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# The Opportunity Cost 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 and the shadow price of food risk. Such measures 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. Further, comparing the implicit shadow price of food risk and willingness to pay for food safety can bridge the gap of understanding how valuable safer foods are from the perspective of two different market participants - consumers and firms respectively.

**Keywords**: food safety regulation, directional distance function, shadow price of food risk, compliance cost

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## 1. Introduction

Comparing the impact of regulatory options is an important task in risk management. One obvious role for economics in this context is the measurement of benefits and costs of food safety regulation. As part of such an assessment, this paper investigates a simple economic question: what is the opportunity cost of food safety regulation? In estimating such an impact of food safety regulation, both the cost of compliance and the effect of the regulation on the operating efficiency of firms should be considered (Antle, 2001). According to Antle (2001), there are three different approaches to estimate the 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. Yet these 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 efficiency due to refinements in the production process (Antle, 1996).

In order to answer the question raised above requires a focus be placed on the effect of the regulation on firm behavior. That is, loss in efficiency due to a regulation which reduces a firms' choice of behavior has a potential 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. 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 quality 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. This allows for the modeling of the technology producing desirable output while reducing undesirable output. With this assumption, an output directional distance function approach is employed to measure the 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 in the constraints. Second, risk in food can be explicitly included as an argument in the model. Thus, the research can make use of the result 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 a "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 the undesirable output appropriately. 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 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 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 used to calculate shadow prices of outputs under a weak output disposability assumption and a null jointness assumption[1]. Further, it has been shown that the reciprocal of 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). However, 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, et al. 1996; Chung, et al. 1997; Chambers, et al. 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, et al. (1998) show that the directional distance function is dual to the profit function. Using duality, Chambers, et al. (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.

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 utilizes radial distance functions. Measuring shadow prices of undesirable output Lee, et al. (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, et al. (1997), we first present a directional distance function and then discuss the selection of an appropriate reference vector.

### *3.1 Assumptions*

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

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

Weak disposability of undesirable output is imposed in the model.

**Assumption A1** (Weak Disposability of Undesirable Output)

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

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)

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

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)

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

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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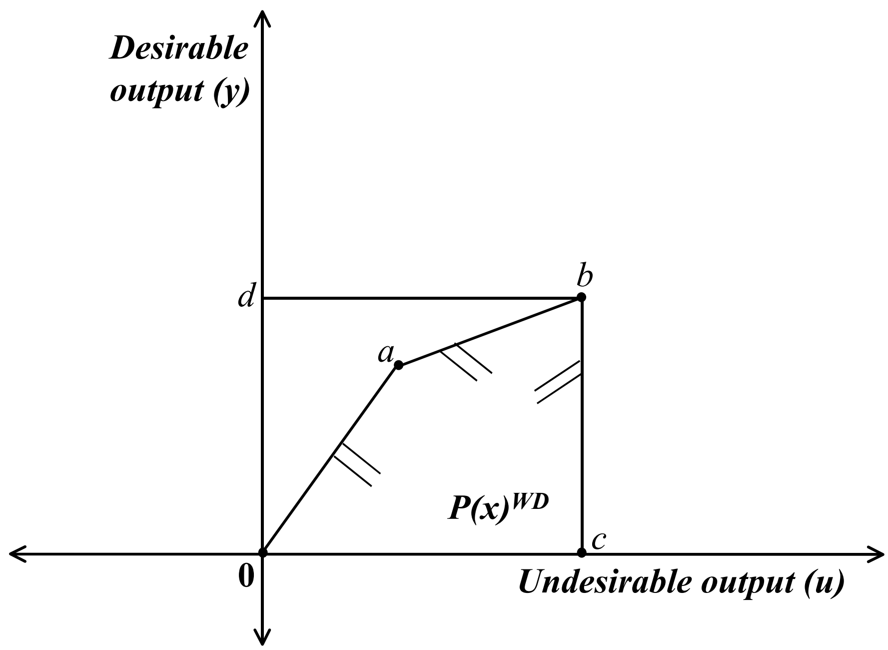


**Figure 1 Output Sets under Weak Disposability**

*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 $\boldsymbol{T} =\{(x, y, u): x \in \Re_+^{\mathrm{N}}, (y, u) \in \Re_+^M, x$ 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, et al. (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

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

where $\boldsymbol{g} = (g_y, g_u) \in \Re_+^M$ 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 that we have $I$ observations. For simplicity, we 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

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

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 $\boldsymbol{g}$, 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 $\boldsymbol{g}$ has been selected by the researcher. When undesirable outputs are considered, it is common to assume $\boldsymbol{g} = (-u, y) \in \Re^{m+m'}$ when $u \in \Re_+^{m}$ represents undesirable outputs, $y \in \Re_+^{m'}$ represents desirable outputs, and $m+m'=M$. 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 ($u_i$, $y_i$), using the the *i-th* firm's technology

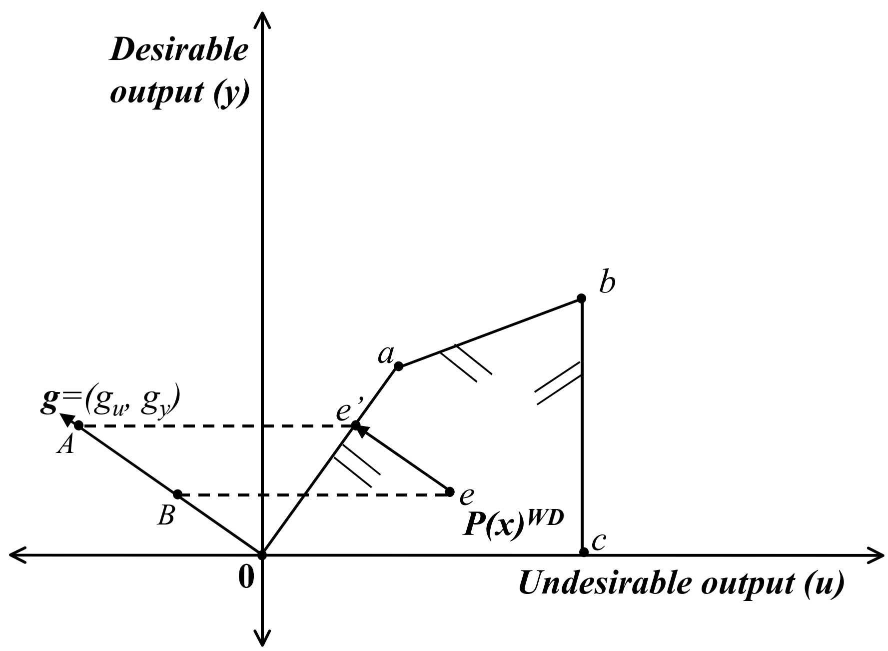


**Figure 2 Directional Distance Function**

*3.4 Dualities*

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

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

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

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

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

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

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

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

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

By 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 $p \cdot g_{\tilde{y}}$. Note that the revenue under regulation $(p_y \cdot y + p_u \cdot u)$ 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 $(= p_y \cdot y)$ 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 ***g*** with ($y$, $-u$), 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 $p \cdot g_y$ 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 direction vector of (*y, -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):

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

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 $p \cdot g_{\tilde{y}}$. For example, for the *m'-th* output case,

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

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

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

In the case of more than one output with a market price, use can be made of the observed revenue following Färe et al. (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.

## 4. Shadow Prices of Undesirable Outputs

**Assumption A4 (Production Possibility Curve)**

Suppose that the production possibility set *P(x)*, given an input vector $x$ , can be represented as the following function, $F: \Re^2 \rightarrow \Re$ which is differentiable.

$$F(u, y) = 0 \tag{14}$$

It is possible to represent the line tangent to this production possibility curve using the equation of the tangent plane to the level surface[5].

**Definition 4.1 (Tangent Plane to Level Surface)**

Following Marsden and Tromba (1996), the tangent line at the point ($u_0, y_0$) can be represented as follows.

$$\nabla F(u, y) \cdot (u - u_0, y - y_0) = 0 \quad if \ \nabla F(u, y) \neq 0 \tag{15}$$

Based on Assumption A4 and Definition 4.1, the tangent line to the production possibility curve at the point ($u_0 + \beta \cdot g_u, y_0 + \beta \cdot g_y$) can be derived.

$$\frac{\partial F(y_0+\beta g_y)}{\partial y}\cdot\left(y-(y_0+\beta g_y)\right)+\frac{\partial F(u_0+\beta g_u)}{\partial u}\cdot\left(u-(u_0+\beta g_u)\right)=0 \tag{16}$$

Denote $\partial F(y_0+\beta\cdot g_y)/\partial y$ as $F_y$ and $\partial F(u_0+\beta\cdot g_u)/\partial u$ as $F_u$. Rearranging the equation

$$y=-\left(\frac{F_u}{F_y}\right)\cdot b+\left\{\left(y-\frac{F_u}{F_y}\right)u_0+\beta\left(g_y+\frac{F_u}{F_y}\right)\right\} \tag{17}$$

Since the slope of the tangent line is equal to the price ratio at the revenue maximization point,

$$-\frac{F_u}{F_y}=-\frac{p_y}{p_u} \tag{18}$$

Note that Equation (18) states that the marginal rate of transformation equals the price ratio. Therefore, the unknown price ratio can be identified by the slope of the frontier.

In a nonparametric analysis of directional distance functions, there are two ways to measure the slope of the frontier. One uses the finite difference of outputs as proposed by Charnes et al. (1978). The other employs the dual value of the constraints of desirable and undesirable outputs in the linear programming problem as applied by Lee, et al. (2002). In this research, the latter method will be applied to recover the derivative of the frontier. Nevertheless, there appears to be no optimal way to measure the slope at the kinked points of the frontier.

## 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.

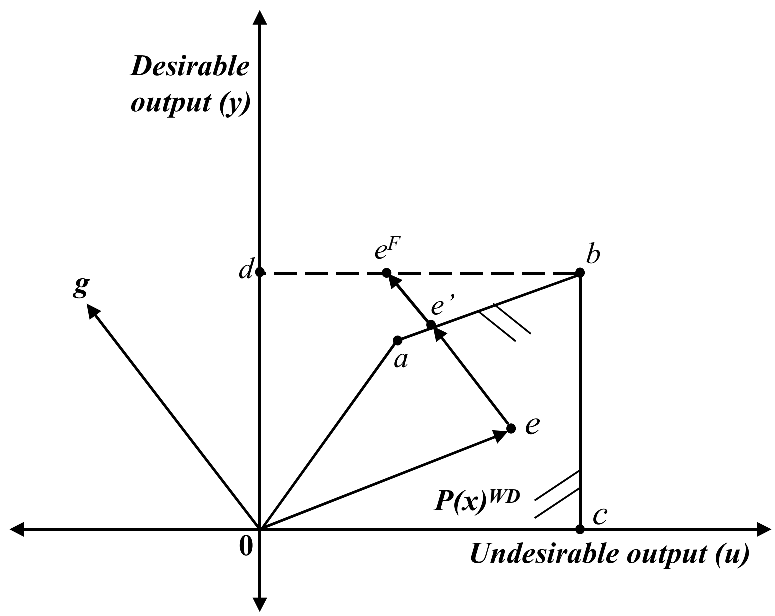


**Figure 3 Measuring the impact of food safety regulation**

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. More generally though, the directional distance function under free disposability of undesirable output for each firm *j* is as follows.

$$\vec{D}_o^F(L_j, K_j, y_j, u_j \mid (g_y, g_u)) = \max_{\beta} \beta^F \tag{19}$$

subject to

$$\begin{aligned}
&\sum_{i=1}^{I} z_i y_i \geq y_j + \beta^F g_y \\
&\sum_{i=1}^{I} z_i u_i \geq u_j + \beta^F g_u \\
&\sum_{i=1}^{I} z_i L_i \leq L_j \\
&\sum_{i=1}^{I} z_i K_i \leq K_j \\
&\sum_{i=1}^{I} z_i = 1 \\
&z_i \geq 0 \quad (i = 1, 2, \ldots, I)
\end{aligned} \tag{20}$$

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 $\beta^F$. Based on the discussion above, the impact of the food safety regulation on any firm $j$ can be calculated as

$$Difference_j = \vec{D}_o^F(L_j, K_j, y_j, u_j \mid (g_y, g_u)) - \vec{D}_o(L_j, K_j, y_j, u_j \mid (g_y, g_u)) \tag{21}$$

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 the price of desirable output, we can obtain the value of the output loss due to food safety regulation, $L_j \times p_y$.

## 6. Discussion

An output directional distance function approach is useful in estimating changes in efficiency as well as the forgone revenue due to regulation of food safety. This technique can be extended to other applications based on the availability of indicators of undesirable output such as chemical or physical hazards 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 the analysis of science-based food safety regulation permitting the incorporation of risk assessment measures.

In addition, a directional distance function approach may be applicable to consumer analysis. The recent trend towards a system level risk-based food safety approach requires the valuation of the benefits of food risk reduction (rather than hazard reduction). This approach must systematically integrate risk assessment models. In this sense, it is important to measure consumer benefits from food risk avoidance associated with specific pathogens in a range of food products. In addition to existing methodologies such as contingent valuation methods or auctions, a benefit function can be estimated using a directional distance function approach. Such a benefit function, originally discussed by Luenberger (1995), can represent the preference structure of consumers over possible states such as high or low foodborne risk (Quiggin and Chambers, 1998). One immediate advantage is, using one of the features of the benefit function (translation property), that a certainty equivalent and risk premium can be calculated. A food risk premium can play a counterpart role to the shadow price of food risk from the firm's side. For example, if the shadow price of food risk exceeds the risk premium, in the virtual market for food safety, the firm oversupplies food safety. Finally, the aggregate benefit function for a group of consumers can be defined by adding their individual benefits up (Luenberger, 1995). That is, it is possible to sum up the benefit functions across different types of consumers (sucha as the immuno-compromised) to get or aggregate measure of benefits, which can be an alternative way to measure willingness-to-pay.

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**Endnotes**

[1] A nonparametric analysis is also possible (see Färe, et al., 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, et al. (1998), based on the assumption of weak disposability of outputs, present a nonparametric analysis to estimate 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, et al., 1998).

[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.

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

[5] In this two dimensional case the equation of the tangent is a line, not a plane (Marsden and Tromba, 1996).