Technical efficiency and impact of environmental regulations in farrow-to-finish swine production in Taiwan

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Abstract

This article demonstrates how technical efficiency and the impact of environmental regulations of Taiwanese farrow-to-finish swine production can be estimated in the presence of undesirable outputs. The issue of measuring technical efficiencies while considering undesirable outputs has been addressed by past studies. But the proper method of including undesirable outputs has always been a subject of debate. This article develops a data envelopment analysis (DEA)-based model that includes undesirable outputs. The technologies of desirable output production and undesirable output control are considered simultaneously. This allows one to transform undesirable output into desirable output, whereby a traditional Shephard distance function can be used to measure technical efficiencies. An approach to measuring the impacts due to environmental regulations is then derived. Empirical results show that larger farms are more technically efficient than small-sized farms, but no clear conclusions can be reached for the measures of regulatory impact among farms with different sizes. On average, the sample farms incurred an opportunity cost due to environmental regulations equivalent to 9.8% of market value. Opportunity costs rise with efficiency.

JEL classification: C14, C61, D21, Q12, Q16, Q53

Keywords: Data envelopment analysis; Undesirable outputs; Environmental regulations

1. Introduction

The swine sector is an important agricultural industry in Taiwan. There are many operational types including farrow-to-finish, feeder pig production, feeder pig finishing operators, etc., among which over 70% are farrow-to-finish pig farms (Huang, 2002). Taiwan’s pig sector has the highest output value among all agriculture and livestock sectors. In 2006, its output value was about 55,500 million N.T. dollars, corresponding to 14.7% of the total output value of agriculture. But the pig sector is also a main source of livestock wastewater in Taiwan. It is estimated that the daily biochemical oxygen demand (BOD) quantity is about 2,718 tons in Taiwan (in 2005). Of this, livestock wastewater contributes 717 tons (26%).

Over the past two decades, the development of Taiwan’s pig-raising industry was subjected to a progressive increase in the effluent standards of wastewater, and a higher consumer awareness of environment-related questions. These have created a more difficult operating environment for the industry. Meanwhile, some other events have also forced the industry to change, for example, the outbreak of foot-and-mouth disease in 1997, and Taiwan’s entry into the World Trade Organization (WTO) in 2002. Nevertheless, wastewater control remains an important factor affecting the industry. The statistics of the Council of Agriculture show that the number of pig farms in Taiwan fell from 26,000 in 1995 to 13,000 in 2007. Data show that this change reflects the exit of small pig farms from the industry.

Facing increasingly competitive conditions and stricter environmental regulations, how a pig farm can operate well and compete against its peers is an issue that not only the operators but also many researchers have paid attention to. Reviewing the past literature, the measurement of efficiency for pig farms is an issue many studies have addressed. For example, Sharma et al. (1997, 1999) applied data envelopment analysis (DEA) and stochastic frontier approaches to evaluate the production efficiency of the swine industry in Hawaii; Galanopoulos et al. (2006) used DEA to specify and measure the efficiency of Greek...
commercial pig farms, and to investigate the extent to which a set of alternative breeding and production practices may affect a farm’s performance; Lansink and Reinhard (2004) also employed DEA to investigate the possibilities for improving the technical, economic, and environmental performance of Dutch pig farms relative to currently applied technologies and relative to currently available but not yet applied technologies; and Asmild and Hougaard (2006) adopted DEA to demonstrate how economic and environmental improvement potentials of Danish pig farms can be estimated.

The brief review shows that the DEA approach is widely used in measuring the performance of pig farms. DEA is a non-parametric programming technique for estimating the relative efficiency of decision making units (DMUs) that perform the same or similar tasks in a production system. It was first developed by Charnes et al. (1978). As for applying the technique to evaluate the performance of pig farms, it is worth noting that, since pig production will be accompanied by undesirable outputs (e.g., wastewater emission), measuring a pig farm’s performance must consider the undesirable factor. Among the previous studies we reviewed, Lansink and Reinhard (2004) and Asmild and Hougaard (2006) included the factor, while Sharma et al. (1997, 1999) and Galanopoulos et al. (2006) ignored it. Färe et al. (1989) and Seiford and Zhu (2002) showed that whether the undesirable outputs were included in a DEA model or not would result in different efficiency scores and rankings. In other words, a model that does not consider undesirable outputs cannot demonstrate the true relative efficiency of the DMUs. Since the undesirable outputs are bad, that is substantially different from the normal desirable outputs. Moreover, while a greater number of desirable outputs are better than less, fewer undesirable outputs are preferable, this results in the problem of how to include them in a DEA model.

Environmental regulations have another effect on the production of pig farms, in that they force producers to reduce pollution. As a result, a part of production resources will be diverted to control pollution, reducing the resources available for pig production. Previous studies do not evaluate this effect. Evaluating the effect is important for two reasons. First, environmental regulations may bring a social benefit. This benefit could be evaluated, for example, by a contingent valuation method, although the production losses of pig farms due to the environmental regulations giving rise to the environmental benefits should be deducted from the evaluated benefits. Second, the regulatory authority may be very concerned about its policy impact, so evaluating the costs due to environmental regulations will provide valuable information for the government in adjusting its regulatory policy.

2. Review of existing approaches

Undesirable outputs refer to the wastewater, particulate matter, noise, etc., generated as a by-product of a production process. To our knowledge, there are three main ways to include undesirable outputs in models in the DEA literature. First, weak disposability is widely used (e.g., Boyd and McClelland, 1999; Färe et al., 1989; Zofio and Prieto, 2001), which assumes that reducing undesirable outputs must be accompanied by a price for either decreasing desirable outputs or increasing inputs. In other words, it is costly. An example, illustrated by Färe and Primont (1995), is production of electricity (output 1) by burning coal, which also generates sulfur dioxide emissions (output 2). Weak disposability implies that a 10% reduction in sulfur dioxide emissions is possible if accompanied by a 10% reduction in the output of electricity, holding the input vector constant. However, according to Dyckhoff and Allen (2001, p. 317).

“The alternative approach of assuming weak disposability as a special case in practical applications. It should not be used unless the decision maker is absolutely certain about the technical relationship between the undesirable output and certain input or output. Especially, when highly aggregated data are used, the assumption may not be reasonable.”

Since a piecewise linear reference technology with assumption of weak disposability in undesirable outputs is arranged with strict equality constraints for those outputs, Hailu and Veeman (2001, p. 607) commented on the modeling issue:

“The approach using strict equality constraints on undesirable outputs, . . . is equivalent to the treatment of undesirable outputs as neutral variables rather than as inputs or outputs . . . , the use of an equality restriction can reduce the reference set and thus greatly inflate the efficiency scores . . . positive and negative pollution shadow prices are compatible with the ‘weakly disposable’ formulation since the equality restriction leaves the effect of undesirable outputs on efficiency undetermined.”

Additional debate is provided by Färe and Grosskopf (2003) and Hailu (2003). Moreover, in recent research, Coelli et al. (2007) argue that the assumption of weak disposability is likely to suffer from certain problems when the materials balance condition is applicable.

Many studies refer to undesirable outputs as “bads,” but Lewis and Sexton (2004a, 2004b) call them “reverse outputs,” implying that their magnitude has an effect opposite to that of a normal output. Lewis and Sexton analyzed the productive process of a baseball team in Major League Baseball: position players provided their team with offensive production, measured in terms of total bases and walks gained. Defensive errors were considered as a reverse output. In this case, reverse output might not be accompanied by normal outputs. This is an exceptional example in which weak disposability could apply. However, weak disposability might be suitable in a case producing undesirable outputs with a characteristic of externality, but might not suit a case of reverse outputs.

The second modeling method is to treat undesirable outputs as inputs (Hailu and Veeman, 2001; Haynes et al., 1994; Lansink and Reinhard, 2004). Strictly speaking, the undesirable outputs...
are not inputs. But producing fewer of these outputs is preferable if we hold the desirable outputs constant, and so is using fewer inputs. As a result, many studies treat undesirable outputs as inputs. However, Seiford and Zhu (2002, p. 17) argue that “if one treats the undesirable outputs as inputs, the resulting DEA model does not reflect the true production process.” Färe and Grosskopf (2004a, p. 49) “also find the idea of modeling undesirables as inputs problematic in the sense that typically we think of inputs as strongly disposable, and that the production set is not bounded in those inputs. . . . Unlimited increases in undesirables (holding other inputs constant) is not technically possible.”

A third approach to dealing with undesirable outputs is a transforming method, either taking the reciprocal of undesirable outputs (Lovell et al., 1995) or subtracting them from some large-enough numbers (Jahanshahloo et al., 2004; Seiford and Zhu, 2002), and then treating them as normal outputs. Dyckhoff and Allen (2001, pp. 316–317) commented that “. . . taking its reciprocal has the disadvantage that the scale and intervals of the original data get lost and the reciprocal of a zero value does not exist. Either for reciprocal or translation, the data has to be transformed back when interpreting the result.” However, this approach transforms undesirable outputs into some desirable but meaningless data that incur a problem in interpreting the results. Besides, Färe and Grosskopf (2004b) incorporated weak disposability and null jointness into a production technology and demonstrated that the transforming method proposed by Seiford and Zhu (2002) might produce a biased efficiency score. For further discussion of their approaches see Färe and Grosskopf (2004b) and Seiford and Zhu (2005).

Given the nature of this debate, this article provides an alternative method and demonstrates its merits and practicability. In addition to measuring technical efficiency, this approach can also be applied to measure environmental impacts at the firm level.

3. Methodology

3.1. Efficiency measurement model

If environmental regulations are absent, undesirable outputs will be freely disposable and can be ignored from a production set. But environmental regulations usually exist, and should be included in a DEA model. In such circumstances, undesirable outputs would not be freely disposable, and reducing them has to be costly. To reduce the undesirable outputs another productive activity, different from normal production, must be pursued. For example, we can call this a pollution treatment technology if the undesirable outputs are pollutants. This raises the question of what the inputs and outputs for this process might be. Hsiao and Yang (2007) measured the performance in wastewater control of pig farms in which the wastewater control is a pollution abatement activity; pig producers use pollution control inputs to produce pollutant removal. However, the outputs are desirable and thus do not suffer from the problem of how to model them.

Suppose environmental regulations are imposed on producers, and DMUs are required by regulations to install pollution abatement devices. For each DMU, the whole production process is illustrated in Fig. 1. There are \( k = 1, \ldots, N \) DMUs using \( m = 1, \ldots, M \) inputs, \( x \in R^M_+ \), to produce \( s = 1, \ldots, S \) desirable outputs, \( y \in R^S_+ \), which will be accompanied by \( w = 1, \ldots, W \) undesirable outputs, \( b^w \in R^W_+ \). Among them, inputs \( x \) are divided into two parts \( x_1 \) and \( x_2 \), where \( x_1 \in R^M_+ \) are used to produce normal outputs, and \( x_2 \in R^M_+ \) are used for pollution control.

Supposing the initial quantity of pollutants before they are treated is \( d \in R^W_+ \), then the device has removed \( d - b \) pollutants. Let the removed quantity be \( t \), and \( t = d - b \). Then the technology of pollution abatement can be described as transforming inputs \( x_2 \) to produce \( t \). Relative to other translation approaches mentioned in Section 2, the transformed vector \( t \) not only is desirable, but also consists of meaningful data.

In an environmental regulation scheme of command and control, \( t \) represents the decontaminating ability of DMUs, but it cannot reflect DMU’s ability to comply with regulations. For example, consider a firm with a very large number of initial pollutants \( d \). Even if it has a good decontaminating ability (i.e., its \( t \) is also very large), it may still have a vast number of final pollutants, so \( t \) can only capture a partial output effect of pollution abatement activity. We further include emission standards to transform a new output vector for supplementing the ability of \( t \). In the scheme of command and control, final pollutants are subject to emission standards. For each kind of pollutant, let \( c, c \in R^W_+ \), denote the pass rate and represent the degree of final pollution able to comply with the standards. Then vector \( c \) can be defined as

\[
c = \frac{\text{Number of tests passing the emission standards}}{\text{Number of tests for each kind of pollutant with emission standards}}.
\]

(1)

However, if the DMU wants to increase both \( t \) and \( c \), more inputs \( (x_2) \) for pollution abatement must be used, which will crowd normal production inputs \( (x_1) \) out. As a result, \( y \) will decrease. This is, increasing \( y \) will offset the increase of \( t \) (and/or \( c \)), while under the assumption of weak disposability, increasing \( y \) will be accompanied by the increase of undesirable outputs \( b^w \). That is, increasing \( y \) and \( t \) (and \( c \)) would follow the assumption of strong disposability. That is, reducing \( y \), \( t \) (and \( c \)) would be

\[\footnote{This productive process is similar to but differs from the case studied in Färe and Grosskopf (2004a, pp. 66–70). First, the idea of Färe and Grosskopf focuses on a production system in which an upstream agent produces good and bad outputs, and the bad outputs adversely affect the downstream agent’s production opportunity. But Fig. 1 concentrates on just one production agent, which performs two activities—producing desirable outputs and controlling undesirable outputs. Secondly, Fig. 1 includes decontaminating work within a production agent. In this way, the undesirable outputs not only are transformed to desirable ones, but also follow the assumption of strong disposability. But in the idea of Färe and Grosskopf, the technology of controlling bad outputs is excluded, and production technology exhibits weak disposability on undesirable outputs.} \]
costless. Consider the output set \( P(x) \):

\[
P(x) = \{(y, t, c) | x_1 \text{ can produce } y, \text{ and } x_2 \text{ can produce } (t, c), x_1 + x_2 = x \}
\]

\[
= \{(y, t, c) | x \text{ can produce } (y, t, c)\}. \tag{2}
\]

To simplify notation, combine \((y, t, c)\) into a vector \(u\), \(u \in \mathbb{R}_+^{w+w} \), which denotes a total output vector, and rewrite Eq. (2) as

\[
P(x) = \{u | x \text{ can produce } u\}. \tag{3}
\]

The standard properties of this output set (Shephard, 1970) are summarized as

\[
P1 \ (a) \ 0 \notin P(x), \forall x \in \mathbb{R}_+^M, \ (b) \ u \notin P(0), u > 0;
\]

\[
P2 \ \forall x, x' \in \mathbb{R}_+^M, x' \geq x \Rightarrow P(x) \subseteq P(x');
\]

\[
P3 \ \forall x \in \mathbb{R}_+^M, u' \in P(x) \text{ and } 0 \leq u \leq u' \Rightarrow u \subseteq P(x);
\]

\[
P4 \ P(x) \text{ is a convex compact set.}
\]

Here, \(P1(a)\) is the axiom of inaction, implying it is possible that using any nonzero input could produce nothing and have no effect in pollution abatement. \(P1(b)\) implies “no free lunch,” indicating that zero inputs absolutely cannot produce anything and have no effect in pollution abatement. \(P2\) assumes strong disposability of inputs, indicating the inputs are harmless, and the normal production and pollutant treatment are at least at their original level after increasing inputs. \(P3\) assumes strong disposability of outputs, indicating the firm need not invest extra inputs to reduce normal outputs or pollutant removal, and also indicating that reducing normal outputs or pollutant removal is not difficult when holding the inputs constant. \(P4\) indicates the production frontier exists, and it is impossible to produce endless normal outputs and pollutant removal.

Because \(y\), \(t\), and \(c\) are all desirable outputs, it is intuitive that the output set (2) would not violate standard axioms. The above inferences confirm this view.

Since there are two technologies implied in Eq. (2), Färe and Grosskopf (2000) developed a network reference technology to display such productive process with multiactivity. The constraint sets of Eq. (2) can be shown as

\[
\hat{P}(x) = \{ (y, t, c) | \ Yz \geq y, \ Xz \geq x, \ Cz \geq c, \ x_1 \geq x, \ z_1 \leq z_2 \in \mathbb{R}_+^N \}, \tag{4}
\]

where the \( S \times N \) (normal) output matrix \( Y \), \( M \times N \) input matrices \( X_1 \) and \( X_2 \), \( W \times N \) (pollutant removal) output matrix \( T \), and \( W \times N \) (pass rates) output matrix \( C \) represent the data for all \( N \) firms in the sample, \( z_1 \) and \( z_2 \) are \( N \times 1 \) vectors, representing intensity variables providing weights that facilitate the construction of the segments of the piecewise linear frontier of the technology.

Total inputs \((x)\) are usually indivisible. Assume that total inputs cannot be separated. One can regard the whole production process as just one technology, although in spirit, it consists of two. Rewrite expression (4) as

\[
\hat{P}(x) = \{ (y, t, c) | Yz \geq y, \ Tz \geq t, \ Cz \geq c, \ Xz \leq x, \ z \in \mathbb{R}_+^N \}, \tag{5}
\]

where \( z \) is an \( N \times 1 \) vector of intensity variables. Compared to Eq. (5), the technology described by the “weak disposability” approach could be shown as

\[
\hat{P}(x) = \{ (y, b) | Yz \geq y, Bz = b, Xz \leq x, \ z \in \mathbb{R}_+^N \},
\]

where the \( W \times N \) final undesirable output matrix \( B \) represents the data for all \( N \) firms in the sample. Under this approach, additional data \((b)\) are required.

The interest lies in the outputs effect when environmental regulations are imposed. The Shephard output distance function can be used to measure technical efficiencies. For each DMU the distance function based upon output set, \( \hat{P}(x) \), can be computed by solving the following mathematical programming problems, respectively. For DMU \( k \) one calculates the programming problem:

\[
(D_{b}^k(x^k, y^k, t^k, c^k))^{-1} = \max \beta
\]

s.t. \( Yz \geq \beta y^k, Tz \geq \beta t^k, Cz \geq \beta c^k, Xz \leq x^k, z \in \mathbb{R}_+^N \), \tag{6}

Fig. 1. Production process with pollution abatement technology.
where $D^R_O(x, y, t, c)$ is a Shephard output distance function, and superscript $R$ denotes the measure is obtained under a regulatory scenario. Model (6) gives rise to a Farrell-type technical efficiency (1957) of DMU $k$.

Although how to include undesirable outputs in a DEA-based model is a controversial issue, the approach taken here is to separate the whole production process into two activities—normal production and pollution abatement, and to introduce environmental regulations to transform undesirable outputs. This allows one to employ a traditional Shephard distance function to measure technical efficiencies. The advantages of this approach include: (i) the transformed data are still treated as output variables; (ii) the assumption of strong disposability for all output terms is maintained; (iii) the transformed data are meaningful, in terms of quantity of pollutant removed, and the degree of compliance with environmental regulations; (iv) the measured technical efficiencies explicitly include the DMUs’ ability to comply with environmental rules; and (v) the method covers both activities—producing desirable outputs and controlling undesirable outputs.

### 3.2. Estimating the impacts of environmental regulations

The impacts of environmental regulation arise because undesirable outputs are not freely disposable. This article does not consider the Porter hypothesis (Porter and van der Linde, 1995), which suggests that environmental regulations will induce technical innovation and stimulate the growth of production. The hypothesis remains an issue of debate (Palmer et al., 1995).

Färe et al. (1989) and Boyd and McClelland (1999) measured the costs of environmental regulation by using different hyperbolic distance functions derived from production sets with and without the assumption of strong disposability of undesirable outputs. This analysis relies on transforming all undesirable outputs into desirable ones. Increasing them will be costly, which corresponds to the fact that reducing undesirable outputs will be costly and also implying a property of weak disposability of undesirable outputs. In fact, output set (5) assumes strong disposability for all variables, which implies that the approach used by Färe et al. (1989) and Boyd and McClelland (1999) can no longer be applied. Instead, we propose an alternative approach, similar to the approach used by Färe et al. (1989). Comparing the production sets with and without consideration of environmental regulations, the former output set is defined as (5), and its possible output set is the region OFGH illustrated in Fig. 2. If regulations do not exist, terms $t$ and $c$ also will not exist, so each producer can divert the resources treating pollution into production of normal goods. This implies the desirable outputs $y$ will increase. Let this increased quantity be a vector $\bar{y}$, $\bar{y} \in R^N_{+}$. Then the output set will be:

$$\bar{P}(x) = \{ y + \bar{y} | (y + \bar{y})z \leq (Y + \bar{Y})z , xz \leq x, z \in R^N_{+} \}, \quad (7)$$

where the $S \times N$ matrix $\bar{Y}$ represents the data for all $N$ firms in the sample. Actually, the data of $\bar{y}$ (and $\bar{Y}$) may not be available. Neglecting these data momentarily, output set (5) can be simplified as:

$$\bar{P}(x) = \{ y | y \leq Yz, xz \leq x, z \in R^N_{+} \}. \quad (8)$$

The output set $\bar{P}(x)$ is the region OCDE illustrated in Fig. 2. Comparing the feasible region between $\bar{P}(x)$ and $\bar{P}(x)$, region CEHF is a feasible set but becomes infeasible when environmental regulations are imposed. Point A shown in Fig. 2 represents the output combination of an inefficient DMU, facing two production frontiers $\bar{P}(x)$ and $\bar{P}(x)$. The different distance functions based on the two frontiers can be calculated. These are Eqs. (9) and (10), respectively.

$$D^R_O(x, y, t, c) = \min \{ \phi : (y, t, c) \in \bar{P}(x) \}. \quad (9)$$

$$D^U_O(x, y) = \min \{ \phi : y \phi \in \bar{P}(x) \}. \quad (10)$$

The difference between the two function values indicates the regulatory impact ($RI$) due to environmental rules. This can be estimated by Eq. (11).

$$RI = \frac{(D^U_O(x, y))^{-1} - (D^R_O(x, y, t, c))^{-1}}{(D^R_O(x, y))^{-1}}. \quad (11)$$

where $D^U_O(x, y)$ is a Shephard output distance function, and superscript $U$ denotes that the measure is obtained under an unregulated scenario. Here $RI$ represents regulatory impact, a ratio of the reduced outputs due to environmental regulation to the potential outputs when regulation is removed. Equation (11) takes a value between zero and one, and a value greater than zero may be interpreted as a reduction of productivity due to regulation. On the other hand, when it is equal to zero, regulation is not binding for the firm evaluated. For firm A, as shown in Fig. 2, geographically, its $(D^U_O(x, y))^{-1}$ is $OD/OA$, and $(D^R_O(x, y, t, c))^{-1}$ equals $OG/OA$, then the $RI$ will be $GD/OD$, where $GD$ represents the reduced outputs due to environmental regulations, and $OD$ represents the potential outputs when regulation is removed.
However, Eq. (8) underestimates outputs because it ignores \( \tilde{y} \) and \( \tilde{Y} \), and therefore ratio \( RI \) is underestimated as well. One can find the inputs in Eq. (8) including the inputs for normal production and pollution abatement, but its outputs only include the normal goods. If the decontaminating inputs are diverted to produce normal goods, the true outputs frontier must be shown more to the northeast place from its original position, which implies the \( RI \) in Eq. (11) is underestimated, and is merely a minimum ratio of impact. Only one situation in Eq. (11) provides an exact estimate, and that is when the decontaminating inputs are all inactively transformed to produce normal goods.

The distance functions \( D^{U}_{O}(x, y) \) and \( D^{R}_{O}(x, y, t, c) \) must be calculated before estimating \( RI \). Equation (6) can be used to find \( D^{U}_{O}(x, y, t, c) \), while \( D^{R}_{O}(x, y) \) can be obtained by solving the following programming problem:

\[
(D^{U}_{O}(x^k, y^k))^{-1} = \max \beta \\
\text{s.t. } Yz \geq \beta y^k, Xz \leq x^k, z \in R^N_+.
\]

(12)

Here \( RI \) is an index of regulatory impact, which provides a way to measure the costs of environmental regulation (CostER) in physical scale of desirable output losses. For example, the losses of desirable output \( s \) for firm \( k \) are:

\[
\text{CostER}^k_s = \tilde{y}^k \times (D^{U}_{O})^{-1} \times RI = \tilde{y}^k \times [(D^{U}_{O})^{-1} - (D^{R}_{O})^{-1}].
\]

(13)

where \( \text{CostER}^k_s \) is composed of \( \tilde{y}^k \times (D^{U}_{O})^{-1} \) and \( RI \). Term \( \tilde{y}^k \times (D^{U}_{O})^{-1} \) denotes the potential outputs when regulations are removed, and term \( RI \) denotes the loss rate of desirable output due to environmental regulation.

4. Data and variables

The operational types of pig farms in Taiwan include farrow-to-finish, feeder pig production, feeder pig finishing operators, etc. This study focuses on the farrow-to-finish pig farms, since over 70% of Taiwan’s pig farm are farrow-to-finishes and this type of production involves the widest range of management skills. However, pig production features multiple outputs and multiple inputs. The output and input variables required in this study are described below. Output variables include normal outputs \( (v) \) and environmental outputs \( (r \) and \( c) \). Normal output is aggregated into one category—finish hogs sold on market, environmental outputs into four categories—BOD, chemical oxygen demand (COD), suspended solid (SS) removal, and the total rate of the three kinds of pollutants passing emission standards. Inputs are grouped into three categories—labor, capital, and variable expenses.

4.1. Outputs

In Taiwan, wastewater from pig farms has been a major source of water pollution for many years. In order to properly control water pollution from pig farms, the Environmental Protection Administration (EPA) of Taiwan has enacted a code called “Effluent Standards” since 1987. This code now limits its BOD, COD, and SS to maximum levels at 80, 600, and 150 mg/L, respectively. To ensure discharge meets standards, pig farms have constructed wastewater treatment facilities, the so-called “three-stage wastewater treatment system (TSWTS),” which mainly consists of solid/liquid separator, anaerobic fermentation tanks, and aerobic fermentation tanks. With the purpose of collecting wastewater, raw wastewater tanks located ahead of solid/liquid separator are required. And after the process of aerobic fermentation, sediment tanks are installed to further deposit sludge. The flow diagram of TSWTS is illustrated in Fig. 3.

In 1999, the EPA further enacted a code, called “Soil Treatment Standards,” to control the discharge of wastewater into irrigation for soil that receives wastewater or sewage. The annual total nitrogen quantity of wastewater or sewage used for irrigation is limited to a maximum of 400 kilograms per hectare of land. However, data on nitrogen quantities received by soil for each farm in the sample studied here are not available. As a result, the environmental outputs analyzed in this article are limited to effluents.

![Fig. 3. Flow diagram of TSWTS.](image-url)
According to the Effluent Standards, the inspected indicators of wastewater pollution in a pig farm include BOD, COD, and SS (in mg/L). Thus, the amounts of those three kinds of pollutants removed by the TSWTS and their pass rates are the proxies of the environmental outputs of Eq. (6). As for the data collection, as shown in Fig. 3, wastewater was drawn from the raw tank and the sediment tank for inspecting the concentrations of BOD, COD, and SS at each farm. The differential values between raw and sediment tanks constitute pollutant removal (t). Comparing the concentrations inspected from the sediment tank with the effluent standards provides pass rates (c). However, in the available data, only 5–9 inspected samples for each farm are available. This may not be enough to calculate representative pass rates of BOD, COD, and SS, respectively. Therefore, BOD, COD, and SS are combined to calculate a total pass ratio. The vector $c \in R^5_+$ in Eq. (1) is modified to be the following scalar:

$$c = \frac{\text{Number of tests passing the Effluent Standards}}{\text{Number of tests of all BOD, COD, and SS with Effluent Standards}}.$$

(14)

The normal desirable output is defined as finished hogs sold on the market. This variable is normalized by the number of sows, both in order to increase the variation of the selected variables (Galanopoulos et al., 2006) and to enable comparison of different output losses of farms of different sizes.

4.2. Inputs

Three inputs are used to produce pigs and remove waste: labor, capital, and variable expenses. Labor covers family members and the hired labor dedicated to pig production or pollutant treatment. It is measured in hours per year. Capital represents the annual depreciation of fixed assets, including the buildings and barn for pig production, and the TSWTS investment for wastewater treatment. Variable expenses represent the annual cost for feedstuff, transportation, electricity, veterinary care, insurance, etc. As with output, again, all variables are normalized by the number of sows.

Table 1 presents descriptive statistics of the input and output variables. Wide variations are observed in the inputs and the outputs. Inputs on some farms are, on average 2–5 times larger than other farms. Variation in pollution treatment is even greater. Some farms had $t_{SS}$ measures 12 times higher than others. Such variations imply poor resource management by farm owners and suggest that there may be a wide variation in their technical efficiencies or regulatory impacts. The pass ratio (c) also shows wide variation, with a mean of just 0.56, which suggests that the effluent standards are not easily met, and also indicates the limited effectiveness of TSWTS under the current regulations.

4.3. Data

Data for this study were taken from surveys conducted for a project co-sponsored by the EPA and the Council of Agriculture of Taiwan. Surveys were completed in 2003 and 2004, respectively. A total of 39 farmers were randomly selected for interviews but only 31 observations are used in this study because those with missing information and breeding farms or feeder pig finishing farms are excluded. The pig production data were collected through a questionnaire, while the inspection data of BOD, COD, and SS were drawn bimonthly from the raw tank and the sediment tank of TSWTS. The samples used came from a specific geographical region in central and southern counties of Taiwan (Taichung, Changhua, Chia-I, Tainan, Kaohsiung, and Pingtung). These are the main productive districts in Taiwan and account for over 70% of pig production. Because of close geographical proximity and similar production type, the sample farms are assumed to be homogenous in terms of market and production type. This implies that any observed differences in performance are the result of difference in management.

5. Results and implication

5.1. Results

Results obtained by Eqs. (6), (11), (12), and (13) are illustrated in Table 2. The average technical inefficiency (shown as column 2) is 1.528. This implies that, on average, farms could increase outputs by 52.8% while maintaining the same input levels. At a disaggregate level, there is considerable variation in the performance. Only eight farms (25.8%) use the best practices, while at about half the pig farms (51.6%), the technical inefficiencies are greater than 1.5. This implies there is a
the findings in Färe et al. (1989) and Seiford and Zhu (2002). Also, the rankings of DMUs are distorted. These results confirm that both efficiency scores belong to the same population or not, a Wilcoxon signed-rank test is used, to test whether both technical inefficiencies come from the results estimated from Eq. (12), which ignores pollutants. To understand whether significant differences exist in the costs of environmental regulation (CostER) among farms with different technical efficiencies, (and CostER) among farms with different technical efficiencies, (6) and (12), recall that the undesirable outputs are dropped from the latter. This causes its output set to be enveloped more loosely than model (6). Accordingly, the technical inefficiencies obtained by model (12) would not be smaller than those obtained from model (6). When undesirable outputs are added back to the models, implying environmental regulations are imposed, the feasible output set is reduced. Farms are forced to give up some feasible production plans. And consequently, they suffer a regulatory impact. The impact is modeled by Eq. (11) and illustrated in column 6 of Table 2. In the sample as a whole, about 9.8% of potential pig production was sacrificed in order to divert productive resources (production of pigs) to treat wastewater. Transforming this loss into a physical measure implies pollution abatement costs each pig farm, on average, 1.965 marketed hogs per sow per year.

Investigating the technical inefficiencies and regulatory impacts by farm size, Figs. 4 and 5 depict the technical inefficiency and regulatory impact for each farm in ascending order of operating scale. The scatter plots show that the larger a pig farm is, the lower its technical inefficiency. However, no pattern emerges between size and regulatory impact. For comparison purposes, we divide the sample into two different size groups according to the number of sows: those with fewer than 110 (16 farms) and those with more than 111 (15 farms). Comparing their technical inefficiencies, Table 4 shows that their means are 1.747 and 1.291, respectively. Again, this shows that farms in the sample with a larger operating scale are more efficient. Tests of differences of inefficiency scores based on analysis of variance (ANOVA) and Mann–Whitney tests both reject the null hypothesis that the average technical inefficiencies of the two groups are the same. Galanopoulos et al. (2006), Sharma et al. (1999), and Lansink and Reinhard (2004) also compared the sizes of pig farms with their technical efficiencies. The first two studies found that large farms are more efficient, although they did not consider undesirable outputs in their measures of efficiency. Lansink and Reinhard considered undesirable outputs, but found no clear relationship between farm size and technical efficiency.

A similar comparison between regulatory impacts and operating scales is carried out as well. The main results are also shown in Table 4. The regulatory impacts (RI) in the two groups (\(\leq 110\) and > 111 sows) are 0.112 and 0.084, respectively. This seems to show that the advantage of scale does not exist anymore. For a confidence level of 95%, the ANOVA and Mann–Whitney tests both reject the null hypothesis that the average regulatory impacts are the same. We convert the measurement of regulatory impacts into the costs of environmental regulation (CostER), and compare the costs with different size intervals. These results are also shown in Table 4. We find that the differences between means of the costs of environmental regulation for the two groups are not significantly different from zero.

To understand whether significant differences exist in the RI (and CostER) among farms with different technical efficiencies,
the sample is divided into two groups—a high-efficiency group (with technical inefficiency less than 1.5) and low-efficiency group (with inefficiency more than 1.5). Results from ANOVA and Mann–Whitney tests are shown in Table 5. One might expect farms with high efficiency to be less affected by regulations, but results do not seem to support this conjecture. For a confidence level of 95%, the difference of $RI$ (and $CostER$) between both efficiency groups of farms are indeed statistically significant, but with farms more affected by regulations showing higher efficiency levels. However, according to the definitions of $RI$ and $CostER$, index $RI$ indicates a ratio of the reduced outputs due to environmental regulations to the output potential when regulation is removed, and index $CostER$ indicates the reduced output potential from an unregulated scenario to a regulatory one. On the methodology, an inefficient farm’s output potential is the same as that of its benchmark farms with full efficiency. Because $RI$ and $CostER$ are estimated based on potential, farms with higher efficiency are not necessarily less affected by regulations, which is a consequence of methodology. Moreover, imagining a scenario involving two farms with different efficiency and the same input use, the high-efficiency farm can produce more output than the low-efficiency one. When the environmental regulations are imposed, one might imagine both farms using the same proportion of their respective inputs to deal with decontamination work. In this case, the high-efficiency farm will face a higher opportunity cost than the low-efficiency one, which is one possible reason why Table 5 reveals an anti-intuitive result.

5.2. Implications

The empirical results have some helpful and useful implications. First, for a pig farm, enlarging its operating size can improve performance and facilitate compliance with current environmental regulations. A measure of regulatory impact, which could be useful for the EPA and the Council of Agriculture to evaluate the impact of the environmental policy, can be derived.
According to the results obtained by Eq. (11), the average producer would be able to increase its desirable outputs by 9.8% if environmental regulations were removed. This opportunity cost must be deducted from the benefit of enforcing regulations when a cost–benefit analysis is conducted.

Finally, since larger pig farms are more efficient, transformation is important. As a result, the EPA and the Council of Agriculture should guide and assist small family-type farms to either transform into larger industrial farms or quit the market. Thus, Taiwan’s pig farms can become more competitive, and also have cleaner production. However, there are still about 7 million pigs being raised in Taiwan. For the sake of environmental protection and as a result of joining the WTO, Taiwan’s pig farms should be reduced greatly in numbers to maintain competitiveness imports. Taiwanese authorities currently plan to cut down on the number of pigs being raised. One of their schemes is to employ monetary compensation for the losses of pig farm owners in the process of downsizing. Based on the results of this study, the compensatory scheme could be designed with incentives to preserve larger farms and encourage smaller farms to quit the market. This study also finds that there is potential for the sample farms to improve pig production by 52.8%. If this potential can be realized, the current pig production value could be achieved by fewer farms. This suggests more downsizing could also be accomplished by improving efficiency—Taiwan would not need so many pig farms if they are all fully efficient.

6. Concluding remarks

Measuring technical efficiency in the presence of undesirable outputs is an issue addressed by many past studies, but how to include the undesirable outputs in a production technology has been a subject of debate. One of the main purposes of this study was to develop an alternative DEA-based model that incorporates the production of undesirable outputs. Besides measuring technical efficiencies, the model presented in this article can also estimate environmental impacts at the firm level. One innovation of this study was to consider the productive subprocess that firms use to reduce undesirable outputs as an independent technology. In this way, undesirable outputs not only are transformed to desirable ones but also are included as meaningful output variables. The proposed approach has the following merits: (i) the transformed data are still treated as output variables; (ii) the approach maintains the assumption of strong disposability for all output variables; (iii) the transformed data are meaningful, in terms of quantity of pollutant removed and the degree of compliance with environmental regulations; (iv) the measured technical efficiencies explicitly include the DMUs’ ability to comply with environmental rules; and (v) the method covers both productive activities—producing desirable outputs and controlling undesirable outputs.

To demonstrate the practicality of the proposed approach, the model was applied to analyze farrow-to-finish pig farms in Taiwan. The results show that larger farms are more technically efficient than small-sized farms. However, no clear conclusions can be reached for the measures of regulatory impact among farms of different sizes. This suggests that enlarging the operating size of pig farms may be helpful in enhancing performance and accommodating the current environmental regulations. As for the government sector, for example the EPA and the Council of Agriculture, our results suggest they could guide and assist small family-type farms to transform into large industrial farms or encourage them to quit the market. Thus, not only could the pig farms be more competitive, but they also could have cleaner production. The empirical results also find that, on average, the sample pig farms incurred 9.8% opportunity cost (measured as market hog losses) due to environmental regulations. Higher efficiency farms are more likely to face higher opportunity costs.

Due to limited data availability, this study considered only wastewater effluent. This is one of the most important
undesirable outputs in Taiwan’s swine sector. However, the discharge of wastewater into irrigation and the use of manure are also important but were not included in this study. Recent research (e.g., Asmild and Hougaard, 2006; and Coelli et al., 2007) provide excellent alternative approaches to assess performance while considering factors we excluded here. Finally, the methodology of this article regards the whole production process as just one technology. Future studies may pursue an alternative track. Presumably environmental regulations will always exist, and these will force firms to perform pollution abatement activity. Accordingly, a firm will face not only normal production technology, but also pollution abatement technology. Given appropriate data, a network DEA (Färe and Grosskopf, 2000; Färe and Grosskopf, 2004a, pp. 66–70) or multicomponent model (Amirteimoori and Shafiei, 2006) might be an appropriate approach.

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References