A CROSS-COUNTRY COMPARISON OF EFFICIENCY OF FIRMS IN THE FOOD INDUSTRY.

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Abstract

Stochastic frontier analysis is used to determine the relative efficiency of firms in the food industry in industrialized countries. Using panel data analysis, the firm-specific factors, firm-size, the corporate tax rate and number of years of operation and country-specific effects as potential sources of efficiency are investigated. Relevant implications are discussed.

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The food industry is characterized by differentiated products and economies associated with size, scope, and scale of operations. These characteristics differentiate the impacts of international commerce in processed foods from those associated with international specialization and the theory of comparative advantage. Rivalry among sellers in the marketplace encourages efficiency and competitive prices, so consumers benefit from the availability of a wider array of products (U.S. Department of Agriculture, ERS, September 1997).

This relative efficiency of firms in the food industry across various countries is an issue of considerable interest to managers engaged in or considering exporting their products. As businesses grow and local markets become saturated, interest in trade possibilities with other countries increases. Krugman (1995) indicates the possibility of capturing economies of scale in finely differentiated markets provides an incentive for most trade to be limited to firms within the food industry among similar developed countries. This has resulted in an increase in intra-industry trade in the food industry across industrialized countries and increased efficiency of firms in the industry.

Knowledge of factors that enhance the efficiency of firms is vital information needed by managers to ensure that firms earn profits. Levels of efficiency scores have been previously used to determine performance. Sedik et al. (1999) used efficiency scores to evaluate corporate farm performance in Russia from 1991 to 1995. Ylvinger (2000) used efficiency measures to estimate the relative industrial performance.

The main objective of this study is to determine the relevance of firm-specific and country specific factors as sources of firm efficiency in industrialized countries' food industry. To achieve this objective, stochastic frontier analysis is used to derive the technical efficiencies of firms in the food industry in three industrialized countries, France, Britain and the United States.

Data and Methods

Unbalanced panel data spanning a ten year period from 1989 to 1998, for 148 firms in the food industry are used. These firms belong to the major group 20 of the Standard Industrial Classification (SIC) Code (Office of Management and Budget 1987). The data are derived from financial statements of firms compiled by Disclosure Incorporated (May 1999).

Theoretical Model

Stochastic frontier analysis is used to estimate an efficient frontier. A stochastic production frontier is used to estimate technical inefficiency (Fried et al. 1993). If producers use inputs $x \in R^n_+$ to produce a scalar output $y \in R^n_+$ with technology

$$y_i = f(x_i;\beta)\exp\{v_i + u_i\}, \gamma i = 1, \ldots\ldots I \quad (1)$$

where β is a vector representing technology parameters estimated for I producers. The disturbance term v_i is statistical noise and the non positive component of the disturbance, u_i measures technical efficiency. The log linear form of equation (1) is used in the estimation of the parameters. This is given as

$$z_i = x_i\beta + v_i + u_i, \quad (2)$$

where z = lny.

The empirical model used in this study is a random effects model. Pitt and Lee (1981) suggest that the log linear version of the stochastic model, equation (2), can be estimated using panel data. In this case, the model is generalized to handle both time-series and cross-section units. This model is comparable to those proposed by Nerlove (1965) and Wallace and Hussain

(1969) except that u_i is one-sided distributed. If the u_{it} terms are replaced by u_i, the model is given as:

$$z_{it} = x_{it}\beta + v_{it} + u_i, \qquad (3) \qquad I=1,\ldots\ldots,N, \quad t=1,\ldots\ldots\ldots,T,$$

where u_i is i.i.d. one-sided distributed with truncated normal density function

$$h(u) = \frac{2}{\sqrt{2\Pi\sigma_u}} \exp\left\{-\frac{u^2}{2\sigma_u^2}\right\}, u \le 0; \ (4)$$

and v_{it} is i.i.d. normal.

The efficiency component is time-invariant and v_{it} and u_i are assumed to be independently and identically distributed. Both generalized least squares and maximum likelihood procedures were used to determine which model best suited the data being used. The likelihood function of this model has been derived by Pitt and Lee (1981) as:

$$\begin{aligned} \ln L = {} & N \ln 2 - \frac{NT}{2}\ln(2\Pi) - \frac{N(T-1)}{2}\ln \sigma_v^2 - \frac{N}{2}\iota_n(\sigma_v^2 + T\sigma_u^2) \\ & - \frac{1}{2\sigma_v^2}\sum_{i=1}^{N}(y_i - x_i\beta)'\left(I_T - \frac{\sigma_u^2}{\sigma_v^2 + T\sigma_u^2}\iota\iota'\right)(y_i - x_i\beta) \\ & + \sum_{i=1}^{N}\ln\left[1 - \Phi\left(\frac{\sigma_u}{\sigma_v(\sigma_v^2 + T\sigma_u^2)^{\frac{1}{2}}}\sum_{t=1}^{T}(y_{it} - x_{it}\beta)\right)\right] \end{aligned} \qquad (5)$$

where $\Phi(x)$ is the standard normal cumulative density function evaluated at x.

The empirical model used in this study is a random effects model. A preliminary analysis of the generalized least squares and maximum likelihood procedures reveals that the maximum likelihood procedure is a better procedure because it produces efficient estimates. Return on Assets, a profitability ratio, has been identified by previous researches as a performance measure. Given return on assets as the output variable, an efficient frontier is determined using marketing-mix variables and market-structure variables as input variables. The marketing-mix variables are sales force expenditure, advertising expenditure, promotional expenditure, and other marketing expenditure. The market-structure variables are industry concentration and capacity utilization.

Panel data analysis using efficiency levels based on the efficient frontier as the dependent variable, firm-specific characteristics as the independent variables and country and time dummies as the effects variable are used to determine the influence of firm-specific, country-specific effects and time effects on efficiency. The empirical model is an effects model of the general form,

$$y_{it} = \alpha_i + \gamma_t + \beta' x_{it} + \varepsilon_{it}. \tag{6}$$

In this model, there are K regressors in x_{it} not including the constant term. From (6), five variants of the model are derived. These are the ordinary least squares model (OLS), one and two-factor fixed effects models (FEM), and one and two-factor random effects models (REM) (Greene, 1995, p.310). The five models are given below:

(i) The OLS model:

$$y_{it} = \alpha + \beta' x_{it} + \varepsilon_{it}. \tag{7}$$

(ii) The One-Factor Fixed Effects Model:

$$y_{it} = \alpha_i + \beta^{'} x_{it} + \varepsilon_{it}. \tag{8}$$

(iii) The Two-Factor Fixed Effects Model:

$$y_{it} = \alpha_0 + \alpha_i + \gamma_t \beta^{'} x_{it} + \varepsilon_{it}. \tag{9}$$

(iv) The One-Factor Random Effects Model:

$$y_{it} = \alpha_i + \beta^{'} x_{it} + \varepsilon_{it} + u_i. \tag{10}$$

(v) The Two-Factor Random Effects Model:

$$y_{it} = \alpha + \beta^{'} x_{it} + \varepsilon_{it} + u_i + w_i. \tag{11}$$

In panel data analysis, dummy variables, are used to account for factors unique to various parts of the panel which cannot be explained by the regressors. The regressors are the firm-specific factors, total assets and corporate tax. Total assets is denoted as ASSETS, while corporate tax is denoted as TAX. Dummy variables in the one-factor model represent countries, while in the two-factor model they represent countries and time. The time dummy variables represent the number of years of operation of each firm. Each of these models can be estimated in a fixed effects or random effects framework.

In the FEM, differences across units are captured by differences in the group-specific constant term, α. The REM differs from the FEM in that for the REM the dummies or individual specific constant terms are randomly distributed over cross-sectional units. Therefore in the analysis of countries, the dummy variables are a collection of factors that pertain to the group of countries that the sample is drawn from. Generalized Least Squares (GLS) is necessary to estimate the REM (Green, 1995, p.289).

Two specification test statistics are used in the panel data analysis. A Lagrange multiplier (LM) statistic developed by Breusch and Pagan is used for testing the REM against the OLS model (Greene, 1995, p.291). The LM test for the REM is based on OLS residuals to check for evidence, or the absence of such evidence, that suggests that the error components model is favored. Large values of the LM statistic favor either the REM or the FEM over OLS model.

The other specification test, Hausman's (H) test is based on the fact that under the hypothesis of no correlation, both FEM and GLS are consistent but OLS is inefficient. Thus under the null hypothesis, the two estimates should not differ systematically. A large value of the H statistic argue in favor of the FEM over the REM.

Results and Discussion

One Factor Models

The results for these models are shown in Table IV. The LM test was significant for the REM. This indicates that the dummy variables for country add explanatory power to the model. Also, the REM was favored over the FEM since the H statistic was not significant. Therefore the firm-specific effects are randomly distributed across the countries being analyzed. This means that inferences pertain to industrialized countries as a whole and not to the individual countries. Therefore, without considering time effects, firm-specific factors are important in explaining efficiency in industrialized countries.

Two Factor Models

Dummy variables for country and time effects were significant. This inference was made from a significant LM statistic shown in Table IV. Furthermore, the H statistic was significant (Table IV). Therefore the FEM was favored over the REM.

Firm-specific measures are found to be relevant in explaining the efficiency of firms in the food industry. Furthermore, the factors characteristic to the various countries and the number of years of operation are important in explaining differences in firm efficiency across each country.

Implications of this Research

This study reveals the firm-specific factors which managers can employ when making decisions to improve the efficiency of their firms. It also indicates country-specific factors are important determinants of firm efficiency in the food industry, which is useful information for managers faced with formulating strategies for both domestic and foreign operations. Efficiency comparison across countries could clearly reflect the performance of foreign operations and their contribution to total corporate profits. This can be used as a guide to foreign operations that need improvement.

Information about cross country efficiency in the food industry is also useful information for investors who seek to hold diversified portfolios in other countries. A knowledge of performance based on efficiency will guide in their investment decisions.

This research can be used for policy purposes. Information of relative efficiency across countries serve as a measure by which policy concerning international trade can be made. Choices of more efficient foreign investments can be made for increased revenue. Policy can also be formulated for countries with less efficient firms in order to improve performance.

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Table I. Descriptive Statistics for France

Variable	Mean	Minimum Value	Maximum Value	Number of Observations
ASSETS	13883644.20	6409989.00	19435824.00	10.00
TAX	0.36	0.32	0.43	10.00
EFFICIENCY	0.22	0.17	0.31	10.00

Table II. Descriptive Statistics for Britain

Variable	Mean	Minimum Value	Maximum Value	Number of Observations
ASSETS	2629095.71	83570.00	7866360.00	51.00
TAX	0.29	0.10	0.37	51.00
EFFICIENCY	0.23	0.11	0.50	51.00

Table III. Descriptive Statistics for the US

Variable	Mean	Minimum Value	Maximum Value	Number of Observations
ASSETS	4486198.28	498624.00	13833534.00	87.00
TAX	0.39	0.28	1.02	87.00
EFFICIENCY	0.25	0.14	0.79	87.00

Table IV. Regression Coefficients

Variable	Base OLS	One Factor FEM	One Factor REM	Two Factor FEM	Two Factor REM
Intercept[a]	0.05 (2.18)[b]		0.32E-04 (0.00)	-0.27E-01 (-0.97)	-0.64 (-0.19)
ASSETS	-0.69E-09 (-0.45)	0.27E-08 (1.33)	0.14E-08 (0.77)	0.28E-09 (0.14)	0.20 (0.11)
TAX	0.05 (8.21)	0.68 (9.32)	0.66 (9.18)	0.76 (10.40)	0.70 (10.00)
FRANCE		-0.06 (-1.32)		-0.03 (-0.95)	
BRITAIN		0.03 (1.24)		0.04 (3.98)	
UNITED STATES		-0.03 (-0.92)		-0.02 (-3.65)	
1989				-0.04 (-2.47)	
1990				-0.04 (-2.39)	
1991				-0.03 (-1.49)	
1992				-0.00 (-0.14)	
1993				0.04 (2.15)	
1994				0.02 (1.24)	

Table IV. Regression Coefficients (continued)

Variable	Base OLS	One Factor FEM	One Factor REM	Two Factor FEM	Two Factor REM
1995				0.02 (0.95)	
1996				0.02 (0.94)	
1997				0.01 (0.80)	
1998				0.02 (0.82)	
N	148				
R^2	0.32	0.38		0.47	
F (Regression)	33.75[c]	22.36[d]		8.56[e]	
H statistic[f]			3.19		8.35
LM statistic			7.23[f]		9.84[g]

[a] No intercept for the one-factor FEM model (Greene, 1995, p.289).
[b] t statistics are in parentheses.
[c] F(2,145) at the 0.95 probability level is 3.00.
[d] F(4,143) at the 0.95 level is 2.37.
[e] F(14,133) at the 0.95 level is 1.67.
[f] Chi square statistic for 1 degree of freedom at the 0.95 level is 3.84.
[g] Chi square statistic for 2 degrees of freedom at the 0.95 level is 5.99.