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Measuring the Impact of Food Safety Regulation

- An Output Directional Distance Function Approach

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Abstract

This paper provides a novel methodology to measure the impact of food safety regulation. An output directional distance function approach is applied to estimate the opportunity cost of food safety regulation. Such a measure should be included as part of the overall cost of compliance for a more precise comparison of the benefits and costs of food safety regulation. Using US Census and food safety recall data, the value of potential output loss due to food safety regulation is measured. The result suggests an opportunity cost of $2.5 billion in 1997, almost 5% of the annual value of shipments for the meat and poultry processing industry.

Keywords: compliance cost, directional distance function, food safety regulation

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1. Introduction

Comparing the impact of alternative forms of food safety regulations is an important task in risk management. One obvious role for economists in this context is the measurement of the benefits and costs of food safety regulations. As part of such an assessment, this paper investigates a simple economic question: what is the opportunity cost of stricter controls placed upon food firms? In estimating such an impact of food safety regulation, both the cost of compliance and the effect of the regulation on the operational efficiency of firms should be considered (Antle, 2001). According to Antle (2001), there are three different approaches to estimate traditional costs of food safety regulation; accounting, economic-engineering and econometric. In the accounting approach, the effect of regulations on employment, capital stock and other inputs is calculated in terms of explicit costs. The economic-engineering approach combines engineering and economic data such as input costs. The econometric approach applies statistical techniques to estimate costs using industry data. Regardless of the technique adopted traditional compliance cost estimates of regulations such as those based on Hazard Analysis and Critical Control Point (HACCP) systems (USDA, 1996; FDA 1995) ignore changes in overall firm efficiency due to refinements in the production process (Antle, 1996).

To answer the question raised above requires a focus on the effect of the regulation on firm behavior. A loss in efficiency is observed following a regulation which restricts firm behavior. This loss can have an impact on “economic” revenue. This change in revenue is the opportunity cost of compliance with the regulation. Such an opportunity cost can be defined as the shadow value of productive resources used to enhance food safety that could alternatively be used to increase revenue through the sale of a larger volume of output. While traditional measures of compliance costs reflect explicit changes in input demand, this opportunity cost reflects the value forgone through input reallocation. Therefore, in addition to explicit changes in cost, estimating the opportunity cost of compliance enhances the "economic" analysis of food safety policy.

In this paper, two types of outputs: desirable and undesirable are considered. Specifically, desirable output represents food production and undesirable output represents risk in food. These outputs are assumed to be joint products. Therefore, a multi-output technology is required. A common assumption in the literature is that a particular food safety production function can be characterized using a multiple output technology jointly producing physical output and food quality (Antle, 2000a, b). However, here food safety is distinguished from food quality. As a refinement of this technique, it is argued that improvements in safety can be achieved by reducing potential risk, but that quality can be increased without decreasing risk. The former statement assumes that one can measure safety as a desirable output while the latter assumes that certain levels of quality may be undesirable and can only be reduced with safety-enhancing inputs within a multiple-output model. As quality is composed of various attributes including safety, food safety enhancements can improve overall product quality but enhancing non-safety quality attributes does not necessarily lead to food safety improvements. From the viewpoint of risk analysis, food safety can be considered to be a set of measurable attributes which are scientifically sound. Through their control direct public health benefits are seen. Strictly speaking, in this sense, to better understand food safety policy one should be clear about the relationship between risk in food and the appropriate level of public health protection. Accordingly, a food safety technology is defined here as a risk (or damage) control technology, not just a broadly-defined quality-enhancing technology. This permits the assessment of the effectiveness of a food safety technology (a voluntary adoption issue) or regulation (mandatory).

In order to incorporate undesirable output it is necessary to impose "weak disposability" and "null-joint" assumptions on the production possibilities set. This allows the modeling of a technology capable of producing desirable output while reducing undesirable output. With this assumption, an output directional distance function approach is employed to measure efficiency. Two attractive features of this framework are as follows. First, this model can assess various regulatory designs such as performance, process and even combined standards as constraints in a mathematical programming problem. In the case of an output directional distance function, a performance standard on undesirable output can be included as a constraint. Second, risk in food can be explicitly included as an argument in the model. Thus, the research can make use of the results of risk assessments providing an appropriate integration of risk management within broader risk analysis models. Following a brief literature review, the production economics basis of the model is presented. Finally, an application evaluating food safety regulation is discussed.

2. Literature Review

Unlike conventional models of multi-output production functions, the incorporation of food safety requires "good" (food production) and "bad" (risk) outputs. Scheel (1998) compares various modeling approaches incorporating undesirable outputs. According to his classification, there are direct and indirect approaches. The indirect approach treats undesirable outputs differently from desirable outputs by applying a transformation using a monotonically decreasing function such as $f(u) = -u$ where u represents undesirable output in $\Re^{+}$. The direct approach modifies the assumption of free disposability of undesirable outputs but does not prescribe any formal treatment of the data. For example, weak disposability is often applied to treat undesirable output. In what follows, we briefly discuss the evolution of frameworks of efficiency measurement considering undesirable output and the computational steps required to recover shadow prices.

To be in compliance with the relevant (food safety) regulation, a firm cannot simply dispose of the undesirable output (food risk) without incurring some form of cost. Thus, the firm must allocate resources to reduce undesirable output. For example, a firm can purchase a new piece of equipment which lowers food risk and incur ongoing variable costs (e.g., labor). In so doing, the firm loses the chance to use these resources for the production of more desirable output. This is the essence of ***weak disposability*** (Färe and Primont, 1995). In addition, a ***null-jointness*** assumption dictates that undesirable output will always be a byproduct of desirable output. Every level of food production has some risk, zero risk is only achievable with zero food production.

In a sequence of research using these two assumptions, the distance function approach has emerged as a valuable tool. A distance function is an alternative representation of the impact of a regulation and is a convenient way to characterize multi-input, multi-output technologies. Using input and output distance functions, one can model various functional forms of a multi-output technology. It can further be shown that the input distance function is dual to the cost function and the output distance function is dual to the revenue function (Färe and Primont, 1995). This allows for empirical applications. For example, Färe, et al. (1995) show how an output distance function can identify the structure of a production technology, measure productive efficiency and be used to calculate shadow prices of outputs under such weak output disposability and null jointness assumptions[1]. Further, it has been shown that the reciprocal of

[1] A nonparametric analysis is also possible (see Färe and Grosskopf, 1998). Such analysis has been used to measure the efficiency of decision-making units under the assumption that inputs produce desirable and marketable outputs (Hanoch and Rothschild, 1972; Varian, 1984). Färe and Grosskopf (1998), using the assumption of weak

the distance function provides a measure of Farrell technical efficiency and that an input (or output) quantity index can be recovered from the ratio of input (or output) distance functions. In addition, using the input distance function it is possible to calculate the elasticity of scale and identify the structure of the technology (Färe and Primont, 1995). Unfortunately, this technique is not suitable when desirable and undesirable outputs are jointly produced. An alternative method – a directional distance function approach – has emerged in the literature for such situations.

A series of publications (Chambers, Chung and Färe 1996; Chung, Chambers and Grosskopf. 1997; Chambers, Chung and Färe. 1998) developed and applied directional distance functions testing Nerlovian profit efficiency. The directional function allows a translation of the input or output vectors to the technology frontier in a pre-assigned direction. This pre-assigned direction is not necessarily radial from the origin, with this feature distinguishing input or output distance functions from directional distance functions[2]. Chambers, Chung and Färe (1998) show that the directional distance function is dual to the profit function. Using duality, Chambers, Chung and Färe (1998) also discuss how Nerlovian efficiency can be measured using the directional distance function. Nerlovian efficiency is a profit-based efficiency measure made up of both technical and economic efficiency. As mentioned in Färe and Grosskopf (2000), allowing the simultaneous adjustment of inputs and outputs in a given direction demonstrates the duality between the profit function and directional distance function. Recently, Färe and Grosskopf (2003) provide a novel modeling approach for undesirable outputs using data envelopment analysis focusing on the weak disposability assumption.

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disposability of outputs, present a nonparametric estimation of productivity changes in the presence of an environmental regulation.

[2] In order to distinguish them, distance functions are referred to as Shephard's (radial) distance functions (Chambers, Chung and Färe, 1998).

There is an impressive literature measuring shadow prices of undesirable outputs applying a distance function approach. Färe, et al. (1993) estimate productivity using a translog distance function applied to Michigan and Wisconsin paper and pulp milling industry data assuming weak disposability of the pollutant – solid waste. Further, they show how to derive a shadow price of the undesirable output from the distance function using duality. Coggins and Swinton (1996) apply the same models to data from Wisconsin coal-burning utility plants. A general discussion about how to recover shadow prices of undesirable outputs using duality theory can be found in Färe and Grosskopf (1998). This approach employs weak disposability to treat undesirable outputs differently from desirable outputs. However, each of these papers apply radial distance functions. Measuring shadow prices of undesirable output Lee, Park and Kim (2002) estimate an output directional distance function using data representing the Korean electricity power industry. They calculate a reference vector using the annual abatement schedules of pollutants and the production plans of desirable output. In their nonparametric model, the derivatives of the production frontier are computed as the ratio of the dual values of the constraints of both undesirable and desirable outputs.

3. A Model Incorporating Goods and Bads

Following the model developed by Chung, Chambers and Grosskopf (1997), the directional distance function is first presented leading to a discussion of the selection of an appropriate reference vector.

3.1 Assumptions

In order to model undesirable output (**u**), here risk in food, recognize that $\mathbf{u} \in \Re_+^{M\text{-}m'}$ is jointly produced with the desirable output (food) denoted by $\mathbf{y} \in \Re_+^{m'}$, leading to the output set:

$$P(x) = \{(\mathbf{y},\mathbf{u}) \in \Re_+^M \mid \mathbf{x} \in \Re_+^N \ \textit{can produce} \ (\mathbf{y},\mathbf{u})\} \tag{1}$$

Weak disposability of undesirable output is imposed in the model.

Assumption A1 (Weak Disposability of Undesirable Output)

$$(\mathbf{y},\mathbf{u}) \in P(\mathbf{x}) \ \textit{and} \ 0 \le \theta \le 1 \ \textit{implies} \ (\theta\mathbf{y},\theta\mathbf{u}) \in P(\mathbf{x}) \tag{2}$$

Assumption 1 implies that given inputs **x**, a reduction of undesirable output (**u**) is only possible when it is accompanied with a reduction of desirable output (**y**). In contrast, free disposability of desirable output is assumed.

Assumption A2 (Free Disposability of Desirable Output)

$$(\mathbf{y},\mathbf{u}) \in P(\mathbf{x}) \ \textit{and} \ \mathbf{y}' \le \mathbf{y} \ \textit{implies} \ (\mathbf{y}',\mathbf{u}) \in P(\mathbf{x}) \tag{3}$$

In addition, we require the assumption that zero undesirable output is only feasible when zero desirable output is produced. That is, a positive amount of desirable output is jointly produced with a positive amount of undesirable output - implying that zero risk in food is impossible.

Assumption A3 (Null-Jointness of Outputs)

$$\textit{If} \ (\mathbf{y},\mathbf{u}) \in P(\mathbf{x}) \ \textit{and} \ \mathbf{u} = 0, \textit{then} \ \mathbf{y} = 0. \tag{4}$$

Based on these three assumptions, the output set seen in Figure 1 can be constructed. Suppose two observations (*a* and *b*) are available. The output set based on these two points under strong disposability is *0dbc0*. However, under weak disposability, the output set is *0abc0*.

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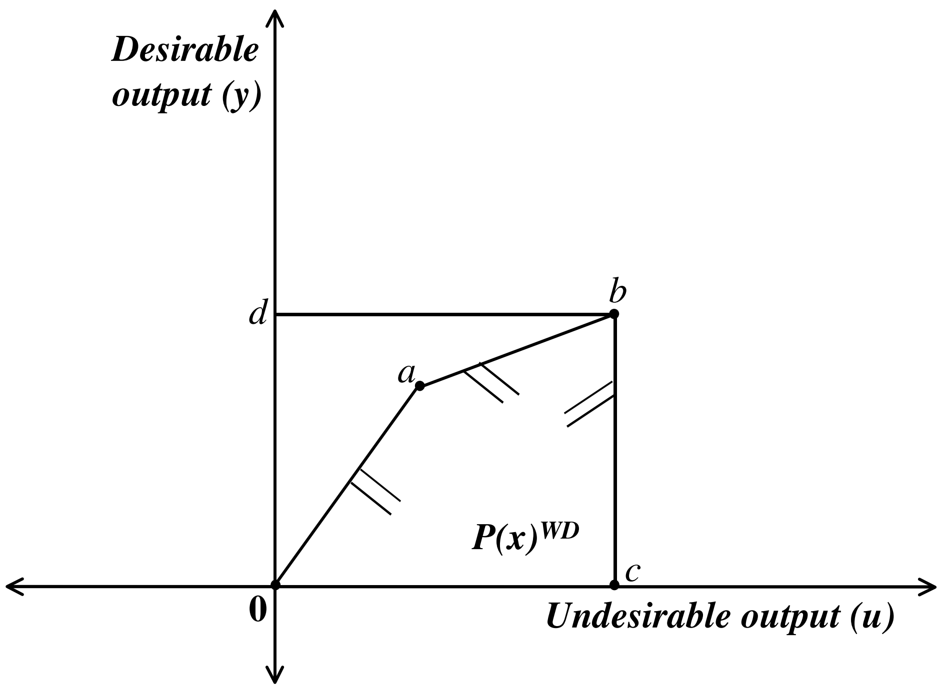

Figure 1 Output Sets under Weak Disposability

3.2 An Output Directional Distance Function

The vector of inputs is **x**= $(x_1, x_2,...,x_N) \in \Re^N$ and the vector of outputs (**y**, **u**) $\in \Re^M$. The technology set is $\boldsymbol{T}$ ={(**x**, **y**, **u**): **x** $\in \Re_+^N$, (**y**, **u**) $\in \Re_+^M$, **x** can produce (**y**, **u**)}, where $\Re_+^N$ is the set of nonnegative, real N-tuples.

Using assumptions A1 and A2, an output directional distance function based on Chung, Chambers and Grosskopf (1997) can be applied to allow for an asymmetric change in outputs from desirable to undesirable in response to a food safety regulation. This permits the modeling of a performance standard[3]. The output-oriented directional distance function can be defined as:

Definition 3.1 (Output Directional Distance Function)

$\vec{D}_o : \Re_+^N \times \Re_+^M \times \Re_+^M \rightarrow \Re$ is defined by

$$\vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{u} \mid \mathbf{g}) = \sup\{\beta \mid (\mathbf{y}, \mathbf{u}) + \beta \cdot \mathbf{g} \in P(\mathbf{x})\} \tag{5}$$

where $\mathbf{g} = (\mathbf{g_y}, \mathbf{g_u}) \in \Re_+^M$ is the vector of directions in which output is scaled.

An output directional distance function is the solution to the following linear programming problem for each observation. Suppose there are I observations. For simplicity, consider a two-output (desirable and undesirable), two-input (labor (L) and capital (K)) case. For individual observation j, the linear programming problem under weak disposability can be shown to be the following.

$$\vec{D}_o(L_j, K_j, y_j, u_j \mid (g_y, g_u)) = \max_{\beta} \beta \tag{6}$$

subject to

[3] It is also possible to model a process or combined standard using an input directional distance function or an input-output directional distance function, respectively.

$$\sum_{i=1}^{I} z_i y_i \geq y_j + \beta g_y$$
$$\sum_{i=1}^{I} z_i u_i = u_j + \beta g_u$$
$$\sum_{i=1}^{I} z_i L_i \leq L_j$$
$$\sum_{i=1}^{I} z_i K_i \leq K_j$$
$$z_i \geq 0 \quad (i = 1, 2, ..., I)$$

where z_i for all i =1, 2, ... ,I are the intensity variables.

3.3 Selection of the Reference Vector

The directional vector contains two pieces of information. One is the direction of the reference vector. The signs of the elements in the reference vector show whether outputs (or inputs) increase or decrease. The other is the value of the reference vector. Graphically, for an arbitrary vector **g**, the directional distance is measured by a ratio of *0B/0A* as in Figure 2. Thus, selection of the reference vector directly affects the measure of efficiency. In almost all cases in the literature, the directional vector **g** has been selected by the researcher. When undesirable outputs are considered, it is common to assume **g** = (**y**, -**u**) $\in \Re^{m+m'}$ when **u** $\in \Re_+^{m}$ represents undesirable outputs, and **y** $\in \Re_+^{m'}$ represents desirable outputs ($m+m'=M$). This means that desirable outputs increase and undesirable outputs decrease[4]. When the production process includes food safety control(s), an appropriate efficiency measure should incorporate the effort of reducing food risk as well as enhancing the production of desirable outputs. An efficiency measure can be calculated for each observation (y_i, u_i), using the the *i-th* firm's technology.

[4] Lee, Park and Kim (2002) compare previous research efforts incorporating undesirable outputs using different definitions of the directional vectors.

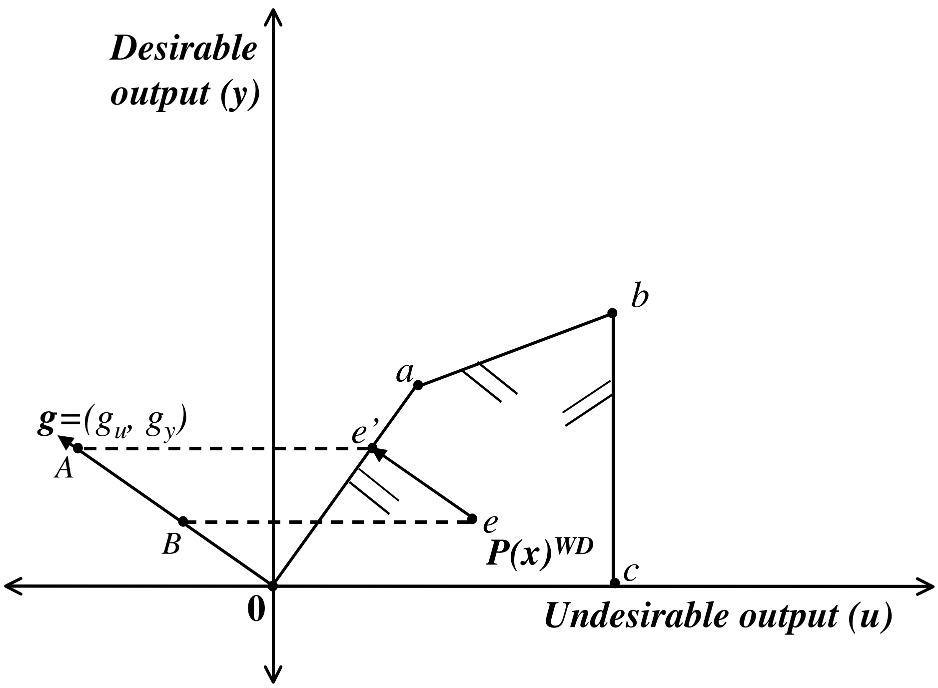

Figure 2 Directional Distance Function

3.4 Dualities

Denote the vector of output prices by $\mathbf{p} = (\mathbf{p_y}, \mathbf{p_u}) \in \Re^M$ and the vector of outputs by $\tilde{\mathbf{y}} = (\mathbf{y}, \mathbf{u}) \in \Re_+^M$. Then, the revenue function is defined as:

$$R(\mathbf{p},\mathbf{x}) = \sup_y \{\mathbf{p}\cdot\tilde{\mathbf{y}} \mid \tilde{\mathbf{y}} = (\mathbf{y},\mathbf{u}) \in P(\mathbf{x})\} \tag{7}$$

Given the vector of output prices the revenue function is greater than or at least equal to any value of feasible outputs. Therefore, we can represent this inequality as:

$$R(\mathbf{p},\mathbf{x}) \geq \mathbf{p}\cdot\tilde{\mathbf{y}} \quad for\ \tilde{\mathbf{y}} = (\mathbf{y},\mathbf{u}) \in P(\mathbf{x}) \tag{8}$$

Since $\tilde{\mathbf{y}} + \vec{D}_o(\mathbf{x}, \tilde{\mathbf{y}} \mid \mathbf{g}_\mathbf{y}) \cdot \mathbf{g}_\mathbf{y}$ is also feasible where $\mathbf{g}_{\tilde{\mathbf{y}}} = (\mathbf{y}, -\mathbf{u})$, this inequality becomes:

$$
\begin{aligned}
R(\mathbf{p}, \mathbf{x}) &\geq \mathbf{p} \cdot (\tilde{\mathbf{y}} + \vec{D}_o(\mathbf{x}, \tilde{\mathbf{y}} \mid \mathbf{g}_{\tilde{\mathbf{y}}}) \cdot \mathbf{g}_{\tilde{\mathbf{y}}}) \\
&\geq \mathbf{p} \cdot \tilde{\mathbf{y}} + \vec{D}_o(\mathbf{x}, \tilde{\mathbf{y}} \mid \mathbf{g}_{\tilde{\mathbf{y}}}) \cdot \mathbf{p} \cdot \mathbf{g}_{\tilde{\mathbf{y}}}
\end{aligned}
$$

Following a proposition from Luenberger (1992), we can derive the following duality:

$$
R(\mathbf{p}, \mathbf{x}) = \sup_{\tilde{\mathbf{y}}} \left\{ \mathbf{p} \cdot \tilde{\mathbf{y}} + \vec{D}_o(\mathbf{x}, \tilde{\mathbf{y}} \mid \mathbf{g}_{\tilde{\mathbf{y}}}) \cdot \mathbf{p} \cdot \mathbf{g}_{\tilde{\mathbf{y}}} \right\} \tag{9}
$$

$$
\vec{D}_o(\mathbf{x}, \tilde{\mathbf{y}} \mid \mathbf{g}_{\tilde{\mathbf{y}}}) = \sup_{\mathbf{p}} \left\{ \frac{R(\mathbf{p}, \mathbf{x}) - \mathbf{p} \cdot \tilde{\mathbf{y}}}{\mathbf{p} \cdot \mathbf{g}_{\tilde{\mathbf{y}}}} \right\} \tag{10}
$$

Applying duality, the directional distance can be shown using the revenue function and values of outputs in Equation (10). This measures the difference between the revenue function and the actual revenue in the direction of the vector $\mathbf{p} \cdot \mathbf{g}_{\tilde{\mathbf{y}}}$. Note that the revenue under regulation ($\mathbf{p}_\mathbf{y} \cdot \mathbf{y} + \mathbf{p}_\mathbf{u} \cdot \mathbf{u}$) is less than the value of the desirable output since the shadow price of undesirable output is negative. That is, revenue in the accounting sense ($= \mathbf{p}_\mathbf{y} \cdot \mathbf{y}$) reflects only the market value of the desirable output. However, the control of food safety risk restricts the firm, forcing it to take the undesirable output into account. Replacing the vector $\boldsymbol{g}$ with ($\mathbf{y}$, -$\mathbf{u}$), greater economic intuition can be obtained for the direction; the regulation restricts revenue by internalizing an externality. As stated above, the shadow price of undesirable output is negative so that $\mathbf{p} \cdot \mathbf{g}_\mathbf{y}$ is the social value of all outputs (food and food risk). Such a social value under the regulation implicitly weights all outputs after undesirable output has been reduced through compliance. Absent the regulation, the firm produces desirable output without consideration of the cost of foodborne illnesses to society. Thus, a directional distance function approach using a reference vector of ($\mathbf{y}$, -$\mathbf{u}$) measures the performance of firms following the internalization of a negative externality.

Assuming that the output directional distance function is differentiable, applying the envelope theorem to Equation (9):

$$p_m = \mathbf{p}\cdot\mathbf{g}_{\tilde{\mathbf{y}}}\frac{\partial \vec{D}_o(\mathbf{x},\tilde{\mathbf{y}}\mid\mathbf{g}_{\tilde{\mathbf{y}}})}{\partial y_m} \quad for\ m = 1,2,\ldots,M \tag{11}$$

The shadow price of *m-th* output can be calculated from Equation (11). Assuming that observed market prices are equivalent to the shadow prices for the output, we can calculate $\mathbf{p}\cdot\mathbf{g}_{\tilde{\mathbf{y}}}$. For example, for the *m'-th* output case,

$$\mathbf{p}\cdot\mathbf{g}_{\tilde{\mathbf{y}}} = \frac{p_{m'}}{\left(\dfrac{\partial \vec{D}_o}{\partial y_{m'}}\right)} \tag{12}$$

The shadow price for non-market output (risk in food) can be calculated by inserting Equation (12) into Equation (11).

$$\begin{aligned} p_l &= \left(\frac{p_{m'}}{\partial \vec{D}_o / \partial y_{m'}}\right)\cdot\frac{\partial \vec{D}_o}{\partial y_l} \\ &= p_{m'}\cdot\left\{\frac{\partial \vec{D}_o / \partial y_l}{\partial \vec{D}_o / \partial y_{m'}}\right\} \qquad (l = m'+1,\ldots,M) \end{aligned} \tag{13}$$

In the case of more than one output with a market price, use can be made of the observed revenue following Färe, Grosskopf and Nelson (1990). Note that in order to calculate shadow prices a parametric form of the output directional distance function is required. A negative shadow value reflects that the chance to produce more desirable output is forgone because of the regulation.

Unfortunately, it is difficult to find a parametric directional distance function which satisfies all the necessary conditions such as the translation property. Thus, a nonparametric estimation of the directional distance function must be performed.

5. The Economic Impact of Food Safety Regulation

Consider a food safety regulation which forces the firm to reduce undesirable output. In the model presented here this constraint has been reflected by imposing weak disposability of undesirable output. When in compliance, the impact of the food safety regulation is the contraction of the frontier (from *0dbc0* to *0abc0*). Hence, it is possible to measure the impact of the regulation as the difference in efficiency measured using a directional distance function under two assumptions, namely, weak disposability of undesirable output and free disposability of undesirable output.

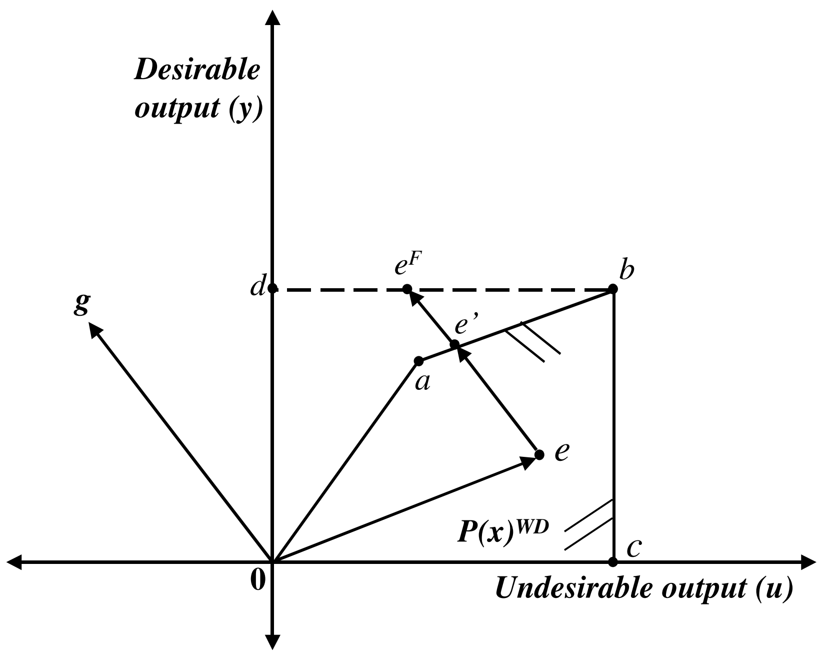

Figure 3 Measuring the impact of food safety regulation

If there is no difference between the measure of efficiency for the firm under each condition (*e'* equals e^F in Figure 3) then this firm is not affected by the regulation (point b). More generally though, the directional distance function under free disposability of undesirable output for each firm *j* is as follows.

$$\vec{D}_o^F(L_j, K_j, y_j, u_j \mid (g_y, g_u)) = \max_{\beta} \beta^F \tag{14}$$

subject to

$$\begin{aligned}
&\sum_{i=1}^{I} z_i y_i \geq y_j + \beta^F g_y \\
&\sum_{i=1}^{I} z_i u_i \geq u_j + \beta^F g_u \\
&\sum_{i=1}^{I} z_i L_i \leq L_j \\
&\sum_{i=1}^{I} z_i K_i \leq K_j \\
&\sum_{i=1}^{I} z_i = 1 \\
&z_i \geq 0 \quad (i = 1, 2, \ldots, I)
\end{aligned} \tag{15}$$

where z_i for all i =1, 2, ... ,I are the intensity variables

In order to distinguish the efficiency score under the two different assumptions, represent efficiency under free disposability as β^F. Based on the discussion above, the impact of the food safety regulation on any firm j can be calculated as:

$$Difference_j = \vec{D}_o^F(L_j, K_j, y_j, u_j \mid (g_y, g_u)) - \vec{D}_o(L_j, K_j, y_j, u_j \mid (g_y, g_u)) \tag{16}$$

where $\vec{D}_o(L_j, K_j, y_j, u_j \mid (g_y, g_u))$ is the directional distance function under weak disposability of undesirable output as a solution of the linear programming problem contained in Equation (6). The loss of desirable output due to the regulation can be simply calculated; multiplying d_j by the observed level of desirable output $L_j = Difference_j \times y^j$. By multiplying by the price of desirable output, $L_j \times p_y$, the value of output loss due to food safety regulation can be obtained.

6. Data and Preliminary Results

6.1 Data

Firm-level data is optimal for data envelopment analysis. However, no firm-level data is currently available, thus the model is tested using State-level data. Each state is treated as one individual decision-making unit. Using 1997 US Economic Census data, desirable output and input data are recorded for the meat and poultry processing industry. Unfortunately, this data set is incomplete for certain of the 50 states. Hence, the analysis is restricted to 38 selected states which account for almost 95% of the value of processed meat and poultry shipments in 1997 (Table 1). Desirable output (Y) is defined as the value of shipments of processed meat and poultry products (NAICS 31162 and 311615) in dollar terms. Inputs are assumed to be total capital expenditure (K), labor (L) - production workers hours, and cost of material (M).

A proxy of undesirable output (U) is based on food safety recall data, namely the total amount pounds recalled (see Teratanavat and Hooker, 2004 for a discussion of this data). Food safety recall data used in the analysis were selected based on the production date rather than the date the recall was initiated to coincide with the 1997 census data. One immediate advantage of using food safety recall data as a proxy is that recalls can occur for not only microbial hazard reasons but also other potential hazard (chemical or physical). Therefore, broader aspects of food safety risk can be considered. However, given the voluntary nature of recalls and the State-level aggregation, caution must be taken when interpreting the preliminary results – provided here mostly to illustrate the directional distance function technique.

Table 1 Meat and Poultry Processing Industry Data for Selected States (1997)

Name	Meat & Poultry (Y) ($1,000)	Total Recall (U) (Pounds)	Total Capital Expenditure (K) ($1,000)	Total Hours Worked (L) (1,000)	Cost of Material (M) ($1,000)	Percentage of National Total (%)
UNITED STATES	**56,661,629**	**28,196,831**	**1,147,548**	**535,066**	**35,524,704**	**100.00%**
ARKANSAS	5,189,282	35,448	92,955	63,849	3,254,864	9.16%
GEORGIA	4,517,151	21,660	101,832	56,367	3,094,592	7.97%
TEXAS	4,190,465	580,560	60,073	35,268	2,505,192	7.40%
WISCONSIN	3,363,038	1,300,000	77,126	20,779	1,958,471	5.94%
NORTH CAROLINA	3,333,221	300,000	55,150	37,348	2,082,953	5.88%
IOWA	2,706,845	33,000	99,002	11,573	1,715,237	4.78%
MISSOURI	2,624,194	507	73,054	24,934	1,316,842	4.63%
CALIFORNIA	2,473,862		55,563	20,484	1,444,245	4.37%
ALABAMA	2,435,700		31,633	31,033	1,319,628	4.30%
PENNSYLVANIA	2,259,371	93,000	33,833	16,769	1,569,085	3.99%
ILLINOIS	2,122,069		42,818	12,114	1,309,543	3.75%
VIRGINIA	2,094,367	70	46,303	22,500	1,497,532	3.70%
MISSISSIPPI	1,672,070		29,972	27,873	1,009,276	2.95%
OHIO	1,591,391		37,353	10,097	1,061,623	2.81%
MINNESOTA	1,413,168	2,034	27,600	15,119	929,823	2.49%
NEW YORK	1,272,666	347	25,818	4,175	850,587	2.25%
TENNESSEE	1,022,024		18,492	10,565	748,611	1.80%
FLORIDA	909,950		17,703	7,954	639,410	1.61%
SOUTH CAROLINA	879,355		15,171	10,894	491,622	1.55%
NEBRASKA	848,321	25,736,428	15,806	6,548	563,046	1.50%
MICHIGAN	823,666		16,893	7,007	438,203	1.45%
INDIANA	741,251		10,772	7,146	477,034	1.31%
KANSAS	691,940		9,427	4,403	455,199	1.22%
OKLAHOMA	690,564	3,042	24,098	7,108	466,225	1.22%
MARYLAND	634,066		5,058	7,506	341,722	1.12%
NEW JERSEY	587,736		14,004	4,917	346,223	1.04%
MASSACHUSETTS	401,125	5,400	8,485	2,661	268,023	0.71%
KENTUCKY	396,720	3,924	5,235	1,826	181,823	0.70%
LOUISIANA	382,586		17,414	6,552	290,312	0.68%
WEST VIRGINIA	374,474	17,434	4,033	5,190	246,269	0.66%
WASHINGTON	303,564	1,877	6,621	1,726	176,270	0.54%
OREGON	186,994		5,028	1,741	119,217	0.33%
COLORADO	172,609	62,000	4,151	889	118,835	0.30%
CONNECTICUT	164,083		2,450	1,073	105,868	0.29%
RHODE ISLAND	41,543		826	300	23,518	0.07%
MONTANA	31,267		697	216	20,932	0.06%
ARIZONA	25,789		611	202	18,004	0.05%
HAWAII	15,244		332	141	7,378	0.03%
38 States	**53,583,731**	**28,196,731**	**1,093,392**	**506,847**	**33,463,237**	**94.57%**

Sources: 1) Economic Census 1997, US Census Bureau, Department of Commerce
2) Teratanavat and Hooker (2004)

In addition, as shown in Table 1, the majority of States saw no recalls in 1997, complicating the creation of an undesirable output measure and in violation of a model assumption (null-jointness). In order to account for this a censored estimation step has been included. A censored estimation model is applied, using Eviews, to estimate an expected volume of meat and poultry recalled by firms in each state (Uhat). This estimation result shows that labor is negatively related to recall volume while material is positively related. Including the capital data did not statistically improve the explanatory power of the model. This permits the use of Uhat rather than U in the remaining portions of the compliance cost estimation.

6.2 Estimation Procedures and Preliminary Results

In estimating the efficiency scores with or without food safety regulation, two linear programming problems with different constraints are solved using the data described above and the MATLAB Optimization Toolbox. Differences in efficiency scores with or without regulation were multiplied by the desirable outputs. In this case, the desirable output is real-valued so it is not necessary to multiply by the price of desirable output. As a result, it is possible to calculate the total sum of the value of potential output loss, $2,538,396,699.88, which is almost 5% of the value of shipment in meat and poultry processing industry.

6.3 Extending this Research

This analysis, we have explores how much the meat and poultry processing industry would have forgone to supply safer meat and poultry products by eliminating all recalls in 1997. Using both Census and food safety recall data aggregated to a State-level instead of firm-level data, a total value of potential output loss, $2.5 billion is estimated, through the reallocation of productive resources.

For a more interesting result this analysis will be extended using 2002 Census data. This will allow for the comparison of forgone revenue over time in addition to assessing productivity changes in the meat and poultry processing industry. However, for a more precise estimate firm-level, physical input-output, data would be optimal. Such a dataset is accessible at Census Research Data Center only upon the approval of the Census Bureau. In addition, an improved food safety risk measure needs to be developed to consider not only the volume of food safety recall but also the potential severity of the underlying hazard. Such a measure should combine science-based food risk assessment results in new measure of food safety risk.

7. Summary

An output directional distance function approach is useful in estimating changes in efficiency as well as the forgone revenue due to food safety regulation. A potential output loss in the meat and poultry processing industry of nearly $2.5 billion is suggested (based on 1997 data) for a hypothetical food safety regulation which reduced to the number of recalls. This technique can be extended to other applications based on the availability of indicators of undesirable output in food. Although this model simply assumes the existence of a food safety regulation without any explicit description of the form of the standard(s), it would be straightforward to characterize a particular regulation. For example, by adding constraints to the model the impact of a performance, process, or combined standard can be assessed. Most of all, this approach is ready for further analysis of science-based food safety regulations permitting the incorporation of risk assessment measures.

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