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TECHNOLOGICAL STRUCTURE AND EFFICIENCY OF KOREAN NATIVE-BEEF PRODUCTION

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I. Introduction

Korean native-beef production sector has made little improvement during the last three decades. Still its large part consists of small scale farms. Under such unadjusted structure, Korean beef farmers are facing more difficult time than ever before, due mainly to the current trade liberalization pressure centered on entire agricultural products.

Today, trade competitive edge in the world market is characterized by technological and/or resource comparative advantages. Even though Korea has little relative advantage in pasture base over the major beef exporting countries, she still preserves genetically unique native-cattle resource. And it is believed that, if a grading system is well established, native-beef consumption may not be substantially substituted by imported beef.

The successful development of beef sector depends on availability of efficient production technologies and farm level performances. Decisions about development strategies in Korean beef industry would basically be guided by farm level performances, as far as profitable production technologies are available. Such performance is measured by relative economic efficiency of which technical efficiency is an important component.

In 1957 Farrel first proposed a deterministic frontier production function to measure technical efficiency. It has only been since the pioneering work of Farrel that serious consideration has been given to the possibility of estimating so called frontier production functions, in an effort to bridge the gap between theory and empirical work. After Farrel, the two epoch-making papers have an particular importance : one is a stochastic frontier function proposed by Aigner et al.(1977) ; another is a frontier cost(dual) function developed by Kopp(1981) and

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Kopp and Diewert(1982). Recently, Yoon and Park(1988) in Korea first employed the stochastic frontier methodology for analyzing Korean milk production efficiency.

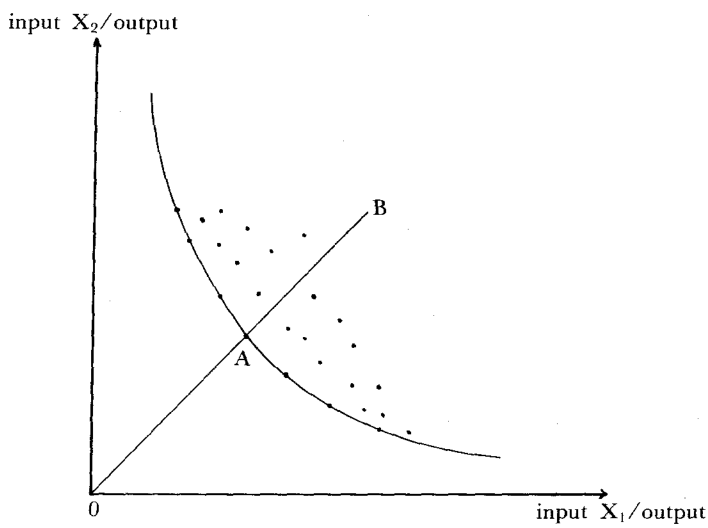
The main purpose of this paper is to examine the technological structure of intensive Korean native–beef production, to estimate farm level technical efficiencies using a stochastic translog frontier function, and to analyze efficiency differences for binary characteristics of cattle size, feeding period, veterinary expense, and labor type.

Next section contains a methodological framework followed by a discussion of the data and model specification and estimation method. The paper then proceeds with results and ends with summary and conclusions.

II. Methodological Framework

The notion of technical efficiency has to do with the relationship of inputs to output. No profit maximizing producer would use more inputs than need be used for a given level of output. By using the Farrell's technique, the efficiency of production activity could be measured and decomposed into technical and allocative efficiency. The Farrell's criterion of efficiency was the frontier unit isoquant.

FIGURE 1 Frontier Unit Isoquant



Consider a sample of farms in Korean beef production sector whose production activities generate the scatter of points in Figure 1. Some farms are on the technically efficient frontier isoquant, while others lie varying distances away from it. One explanation of this pattern is that farms actually face different technologies. If this is true, there would be no basis for analyzing technical efficiency because that concept implies exploitation of a common technology. An alternative illustration is that the pattern do not represent real differences in technology, but arises from random disturbances. This is a common assumption underlying regression estimation of a mean production function which provides no basis for the efficiency measure.

A third explanation suggests that all farms have potential access to the same technology but that some are more successful than others in exploiting it. In this case one may compare relative levels of technical efficiency. In Figure 1 the ratio of distances *OA/OB* is a measure of farm *B*'s relative technical efficiency, in that *B* could reduce its use of inputs *X*1 and *X*2 to *OA* of present levels and still maintain the same output if it became as efficient as *A*. Only those firms on the frontier isoquant have an efficiency rating of 1.0.

However, the Farrell's approach treats regression error terms into inefficiency parameters so regression result provides underestimation of technical efficiency level. To overcome such bias problem, Aigner et. al. (1977) developed a stochastic frontier function model having a composite error term consisting of two distinct components.

Let the production frontier model of a single output and *m* inputs be

(1) $$Q = f(X_1, X_2, X_3, \cdots\cdots, X_m)$$

where Q is the maximum output a farm possibly obtain by using the inputs(x_i's) in a technically efficient manner. Under the existence of an efficient production technology, it would be reasonable to assume that not all farms may be operating on the production frontier. Therefore, the prevailing production process which is specific to a particular individual farm at any particular time period can be written as follows :

(2) $$Qit = f(X_{1it}, X_{2it}, X_{3it}, \cdots\cdots, X_{mit}) - U_{it}$$

where U is the farm–specific technical efficiency parameter and has the value greater than or equal to zero. The value of U_i will vary among farms : if U_i is zero, the ith farm is technically efficient ; the farm with nonzero U is inefficient.

In addition, it is assumed that the frontier output Q varies randomly across farms or over time for some farms due to technical improvement. Adding a random variable V, the above deterministic model can be transformed into the following stochastic function :

(3) $Q = f(.) + V - U$

where $V \gtreqless 0$. Here, it is assumed that $V \overset{iid}{\sim} N(0, \sigma^2_v)$ and $U \overset{iid}{\sim} |N(0, \sigma^2_u)|$. The key feature of this stochastic frontier is that the disturbance term is composed of two parts, a symmetric and a one-sided component. The symmetric part (V) captures the random effects outside of the control of a farm manager. The one-sided component (U) is responsible for deviatons from the frontier owing to inefficiency arising from the manager's controllability of production process. The technical efficiency against the stochastic production frontier is

(4) $U = f(.) - Q + V.$

Now, an important problem is to decompose the error term into the two components. Jondro et al.(1982) proposed a statistical procedure to estimate the firm-specific technical efficiency by computing the mean technical efficiency conditional on the composite disturbance term. This approach makes use of the average of the technical efficiency indices of all firms with the same composite error term.

Following Jondrow et al.(1982), the measurement of U_i for each farm is derived from the conditional distribution of U, given $\varepsilon = V - U$.

(5) $h(U \mid \varepsilon) = \frac{1}{(1-G)\sqrt{2\pi}\,\sigma_*^2} \exp.\left[-\frac{1}{2\sigma_*^2}(U + \frac{\sigma^2_u \varepsilon}{\sigma^2})^2\right]$

where $\sigma_*^2 = \sigma^2_u \sigma^2_v / \sigma^2$, $G =$ the standard normal distribution function, $\sigma^2 = \sigma^2_u + \sigma^2_v$ and cov $(V, U) = 0$. The expectation, $E(U \mid \varepsilon)$, is a pure mean of a half normal distribution :

(6) $E(U \mid \varepsilon) = U_* + \sigma_* \frac{g(-U_*/\sigma_*)}{G(-U_*/\sigma_*)}$

where $U_* = -\frac{\sigma^2_u \varepsilon}{\sigma^2}$ and $g(.)$ is the standard normal density, respectively. Since, however, $-U_*/\sigma_* = \varepsilon\lambda/\sigma$ and $\lambda = \sigma_u/\sigma_v$, the equation (6) can be rewritten as

(7) $E(U \mid \varepsilon) = \sigma_* \left[\frac{g(\varepsilon\lambda/\sigma)}{1-G(\varepsilon\lambda/\sigma)} - \frac{\varepsilon\lambda}{\sigma}\right]$

The conditional expected values of U_i's are nonnegative and simply monotonic transformation in ε. Therfore, the ranking of U_i's is the same as that of the regression residuals.

III. Description of Sample Data

The production information is a survey data collected from eighty farms by the National Livestock Cooperatives Federation during the 1986–1988 calendar years. Most part of the sample is family farms and operates under the conventional production system.

TABLE 1 Summary Statistics

Variable	Mean	S.D.	Min.	Max.
W(kg/head)	132.31	20.13	97.83	192.39
H(head)	12.37	7.59	2.00	38.00
C(kg/head)	724.37	131.71	469.15	1,027.40
R(kg/head)	275.55	84.39	179.30	544.84
L(kg/head)	130.19	63.62	6.65	297.57
M(won/head)	2,953.00	3,078.20	250.60	23,914.00

The details of the data description are available in the annual reports of livestock production cost survey, which are being published by the Federation. Thus, this section describes only the variables used in this research : weight gain (*W*), the number of cattle (*C*), roughage (*R*), labor (*L*), and verterinary expense (*M*). The summary statistics are presented in Table 1.

Availability of feed, labor, high quality cattle, and market is an essential factor for maintaining a profitable beef production. The number of cattle ranged from 2 and 38 heads with an average of 12. Per head feeding period is 165 days and weight gain is 132.3kg during the time period. It is equivalent to 0.8kg weight gain per head/day. Most commercial size cattle are sold at the primary auction markets.

In addition, feed is one of the important beef production inputs. Concentrates are fed about three times as much as roughages. The large portion of concentrate intake tends to be positively correlated with the amount of veterinary expenditure.

Labor is another key production factor. Rural labor force is getting scarce and has multiple purposes for more diversified agricultural activities. In beef production only 14 percent of the sample farms uses hired labor and the rest consists of pure family farms.

IV. Empirical Model, Estimation and Results

1. Model Specification and Estimation Methods

As a flexible representation of beef production technology, the transcendal logarithmic(translog) function proposed by christnesen et al.(1971, 1973) is employed. This functional form has both linear and quadratic terms with an arbitrary number of inputs. It can also be reduced to the multiple-input Cobb-Douglas form as special case. A translog stochastic frontier production function is specified in terms of five inputs as follows :

$$(8)\ \mathrm{Ln}\ W = B_0 + B_1\ \mathrm{Ln}H + B_2\ \mathrm{Ln}C + B_3\ \mathrm{Ln}R + B_4\ \mathrm{Ln}L + B_5\ \mathrm{Ln}M + B_{11}\ (\mathrm{Ln}H)^2/2 + B_{12}\ \mathrm{Ln}(H)\ \mathrm{Ln}(C) + B_{13}\ \mathrm{Ln}(H)\ \mathrm{Ln}(R) + B_{14}\ \mathrm{Ln}(H)\ \mathrm{Ln}(L) + B_{15}\ \mathrm{Ln}(H)\ \mathrm{Ln}(M) + B_{22}(\mathrm{Ln}\ C)^2/2 + B_{23}\ \mathrm{Ln}\ (C)\mathrm{Ln}(R) + B_{24}\ \mathrm{Ln}(C)\mathrm{Ln}(L) + B_{25}\ \mathrm{Ln}(C)\mathrm{Ln}(M) + B_{33}(\mathrm{Ln}\ R)^2/2 + B_{34}\ \mathrm{Ln}(R)\mathrm{Ln}(L) + B_{35}\ \mathrm{Ln}(R)\ \mathrm{Ln}(M) + B_{44}(\mathrm{Ln}\ L)^2/2 + B_{45}\ \mathrm{Ln}\ (L)\ \mathrm{Ln}(M) + B_{55}(\mathrm{Ln}\ M)^2/2 + (V - U)$$

where B is a model parameter vector.

If production possibilities are characterized by constant returns to scale(CRTS), the following relation holds :

$$\mathrm{Ln}W(kH,\ \cdots\cdots,\ kM) = \mathrm{Ln}W(H,\ \cdots\cdots,\ M) + \mathrm{Ln}(k)$$

This implies the following restrictions on the parameters of the translog production function :

$$\sum_i B_i = 1,\ \sum_i B_{ij} = 0,\ \sum_j B_{ij} = 0,\ \sum_i \sum_j B_{ij} = 0$$

If production process is subject to the Cobb–Douglas technology, the parameters of all quadratic terms should be equal to zero. This requires the following additional restrictions on the parameters :

$$B_{ij} = 0, \text{ for all } i, j.$$

In general, a production function is considered to be well–behaved only if output increases monotonically with all inputs and if its isoquants are convex. But the translog function does not satisfy these restrictions globally. In fact when at least $B_{ij} \neq 0$, there exist configurations of inputs such that neither monotonicity nor convexity is satisfied. This follows simply from the quadratic nature of the translog function. On the other hand, there are regions in input space where these conditions are satisfied. These well–behaved regions may be large enough so that the translog function can be a good representation of relevant production possibilities(Bernt and Christensen 1973).

For estimating the stochastic translog production function, the likelihood function of the sample must be formed.

$$(9)\ \mathrm{Ln}\ L(W \mid B, \lambda, \sigma^2) = n\mathrm{Ln}\ \frac{2}{\pi} + n\ \mathrm{Ln}\frac{1}{\sigma} + \sum_i \mathrm{Ln}\ [\ 1 - G(\frac{\varepsilon_i \lambda}{\sigma})\ ] - \frac{1}{\sigma^2} \sum_i \varepsilon_i^2$$

The maximum likelihood (ML) estimators of parameters (B, λ, σ^2) maximizing the above likelihood function are obtained by setting its first order partial derivatives with respect to B, λ, σ^2 equal to zero and solving them simultaneously. Since, however, the parameter estimation involves nonlinearity problems, an appropriate nonlinear optimization technique should be applied. This study chooses the Flecher–Powell–David algorithm(Luenberger 1977).

Another econometric problem encountered is the heteroskedasticity which in usual arises from cross–sectional data. If, under the existence of heteroskedasticity, the least squares formulas applies, the resulting properties will still have some desirable properties : unbiasedness of parameter estimates. But they are not efficient or asymptotically efficient. When we come to using these estimators for testing hypotheses or constructing confidence intervals, we require not only that their estimators themselves be unbiased, but also that their estimated variances be unbiased. Otherwise, the tests are invalid and the constructed confidence intervals are incorrect(Kmenta 1971).

To test for hetoroskedasticity, a χ^2test statistic proposed by Breusch and Pagan(1979) and Godfrey(1978) is employed. Assume that $\sigma^2_t = h(Z_t, \alpha)$ where $h(.)$ is any function independent of t, $Z_t = (1, Z_{t2}, Z_{t3}, \cdots\cdots, Z_{tm})$ is a vector of observalbe explanatory varibles and $\alpha' = (\alpha_1, \alpha_2, \alpha_3, \cdots, \alpha_m)$ is a vector of unknown coefficients. Under the null hypothesis $\alpha^*(\alpha_2, \alpha_3, \cdots, \alpha_m) = 0$, one–half the difference between the total sum of squares and the residual sum of squares from the regression

$$(10) \qquad \frac{\hat{\varepsilon}^2_t}{\sigma^2} = z_t\alpha + w$$

is distributed asymptotically as $\chi^2(m-1)$. The $\hat{\varepsilon}_t = Q_t - X_tB$ is the least squares residuals and $\hat{\sigma}^2 = \Sigma\, \varepsilon^2_i/T$. Note that in the paper X_t is substituted for Z_t. If the test result rejects the joint null hypothesis, a consistent covariance matrix should be formed for necessary statistical tests. As a general formula, we can use the heteroskedasticity-consistent covariance matrix estimator suggested by White(1980).

Once the model parameters and associated standard errors are estimated, the efficiency parameter vector, U, can be calculated by using the conditional expectation formula given in equation (7), Then the analysis proceeds to technical efficiency comparisons for the binary variables, based on an ANOVA model.

$$(11) \qquad EI = r_0 + r_1\, DH + r_2\, DF + r_3\, DL + r_4\, DM$$

Where EI = a technical efficiency index vector,

$DH = 1$ if $H > 20$(0 otherwise),

$DF = 1$ if feeding period > 200 days(0 otherwise),

$DL = 1$ if > 0(0 otherwise),

$DM = 1$ if $M > 6{,}000$ won(0 otherwise) and

r = a parameter vector.

2. Empirical Results

The tests for Cobb–Douglas(C – D) functional specification and constant returns to scale(CRTS) were performed and rejected both hypotheses at the 1 percent level(Table 2). Thus, the stochatic translong frontier beef production function was estimated by the Fletcher–Powell–David nonlinear method. The gradient, function, and parameters were converged at iteration 36. The likelihood ratio–test statistic is found to be 115.19 which is significant at the 1 percent level for 20 degress of freedom. The estimated coefficients and standard errors are in Table 3. Since, however, the heteroskedasticity–test statistic($\chi^2 = 4.546$, D.F.

TABLE 2 Test Statistics

hypothesis	χ^2	D.F
CRTS	31.0150	7
C−D	18.2716	15

TABLE 3 Model Parameter Estimates

Variable	Coefficient	Asymptotic t–ratio
H	0.2853	4.5239***
C	0.6128	10.4138***
R	0.0794	1.8139**
L	0.0733	1.6531**
M	0.0019	0.1021
HH	0.2730	0.9883
HC	−0.2170	−1.1156
HR	0.2879	1.3198*
HL	−0.2882	−1.6222*
HM	−0.0194	−0.3531
CC	0.2377	1.1748
CR	−0.2526	−1.4274*
CL	0.2446	1.7992**
CM	0.0476	1.0709
RR	−0.0341	−0.1756
RL	0.1026	0.7628
RM	−0.0787	−1.5525*
LL	−0.1264	−0.7361
LM	0.0638	1.7327**
MM	−0.0193	−1.2362
One	0.0408	1.8845
$\hat{\lambda}$	2.5581	2.4812***
Log Likelihood	$\chi^2 = 115.19$***	

Note: *** significant at the 1% level
** significant at the 5% level
* significant at the 10% level

= 20) rejected the hypothesis that each disturbance has the same variance, the standard errors were computed by the white consistent covariance estimator.

As seen in Table 3, the ratio of the two standard deviations $\hat{\lambda} = \sigma_u / \sigma_v)$ is 2.558 and statistically significant at the 1 percent level. This suggests that a relatively large portion of technical inefficiency is associated with managerial problems. The implication of $\hat{\lambda}$ may be evidenced from the labor utilization. If we pay a close attention to the facts that 86 percent of the sample farms employed no hired labor during the production period and that entire family labor is not committed to samll scale cattle operations, we can see that beef production activity may be a residual work so there would be little possibility of practicing efficient management.

Based on the parameter estimates, the farm–specific technical efficiency indices are computed by the formula given in equation (7). The results show that there exists a large variation in technical efficiencies among the individual farms(Table 4).

No farm in the sample operates at the efficiency level below 0.6. Some 70 percent of the farms shows an efficiency range of 0.8 to 0.9, while 19 percent are close to the frontier.

To examine whether the technical efficiencies for binary characteristics of cattle size, feeding period, veterinary expense, and labor type are the same, the dummy variable model(equation (10)) was estimated by *OLS*. As in Table 5, the farms of more than 20 heads demonstrated best performanes and the longer feeding period has positive impact on technical efficiency. But the farms which paid more veterinary expense show lower performances.

In terms of labor type, the t–ratio of coefficient $\hat{r}_4$ indicates that there is no difference in technical efficiency between the pure–family and the mixed–labor farms.

TABLE 4 Frequency Distribution of Technical Efficiency

Efficiency Interval	Number of Farms
0.60 − 0.65	1
0.65 − 0.70	0
0.70 − 0.75	3
0.75 − 0.80	5
0.80 − 0.85	14
0.85 − 0.90	42
0.90 − 1.00	15
Total	80

TABLE 5 The ANOVA Results

Variable	Coefficient	t−Ratio
ONE	0.1476	25.0480
DH	−0.0181	−1.3701*
DF	−0.0566	−4.7566***
DL	0.0146	0.7824
DM	0.0225	1.6846**

Note : ***, ** and * are significant at the 1, 5 and 10 percent levels, respectively.

V. Summary and Conclusions

A substantial part of Korean beef production sector still is under the conventional shed system. It tends to be believed that production technologies employed by individual farms are much the same but productivities may vary with a wide dispersion.

The objectives of this paper are (i) to investigate the technological structure of Korean beef production, (ii) to measure farm–specific technical efficiencies, and (iii) to analyze differences in technical efficiencies for binary characteristics of farm scale, feeding days, labor type, and veterinary payment variables. The production records used are the 80 farm cross–sectional and time–series data collected during the 1986–1988 calendar years by the National Livestock Cooperatives Federation.

The stochastic translong frontier function model is used as a flexible representation of Korean beef production technology. The error term is composed of two components : one is symmetric ; another is one-sided.

The relative ratio of the two standard errors ($\hat{\lambda}$) is greater than 2.0 and significant at the 1 percent level. This implies that the composite error therm (ε) has an asymmetric distribution. Thus, the Fletcher–Powell–David nonlinear optimization method is employed for estimating the model parameters. All the economic analyses pursued in this research are made, based on the parameter estimates.

The tests on the hypotheses of technological structure indicate that Korean beef production is subject to increasing returns to scale(i.e., function coefficient = 1.0182) and its technology may be represented by the translog function. This result implies that more efficient beef production requires larger scale at farm level operation.

The efficiency indices show a strong negative skewness. 70 percent of the sample farms falls into 0.85–0.9 efficiency range. Therefore, it seems that the farms of this category requires more intensive extension work to reduce the efficiency gap. Another important result is that the farms of more than 20 cattle demonstrate better performaces relative to those of less than 20 heads. Such result appears to be due mainly to the residual job characteristic of small scale operations.

From the policy point of view, the first priority should be placed upon larger scale farm-level operation and substantial reduction in the existing farm-level technical efficiency gaps. In the intermediate and long run, investment policy should be focused on research and development so that the production frontier shifts upward.

References

Aigner D.J., C.A. Lovell and P. Schmidt((1977) "Formulation and Estimation of Stochastic Frontier Production Models," *J. of Econometrics* 6 : 21–37.

Bernt, Ernst R. and Laurits R. Christensen(1973) "The Translog Function and The Substitution of Equipment, Structure, and Labor in U.S. Manufacturing 1929–68," *Journal of Econometrics* 1 : pp.81–114.

Breusch, T.S. and A.R. Pagan(1979) "A Simple Test for Hetero-scedasticity and Random Coefficient Variation," *Econometrica* 47 : 1287–1294.

Christensen, L.R., D.W. Jorgenson and L.J. Lau(1971) "Conjugate Duality and the Transcendental Logarithmic Production Function," *Econometrica* 39 : 255–256.

Farrell, M.J.(1957) "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society,* Series A, 120 : 253–281.

Godfrey, L.G(1978) "Testing for Multiplicative Heteroscedasticity," *J. of Econometrics* 8 : 227–236.

Jondrow, J., C.A. Lovell, 1, Materov, and P. Schmidt(1982) "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model," *J. of Econometrics* 19 : 233–238.

Kmenta, J.(1971) *Elements of Econometrics,* Macmillan Pub. Co., Inc.

Kopp, Raymond J.(1981) "The Measurement of Productive Efficiency : A Reconsideration," *Quart. J. Econ.,* 96 : 477–503.

Kopp, Raymond J. and W.E. Diewert(1982) "The Decomposition of Frontier Cost Function Deviations into Measures of Technical and Allocative Efficiency," *J. of Econometrics* 19 : 319–31.

Luenberger, D.G.(1977) *Introduction to Linear and Nonlinear Programming.* Addison Wesley Publishing Co.

White, H.(1980) "A Heteroscedasticity-Consistent Covariance Matrix Estimator and A Direct Test For Heteroscedasticity," *Econometrica* 48 : 817–838.

Yoon, J.J. and S.K. Park(1988) "The Measurement of Farm-Specific Technical Efficiency in Kyungki-Region Milk Production : The Stochastic Frontier Production Function Approach," *J. of Rural Development* 11 : 143–154.