

Efficiency Analysis of the Companies in the U.S. Meat Industry

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Abstract

To cope with changes in industrial concentration, consumer preferences, more stringent meat safety measures by the governmental agencies, and the U.S.-Canada Free Trade Agreement and the North America Free Trade Agreement, companies in the U.S. meat industry need to attain as high levels of technical efficiency as possible. The purpose of the study is three-fold: (1) measure the level of pure technical efficiency and scale efficiency attained by the companies in the U.S. meat industry; (2) analyze the relationship between firm size and technical efficiency; and (3) estimate the association of major marketing and operational decision variables with the level of pure technical efficiency attained by the meat companies.

I. Introduction

Since the mid-1970's, there have been significant developments at all levels of the U.S. meat industry. The red meat packing industry has dramatically contracted both in terms of the number of meat companies and employment, while the poultry processing industry has been experiencing substantial sales growth, accompanied by increasing industrial concentration (Henry & Rothwell, 1995; Crom, 1988). Additionally, the meat companies have to meet the increasing changes in consumer preferences (Breidenstein, 1988). Also, the government agency, such as the Food Safety and Inspection Service (FSIS) of the U.S. Department of Agriculture, has implemented stricter measures to ensure meat safety (Karr, 1994; Brown, 1993; Putnam & Allshouse, 1992; Christensen, 1990; Lasley et al., 1988). Finally, the U.S.-Canada Free Trade Agreement (FTA) and the North American Free Trade Agreement (NAFTA) have brought not only competitors from Canada, but also expanding exports to Mexico (Veeman, 1994; Roson, 1993).

To cope with these changes, the companies in the U.S. meat industry need to attain as high levels of technical efficiency as possible. Higher technical efficiency will decrease the costs of production, which in turn will not only make the companies more competitive, but may also improve profitability.

The objective of this study is to evaluate the technical efficiency of firms in the U.S. meat industry. Specifically, the study will:

- 1) Measure the level of pure technical efficiency and scale efficiency attained by the companies in the U.S. meat industry;
- 2) Analyze the relationship between firm size and technical efficiency; and
- 3) Estimate the association of major marketing and operational decision variables with the level of pure technical efficiency attained by the meat companies.

Using a sample of firms in the U.S. meat industry, the study found that high levels of total inefficiency prevail among the firms in the sample. On average, firms in the sample produce about 53.7 percent of their potential output. Of the total output loss due to inefficiency, 60.9 percent is from pure technical inefficiency and 39.1 percent from scale inefficiency. Moreover, larger firms tend to be more totally efficient than smaller ones, evidenced by their actual output as the percentage of potential output. Finally, the study found that larger firms tend to be less pure technically inefficient and more scale inefficient.

The remainder of the paper is organized as follows. Section II reviews the extant literature on the theoretical and empirical issues of estimating the technical efficiency of a firm. Section III describes the methodology employed in this study. Section IV presents the empirical results and section V concludes the paper.

II. Literature Review

Traditionally, three functions of firm performance are of special interest to economists. They are: (1) production function, which gives the *maximum* possible output that can be produced from given quantities of a set of inputs; (2) cost function, which gives the *minimum* level of cost at which to produce certain level of output, given input prices; and (3) profit function, which gives the *maximum* profit that can be attained, given output price and input prices.

According to Forsund et al. (1980), the concept of *frontier* is important to each of the above economic functions. *Frontier* is used to set a limit of the range for possible observations. Thus, for example, one may observe points below the production frontier, which means the firm produces less than maximal possible output, but no points can lie above the production frontier. This concept can be similarly applied to cost or profit frontiers. Furthermore, inefficiency is regarded as the amount by which a firm lies below its production or profit frontiers, or the amount by which it lies above its cost frontier. Thus, the measurement of inefficiency has been the main motivation for the study of frontiers.

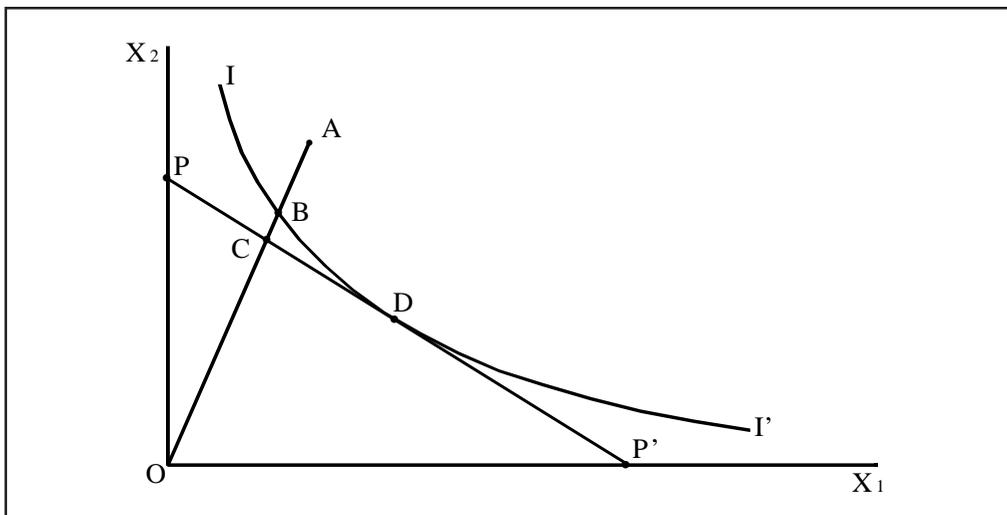
This section is a review of the literature to date on the measurement of *efficiency*. The focus will be on the use of the frontier production function approach in estimating inefficiency, the procedure selected for use in this paper.

Theoretical Issues

The literature covered in this subsection pertains to the various approaches to the estimation of frontier production functions. Although both cost and profit functions have also been used to estimate efficiency through frontier functions, only the frontier production function will be discussed because it is the empirical basis for this paper.

The work of frontiers and efficiency measurement began with Farrell (1957). Farrell showed how the production function could be used in the calculation of both the technical and allocative efficiency of a firm. He demonstrated his theory by assuming a firm which uses two inputs to produce one output, and whose production function is characterized by constant returns to scale. Suppose a firm uses two inputs X_1 and X_2 to produce output Y , and its production function (frontier) is $Y = f(X_1, X_2)$. In Figure 1, II' represents the isoquant of output Q^0 , and the firm is operating at point A to produce Q^0 output.

Figure 1. Farrell Efficiency



Point *B* on the isoquant represents the technically efficient combination of input *X1* and *X2* which is in the same proportion as that of the firm but can not be further reduced in order to produce Q^o output. Farrell described the technical inefficiency of the firm as OB/OA . $(1-OB/OA)$ represents the maximum amount by which the firm can reduce its inputs proportionally and still produce Q^o . Additionally, assume that line PP' represents the firm's expenditure on inputs given the prices of inputs *X1* and *X2*. Thus, point *D*, where the expenditure line is tangent to the isoquant, is the cost minimizing point of producing output Q^o . Farrell showed that the allocative or price inefficiency is given by OC/OB . $(1-OC/OB)$ is the relative reduction in cost that a technically efficient firm can incur to produce Q^o at the minimum cost. Finally, OC/OA represents overall or economic efficiency. It measures the relative savings that can be expected if the firm uses the optimum combination of inputs (a move from point *A* to point *D*).

The primary advantage of Farrell's approach is that his mathematical programming procedure to frontier estimation does not impose any functional forms on the data. Also, estimates of efficiency can be calculated for individual firms. However, there are some disadvantages to this approach. First, the assumption of constant returns to scale is restrictive, and its extension to non-constant returns to scale technologies is cumbersome (Farrell & Fieldhouse 1962; Seitz 1971). Additionally, the frontier is estimated from a supporting subset of observations from the sample, and is therefore very susceptible to extreme observations and measurement error. Finally, the parameters estimated have no statistical properties.

Following Farrell's work, Aigner and Chu (1968) specified a homogeneous Cobb-Douglas production frontier, and required that all observations be on or beneath the frontier. Their model can be written as:

$$\ln y = \ln f(x) - u = \alpha_0 + \sum \alpha_i \ln x_i - u \quad ; \quad u \geq 0, \quad (1)$$

where *y* is output; *x* is the input mix; x_i is the *i*th input; and *u* is the one-sided error term. Because *u* cannot be negative, all observations should be on or below the production frontier. To obtain the estimation of parameters, they suggested using either linear programming, which minimizes the sum of the absolute values of the residuals, or quadratic programming, which minimizes the sum of squared residuals. Both methods require that each residual be non-positive.

The work of Aigner and Chu (1968) allows for a reduction of the frontier production technology into a simple mathematical form. It also relaxes Farrell's assumption of constant returns to scale. However, this approach imposes a limitation on the number of observations that can be technically efficient. The estimated frontier is still very sensitive to outliers. A final problem with this approach is that the parameters to be estimated have no statistical properties.

An alternative method to estimate the production frontier was first proposed by Richmond (1974). He still used the linear Cobb-Douglas function, but made some adjustments to the error term. His model can be specified as:

$$\ln y = (\alpha_0 - \mu) + \sum \alpha_i \ln x_i - (u - \mu) \quad ; \quad (2)$$

where *y* is output, x_i is the *i*th input, *u* is the one-sided error term ($u \geq 0$), and \hat{i} is assumed to be the mean of *u*. Thus $(u - \hat{i})$ has a mean of zero. Equation (2) can then be estimated by ordinary least squares method (OLS) to obtain the best linear unbiased estimates of $(\hat{\alpha}_0 - \hat{i})$ and of the $\hat{\alpha}_i$'s. This procedure provides consistent estimates of all of the parameters of the frontier, and is called the corrected OLS, or COLS.

Another way of estimating the frontier is through what is called the stochastic frontier approach. The essential idea behind the stochastic frontier model (see Aigner et al., 1977; Meeusum & Vanden Broeck, 1977) is that the error term is composed of two parts. The first part is a symmetric component which permits random variation of the frontier across firms, and captures the effects of measurement error, the random shocks outside the firm's control, and other statistical noise. The second term is a one-sided component which captures the effects of the inefficiency relative to the stochastic frontier. The stochastic production frontier model can be written as:

$$Y = f(x) \cdot e^{\hat{a}} \tag{3}$$

with $\hat{a} = v - u$.

The composed error term \hat{a} consists of v , which captures the statistical noise with a normal distribution with mean 0 and variance σ , and of u , which is a non-negative error term representing inefficiency relative to the stochastic production frontier.

The stochastic frontier $f(x) \cdot \exp(\hat{a})$ can be estimated by using either COLS or the maximum likelihood estimation (MLE) method. The major advantage of this approach is that it takes into consideration the factors that are not under the control of the firm, such as weather, luck, and statistical noise. However, it is hard to decompose individual residuals into these two components, and therefore is not possible to estimate technical inefficiency by observations.

In the early stage of econometric analysis of efficiency, homogeneous production functions are commonly used. But since this class of functions can only model very simple technologies, others have been developed. Shephard (1953) introduced the class of homothetic functions, which allows returns to scale to vary with output but not with the input mix. Timmer (1971) introduced the class of ray-homogeneous functions, in which returns to scale can vary with input mix but not with output. Afriat (1972) combined these two classes of functions to obtain the class of ray-homothetic functions, which allow returns to scale to vary both with output and with the input mix. Specific parametric forms for the ray-homothetic function were proposed by Fare et al. (1985), among others, and have since been used extensively (Grabowski & Belbase, 1986; Aly et al., 1987; El Osta et al., 1990; Neff et al., 1991) in the estimation of deterministic statistical frontier production functions.

It is apparent from the above theoretical literature review that each approach to estimating the frontier function has its advantages as well as its disadvantages. It would therefore be hard to say that one approach is better than another since different approaches might be better suited to different situations. In this study, a ray-homothetic deterministic statistical frontier function will be used to measure the inefficiency in the production of meat industry. This approach is used because of its simplicity, and also because of its ability to provide consistent observation-specific measures of technical and scale efficiency.

Empirical Issues

This subsection discusses some empirical issues with the use of ray-homothetic production functions. This approach allows for the possibility that at low output level, the firm shows increasing returns to scale, at a certain output level is constant, and beyond that level decreasing returns to scale prevail.

The ray-homothetic production function can be written as:

$$\Phi(\lambda x) = F(\lambda^{H(x/\|x\|)}) \cdot F^{-1}(\Phi(x)) \tag{4}$$

where x represents the input vector; $\ddot{O}(x)$ is the maximum output attainable from x ; $\|x\|$ denotes the norm of x ; $\ddot{\epsilon} > 0$; and F is a monotonically increasing transformation of $F(\bullet)$. If F is the identity function, then

$$\Phi(\lambda x) = \lambda^{H(x/\|x\|)} \cdot \Phi(x) \tag{5}$$

where $H(x/\|x\|) \geq 0$. Timmer (1971) demonstrated that function (5) represents a ray-homogeneous production function. If $H(x/\|x\|)$ is positively constant for all values of x , then equation (5) becomes a homogeneous production function, and equation (4) becomes a homothetic production function (Shephard 1953). Therefore, the homothetic, homogeneous, and ray-homogeneous functions are special cases of equation (4) (Aly et al. 1987).

The returns to scale function, or elasticity of scale, is defined as:

$$E(x) = \lim_{\lambda \rightarrow 1} \left[\frac{\partial(\phi(\lambda x))}{\partial \lambda} \bullet \frac{\lambda}{\phi(\lambda x)} \right]. \quad (6)$$

Fare demonstrated that the elasticity of scale can also be calculated as the sum of the output elasticity of each input factor:

$$E(x) = \sum e_i(x) \quad , \quad (7)$$

with

$$e_i(x) = \frac{MP_i(x)}{AP_i(x)}. \quad (8)$$

Optimal output of the firm is achieved when the firm experiences constant returns to scale, and therefore, it can be obtained by assuming $E(x) = 1$ in equation (7).

Fare and Yoon (1985) employed the ray-homothetic function in their study of returns to scale and optimal scale of output in the United States coal mining industry over time. The ray-homothetic function they used can be written as:

$$Y = \ln \Phi + a_g \ln G + a_k \frac{K}{K+L} \ln K + a_l \frac{L}{K+L} \ln L + u, \quad (9)$$

where Y represents the mine output; K denotes the quantity of capital used; L denotes the quantity of labor used; G represents the geological condition of the mines and is not considered to be an input; u is the error term and is normally distributed; and Φ is a dummy variable which reflects regional variation and also includes the intercept, i.e.,

$$\Phi = e^{(d_1 + d_2 \text{Midwest} + d_3 \text{West})}. \quad (10)$$

The parameters in equation (9) are estimated by ordinary least squares method (OLS). They are then substituted into the returns to scale function:

$$E = \frac{\left(\frac{a_k K + a_l L}{K + L} \right)}{Y}. \quad (11)$$

If $E > 1$, then the firm is experiencing increasing returns to scale, while $E = 1$ implies constant returns to scale, and $E < 1$ decreasing returns to scale. By assuming $E = 1$ and solving equation (11) for Y , which is optimal scale of output, we can get:

$$OPT(Y) = \frac{a_k K + a_l L}{K + L}, \quad (12)$$

where $OPT(Y)$ is the optimal scale of output of the firm using its specific mix of inputs.

Andre (1995) employed the same technique to measure the technical inefficiency among a sample of Florida and California grapefruit growers, using the deterministic statistical frontier estimated by the corrected ordinary least square (COLS). The model he used is similar to that by Fare and Yoon (1985). The author used seven inputs in his model, namely, labor, capital, fertilizer, chemicals, custom works, energy, and interest. The COLS approach was used to obtain the production frontier. In the COLS procedure, the production function was first estimated using ordinary least square (OLS) method. The intercept was then “corrected” by shifting the function up until no residual is positive and at least one is zero. This production frontier represented the technically efficient output the firm could have produced. Andre found that both Florida and California fresh grapefruit growers were very inefficient, with Florida growers more efficient than those of California.

Other authors (Neff et al., 1991; El Osta et al., 1990; Aly et al., 1987; Grabowski & Belbase, 1986) used the same technique to measure the technical efficiency in agriculture, both in the United States and abroad, using both cross-sectional and/or time series data. The simplicity and flexibility of the ray-homothetic efficiency method have made it widely used in many of the studies recently completed.

III. Methodology

In this study, a ray-homothetic (RH) frontier production function is used to estimate the pure technical and scale efficiency of the meat industry in the United States. First, the ray-homothetic frontier production function of the meat industry is estimated using the corrected ordinary least square method (COLS). Second, the technical and scale efficiency measures are calculated from the estimated production frontier. Finally, major marketing and operating decision variables are regressed against the pure technical efficiency index to characterize variations in the measure.

The empirical model of the ray-homothetic function used in this research is specified as:

$$Y = \beta_0 + \beta_1 C' \ln C + \beta_2 M' \ln M + \beta_3 D' \ln D + \beta_4 I' \ln I + \varepsilon \quad (13)$$

with,

$$C' = \frac{C}{C + M + D + I},$$

$$M' = \frac{M}{C + M + D + I},$$

$$D' = \frac{D}{C + M + D + I},$$

$$I' = \frac{I}{C + M + D + I},$$

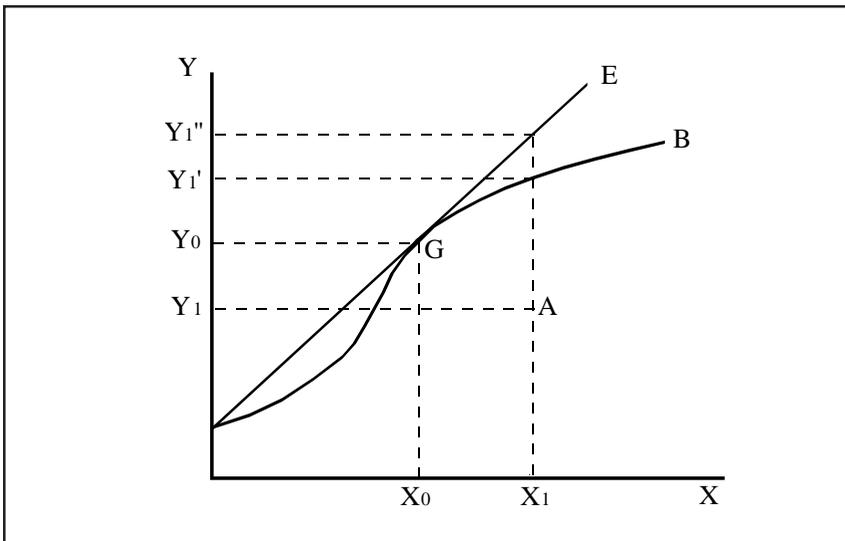
where Y is the total revenue (net sales) of the firm, C is the cost of processing, M is the marketing and administration expenses, D is the depreciation expenses of fixed assets, and I is the interest expense. C' , M' , D' , and I' are the individual input share of total inputs. The $\hat{\alpha}$'s are the parameters to be estimated, and $\hat{\alpha}$ is the disturbance term.

The corrected ordinary least squares (COLS) procedure is used to determine the extent of pure technical inefficiency. Equation (13) is first estimated using OLS. The intercept is then corrected by moving the function upward until no residual is positive and at least one is zero. This corrected function gives the technically efficient output of the firms. The pure technical efficiency index of the firm can then be calculated by taking the ratio of its actual output to its technically efficient output.

The discussion above can be illustrated using Figure 2. The X axis measures the vector of inputs (where movements along the axis represents equa-proportional changes in all inputs), and the Y axis denotes output. Production function B represents the estimated ray-homothetic function whose intercept has been corrected. Firm 1 uses X_1 of inputs and produces an actual output of Y_1 (point A). The firm's technically efficient output is Y_1' , which is on the ray-homothetic production frontier, thus the ratio of Y_1/Y_1' measures the percentage by which actual output falls short of the technically efficient output. Therefore, the pure technical efficiency index ($PTEI$) can be calculated by:

$$PTEI = \frac{Y_1}{Y_1'} \quad (14)$$

Figure 2. Illustration of Technical Efficiency



In addition to pure technical inefficiency, the ray-homothetic function also allows for the possibility of scale inefficiency. Scale inefficiency occurs when a firm operates at non-constant returns to scale. An intuitive explanation of scale inefficiency is presented again using Figure 2. Production function E represents a constant returns to scale function which is tangent to function B at point G , the optimal scale for function B . If firm 1 had used input vector X_1 and achieved constant returns to scale, output would have been Y_1'' . If there were no pure technical inefficiency, actual output would be Y_1' . Therefore, the scale inefficiency can be measured by the scale efficiency index (SEI):

$$SEI = \frac{Y_1'}{Y_1''} \quad (15)$$

As we have already calculated Y_1' (the technically efficient output), to calculate the scale efficiency index, we need to know Y_1'' (the scale efficient output). Following Aly et al. (1987), a simple procedure is developed here. After we estimate the parameters in equation (13), we substitute them into the returns to scale function:

$$E = \frac{\beta_1 C' + \beta_2 M' + \beta_3 D' + \beta_4 T'}{Y} \quad (16)$$

If $E > 1$, the firm is experiencing increasing returns to scale; $E = 1$, constant returns to scale; and $E < 1$, decreasing returns to scale. By assuming $E=1$ and solving equation (16) for Y , we can get the optimal scale of output Y^* , which is:

$$Y^* = \beta_1 C' + \beta_2 M' + \beta_3 D' + \beta_4 I' \quad (17)$$

Multiplying all inputs in equation (13) by \ddot{a} , a constant, and setting equation (13) equal to the optimal level of output Y^* , we get:

$$Y^* = \beta_0 + \beta_1 C' \ln(C \cdot \delta) + \beta_2 M' \ln(M \cdot \delta) + \beta_3 D' \ln(D \cdot \delta) + \beta_4 I' \ln(I \cdot \delta) + \dot{a} \quad (18)$$

Here, \ddot{a} is the number by which we would have to multiply all inputs if the optimal level of output were to be produced. Solving for \ddot{a} gives:

$$\ln \ddot{a} = \frac{Y^* - Y}{\beta_1 C' + \beta_2 M' + \beta_3 D' + \beta_4 I'} \quad (19)$$

Substituting equation (17) into equation (16) and equation (19) gives:

$$\ln \ddot{a} = \frac{Y^* - Y}{Y^*} = 1 - \frac{Y}{Y^*} = 1 - \frac{1}{E} \quad (20)$$

Therefore:

$$\ddot{a} = e^{(1 - Y/Y^*)} = e^{(1 - 1/E)} \quad (21)$$

In Figure 2, point G represents the firm which produces at the optimal scale, using XO inputs and producing YO output. For firm 1, which was operating at decreasing returns to scale, the potential output can thus be calculated by:

$$Y_1'' = Y_0 + \frac{1 - \ddot{a}}{\ddot{a}} Y_0 \quad (22)$$

For firms experiencing increasing returns to scale, the potential output for these firms would be:

$$Y_1'' = Y_0 - \frac{\ddot{a} - 1}{\ddot{a}} Y_0 \quad (23)$$

Additionally, we can find the total output lost (the difference between the potential output Y_1'' and the actual output Y_1), the part of total output loss due to pure technical inefficiency (the difference between the technically efficient output Y_1' and the actual output Y_1), and the part due to scale inefficiency (the difference between the potential output Y_1'' and the technically efficient output Y_1').

The last part of methodology of this study is to estimate the association of major marketing and operating decision variables with the level of pure technical efficiency of the firms. In this part, pure technical efficiency index is regressed against these variables, and the marginal effect of each independent variable is then estimated. Because of the truncated dependent variable, instead of using a linear model, a model employing the logistic functional form is used in the analysis.

In applying this analysis, however, several factors should be taken into consideration. First, for a meat company, it is important to decide whether to incorporate poultry slaughtering and processing operations into its business. The poultry industry is characterized by high degree of industrial concentration, which means the barriers to significant entry into the industry are relatively high. On the other hand, total sales from poultry products have increased dramatically during the last two decades, and the technology of poultry slaughtering is readily accessible. Therefore, incorporating poultry slaughtering and processing operations may still increase the firm's technical efficiency.

Second, meat firms should consider whether to incorporate meat packing facilities into their operations. Some firms in the sample do not have meat packing facilities, but rather process packed meat

purchased from meat packers. These firms realize that the costs of the packed meat would be higher if they operate their own meat packing facilities. But other firms in the sample have their own meat packing facilities. Through vertical integration, the firms can control the margin and the technical inputs at all levels to lower production costs. Therefore, it is expected that vertical integration in the red meat production may increase the firm's technical efficiency.

Third, branding the products is a relatively new concept in the meat industry. Indeed, unless strict laboratory tests are conducted, it is not easy for consumers to tell from appearance the difference in quality among meat products of different firms. For firms which mainly sell their meat products to institutional customers, branding their products may not greatly enhance the revenues. However, at retailing store, branded meat could establish the image of good quality. Brester and Schroeder (1995) found that branded beef and poultry advertising had increased total meat consumption. In this study, estimation of the association between branding advertising and pure technical efficiency will be conducted.

Finally, it would be interesting to study whether diversification can help increase productivity. For a well-diversified company, the lower than expected rate of return of one product can be made up with higher than expected rate of return of another product, and on average the firm gets the market rate of return. However, this reduction of risk is achieved at the expense of specialization in a particular field. Therefore, in the meat industry, it will be interesting to find out whether the firm's diversification into several types of meat is associated with higher technical efficiency.

The statistical model used in this study is specified as:

$$\log\left(\frac{PTEI}{1-PTEI}\right) = \hat{a}_0 + \hat{a}_1 SL + \hat{a}_2 PP + \hat{a}_3 BRD + \hat{a}_4 SGL + \hat{a} \quad (24)$$

where *PTEI* is the pure technical efficiency index. All the explanatory variables are dummy variables. The value of 1 for *SL* means the firm has chicken slaughtering and processing operations and 0 means it does not; 1 for *PP* means the firm has meat packing facilities and 0 means it does not; 1 for *BRD* means the firm brands its meat products and 0 means it does not; and 1 for *SGL* means the firm concentrates on a single type of meat and 0 means its output consists of two or more kinds of meat. The \hat{a} 's are the parameters to be estimated, and \hat{a} is the error term.

After estimating the parameters, the *PTEI* can be estimated as:

$$PTEI' = \frac{e^{\hat{a}'X}}{1+e^{\hat{a}'X}}, \quad (25)$$

where *PTEI'* is the estimation of *PTEI*, \hat{a} is the matrix of coefficients, and *X* is the matrix of dummy variables. According to Byrne (1994), because the coefficients of the logit model are not directly interpretable, the marginal effects (ME) of the dummy variables are calculated as:

$$ME_i = (PTEI' \text{ for } x_i = 1) - (PTEI' \text{ for } x_i = 0) \quad (26)$$

where *ME_i* is the estimation of the marginal effects of dummy variable *x_i* on the pure technical efficiency index.

IV. Empirical Results

Both cross-sectional and time series data are used in this study. The data are collected from the annual financial statements from 1992-2001 of all fifteen publicly held companies in the U.S. meat industry (SIC code of 2011, 2013 and 2015). Therefore, there are 150 firm-year observations in the model. The variables used to estimate the models are collected from the Compustat database and Datastream. Although most of the companies in the meat industry have diversified into businesses other than producing meat products,

we noticed that annual net sales from meat products accounted for more than 75 percent of total sales for each firm-year used in this study. The summary statistics for the variables used in the ray-homothetic production function are presented in Table 1.

The results of the ordinary least square (OLS) estimation of the ray-homothetic function (equation [13]) are presented in Table 2. As can be seen, all parameter estimates are significant at the 95 percent confidence level. The value of R² shows that about 85 percent of the variations in the dependent variable can be explained by the model. Tests of heteroskedasticity are also conducted and the results show that heteroskedasticity is not present in the estimation.

Table 1. Summary Statistics for a Sample of U.S. Meat Companies

<i>Variable</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Minimum</i>	<i>Maximum</i>
Sales (in millions of \$)	489.947	377.234	30.080	1,200.512
Processing Cost (in millions of \$)	404.414	315.143	26.575	973.685
Mkt&A (in millions of \$)	44.574	34.538	3.897	766.500
Depr. Exp. (in millions of \$)	23.814	21.202	0.780	294.000
Interest Exp. (in millions of \$)	9.962	12.365	0.002	147.000
C'	0.820	0.087	0.556	0.921
M'	0.120	0.089	0.033	0.418
D'	0.042	0.024	0.008	0.143
I'	0.018	0.018	0.000	0.079
C'lnC	10.180	1.652	5.660	12.212
M'lnM	1.241	0.923	0.321	4.136
D'lnD	0.415	0.267	0.054	1.476
I'lnI	0.167	0.185	0.000	0.748

Note: *C* represents *Processing Costs*; *M* is *Marketing and Administration Expenses*; *D* is *Depreciation Expenses*; *I* is *Interest expenses*; *C'* is input share of *C*; *M'* is input share of *M*; *D'* is input share of *D*; and *I'* is input share of *I*.

It should be noted that the ray-homothetic function is estimated using 10 yearly observations of all 15 firms in a single OLS regression. Since this is essentially a balanced panel data set, it is necessary to examine whether the firm effect and/or time effect would potentially affect the regression results of OLS. To examine the firm effect, fifteen dummy variables are introduced in equation (13), each corresponding to each individual firm. The new model is usually referred to as the least squares dummy variable (LSDV) model (see Greene 2000, 560). The OLS is run on this new model and a test is performed to examine the null hypothesis that the fifteen dummy variables are not different from one another. The Pr for the F value from the regression to test this hypothesis is 0.2355, and therefore we fail to reject the null hypothesis at any conventional level that there is no significant firm effect in the model. Furthermore, the four variables of interest continue to be statistically significant, and the R² has moderately increased from 0.843 to 0.865. This analysis suggests that the results in Table 2 are not likely due to the differences among the firms in the regression. This is not surprising since these firms are well-established public companies operating in the same industry (i.e., meat industry). It is therefore reasonable to believe that the operating environments are similar across these firms.

This also corroborates the common practice that in the paired-match sample research design, an experimental firm's pair (i.e., comparable firm) is invariably selected within the same industry.

A similar analysis is conducted to examine whether the time difference could affect the results in Table 2. It is found that the results continue to hold after controlling for the time differences. A possible explanation is that since the sample period covered in the study (1992-2001) is generally characterized by stable growth of the whole U.S. economy without major disturbances, the companies' operating environments can be considered to be relatively stable. It is also unlikely that the burst of technology bubble in early 2000 has had much negative impact on the operations of the *meat* industry. Overall, the results in Table 2 are not likely due to the differences in the firms or years of the data set used in the regression.

Table 2. Regression Results from Estimating the Ray-Homothetic Function

Variable	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
Intercept	-3652.567	266.338	-13.714	0.0001
C'lnC	344.500	22.413	15.371	0.0001
M'lnM	390.115	40.007	9.751	0.0001
D'lnD	280.387	83.038	3.377	0.0014
I'lnI	266.160	120.490	2.209	0.0314
Adj. R-square = 0.843				
n = 150				

The results of efficiency measures for each size group are presented in Table 3. As can be seen in the table, as firm size in terms of net sales increases, actual output as a percentage of potential output increases. This study also found that the composition of total inefficiency changes systematically: as firm size increases, pure technical inefficiency decreases and scale inefficiency increases. This pattern is similar to that found by Neff et al. (1991) and Aly et al. (1987).

The final part of this study is to identify major marketing and operating decision variables and to estimate their relationship with the level of technical efficiency. Using equation (24), pure technical efficiency index is regressed against the following dummy variables: whether the firm has poultry slaughtering and processing operations (SL), whether it has meat packing facilities (PP), whether it brands its meat products (BRD), and whether it concentrates on single kind of meat (SGL).

Table 3. Efficiency Results by Size Group for a Sample of Firms in the U.S. Meat Industry

Size Group (Net sales; \$000)	A	<160,000	160,000~750,000	>750,000	Total
Number of Firms	B	50	50	50	150
Actual Net Sales (Mean; \$000)	C	99,706	449,939	941,873	489,946
(% of potential output)	C/E	-25%	-47.90%	-74% -53.70%	
Tech. Eff. Output (Mean; \$000)	D	354,651	822,068	1,086,985	747,297
Potential Output (Mean; \$000)	E	397,525	939,368	1,429,086	912,457
Total Output Loss	F=E-C	297,819	489,429	487,213	422,511
Pure Tech. Ineff. (Mean; \$000)	G=D-C	254,944	372,129	145,111	257,351
(% of total output loss)	G/F	-85.60%	-76.00%	-29.80%	-60.90%
Scale Inefficiency (Mean; \$000)	H=E-D	42,873	117,299	342,102	165,160
(% of total output loss)	H/F	-14.40%	-24.00%	-70.20%	-39.10%
PTE Index (Mean)	I=C/D	0.28	0.55	0.86	0.65
SE Index (Mean)	J=D/E	0.89	0.87	0.76	0.82
RTS Ratio (Mean)	K	4.23	1.58	0.37	1.9

The results of the estimation are presented in Table 4. As shown in the table, all of the parameters are statistically significant at the 95 percent confidence level. Also, the model can explain about 73 percent of the variation in the dependent variable.

Table 4. Regressing Results for the Logistic Analysis

Variable	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
Intercept	-2.044	0.255	-8.003	0.0001
SL	0.954	0.187	5.096	0.0001
PP	0.362	0.178	2.040	0.0466
BRD	1.624	0.244	6.665	0.0001
SGL	0.650	0.232	2.807	0.0071
Adj. R-square = 0.7045				
n = 150				

The estimates of marginal effects of the dummy variables on the pure technical efficiency are summarized in Table 5.

Table 5. Summary Estimation of Effects of Dummy Variables on PTEI

Variable	Marginal Effects on PTEI
SL	0.1865
PP	0.1165
BRD	0.1420
SGL	0.1040

The estimation of marginal effects of the dummy variable SL is 0.1865, which means that firms with poultry slaughtering and processing operations tend to have higher pure technical efficiency than those without. Because the technology of poultry slaughtering is readily accessible, the firms may not be constrained by technological problems and the output can accordingly be enhanced.

The estimation of the coefficient of the dummy variable PP is 0.1165, which means that firms with meat packing facilities are experiencing higher technical efficiency than those without meat packing facilities. Even though there is a high degree of concentration in the U.S. meat packing industry, smaller meat packing firms can still achieve sufficient levels of technical efficiency mainly because of the local market structure of red meat product. Local meat markets are mostly based on live or freshly produced meat products. Therefore, even though the improvements in meat packing technology can allow larger firms to get access to the local markets at acceptable transportation costs, smaller companies can still survive because of their shorter distance from the local markets.

Firms that brand their meat products also have a higher pure technical efficiency value on average. Although branding the firm's products can cause higher promotion expenses, branded products usually indicate good quality and therefore can carry higher prices. Besides, brand loyalty may also cause increased revenues.

Branded products may be repetitively purchased if consumers have had delightful experience with them. Therefore, branding advertising can increase revenues without significantly increasing other inputs.

Finally, firms which concentrate on single kind of meat tend to have higher technical efficiency values than those which produce products of more than one kind of meat. These "single meat" firms might have taken advantage of specialization in their production process. The findings here also indicate that diversification may not be a sign of higher technical efficiency.

V. Conclusions

In this study, the corrected ordinary least square method (COLS) is used to assess the technical inefficiency among 15 publicly held companies in the U.S. meat industry during 1992 -2001. A ray-homothetic form of production function is used to estimate the production frontier. This approach allows to determine the extent of technical inefficiency, and to determine the proportion of the total inefficiency due to pure technical inefficiency and scale inefficiency.

On average, firms in the sample produce about 53.7 percent of their potential output. Of the total output loss due to inefficiency, 60.9 percent is from pure technical inefficiency and 39.1 percent from scale inefficiency. Moreover, larger firms tend to be more totally efficient than smaller ones, evidenced by their actual output as the percentage of potential output. The study also found that larger firms tend to be less pure technically inefficient and more scale inefficient.

Two explanations can be argued for the reasons why larger firms are more totally efficient than smaller ones. First, larger firms tend to adopt the most recently developed technologies faster than smaller firms. This may very well be due to the fact that larger firms have better access to credit, information, and other scarce inputs than smaller firms (Aly et al., 1987). Second, larger firms may also have a better capacity for bearing risks, and thus can take on more risky and innovative projects.

The study also found that high levels of total inefficiency prevail among the firms in the sample. This can be partly explained by the procedure involved in this study. First, the use of COLS approach, which captures all deviations from the frontier as inefficiency, may be too sensitive to outliers. Even after eliminating several observations that seem to be dramatically different from the sample, the research still found large levels of inefficiency. Second, the specification of the ray-homothetic function appears to be imposing rather high levels of decreasing returns to scale for larger firms (Neff et al., 1991). This occurs because of the form for returns to scale function of the ray-homothetic function. In equation (16), the input share is relatively constant for larger firms, while the returns to scale ratio is inversely related to output. As a result, for larger firms, higher levels of scale inefficiency tend to offset the increase in pure technical efficiency.

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