many assumptions that must hold. Key factors that warrant further discussion are the sample representation via Facebook closed group, the application of using hog numbers as inputs and outputs for the DEA method, the reliability of using the DEA method to calculate efficiency changes.

IV. CONCLUSION

Highly contagious diseases often create tremendous impacts on agricultural and food production, and PED did this on a global scale. The impacts of PED were serious in Taiwan and most farmers questioned how best to handle this unfamiliar disease since approximately 70% of hog farms in Taiwan dealt with its impacts during 2014.

Although PED events influence the entire Taiwanese swine industry, many influences can be found, particularly on total mortality, larger scale farms, farms that had been in operation longer, and farms in the central area. In particular, the distribution of kernel density revealed that the PTE lines were not normally distributed. This suggests that the reproductive rate for each hog farm is different with some farms operating at high efficiency and others that still have a lot of room for improvement. It was also interesting that some larger farms (scale over 10,000 head) actually experienced better scale efficiency after PED; this may imply that the larger farms may have lost a fair amount of production, and so the scale efficiency can be enhanced after PED.

Compared to previous applications of the DEA method, the production efficiency calculated in this study can represent the volume change of pig herds as they dealt with PED. Overall, the examination of TE, PTE, and SE was explained

[5] Total head on farms: http://agrstat.coa.gov.tw/sdweb/public/inquiry/InquireAdvance.aspx

[6] 6.6% = (5,422,399-5,806,237) / 5,806,237

reasonably well by sow number, laborers, and head sold per six months. As a result, TE and PTE, on average, declined 8.6% and 6.6%, respectively. These percentage changes were very similar to the percentage changes (6.6%) in total losses (in number of head) on farms reported by the COA, which also supports our empirical results of production efficiency change estimated by the DEA model. PED primarily led to losses related to mortality, and there was little difference from the structure of hog farms. Most hog farms in Taiwan are farrow-to-finish operations, which means they raise pigs from birth-to-finish, so that represented the majority of responses. Therefore, the outcome of this work suggests further discussion and studies are warranted.

In summary, PED in Taiwan not only affected production efficiency, but also led to large efficiency changes. If the value per head for hogs at the auction market were NT$6,000, then the farm-based losses would be around NT$2.3 billion. If the government wishes for the domestic pork supply to return to normal levels within a certain period of time, one option would be to offer assistance to larger hog farms (scale over 10,000 head) as they have a more significant impact on supply. Furthermore, this study has an unexpected finding that the DEA method may be a possible alternative approach to estimate economic losses from large scale outbreaks, such as PED. However, for this to be true, there are many assumptions that must be hold. Key factors that warrant further discussion are the sample representation via Facebook closed group, the application of using pig numbers as inputs and outputs for the DEA method, and the reliability of using DEA method to calculate economic losses.

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