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MULTI-OUTPUT PRODUCTIVITY CHANGE FOR KOREAN AGRICULTURE: NON-FRONTIER PRIMAL MEASURE WITH FARM-LEVEL PANEL DATA

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Abstract
This paper analyzes the productivity growth in Korean agriculture with data on multiple crops over the five years from 1998 to 2002. Measurements are obtained from the estimation of a non-frontier multi-output production function. Multi-output production technology is characterized with a transformation function. For empirical analysis, this study employs the generalized linear transformation function, which extends a linear functional form by allowing a full set of interactions among arguments in the function. The results find that technological change has led a significant productivity change. Larger farms experience the highest rate of productivity growth by the greatest rate of scale effect. More human capital also leads higher productivity growth rates.

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I. Introduction

Improving productivity is now an important topic in Korean agriculture, particularly in the context of market opening for international competitiveness. Agricultural imports are expected to increase through further market liberalization given the current trade agreements and negotiations such as DDA and FTAs.

Many Korean commentaries have discussed the influence of trade reform on Korean agriculture(e.g., Choi et al., 2000; Kim and Lee, 2004), noting that domestic prices in Korea are far above import prices for many agricultural commodities. Productivity gains have been regarded by some agricultural economists and agricultural policy practitioners as one of the ways for Korean agriculture to compete with imports and considerable public efforts have thus been devoted to improving productivity.

Though these initiatives are widely acknowledged, issues relating to productivity growth in Korean agriculture are understudied. There has been little empirical work measuring productivity change with the recent farm-level data, particularly in the context of multi-output framework. The primary objective of the paper is designed to contribute to a better understanding of productivity change measures in the context of multi-output production technology.

The analysis of farms producing multi crops from different regions over time yields indications of heterogeneous productivity changes in agricultural production patterns. Estimates based on a single production function ignore technological interdependence, thus a single production function cannot capture the changes in complex agricultural production patterns. Further, implications from a single output model may lead to misleading policy directions by ignoring the interaction with other markets.

The multi-output framework is particularly relevant to the Korean situation. With rice having been a dominant crop in the country, Korean farmers have, in the past, shown a typical mono-production pattern. However, since the Uruguay Round Agriculture Agreement (URAA) in 1994, the Korean rice market has been opened slightly and the prospect is for more opening. The gaps between the domestic and world market prices are expected to narrow in the future and more farmers may be leaving rice farming to shift to other crops for adjustment. With this on-going change in the country, the multi-output production approach reflects productivity change by adjsutment of production patterns in Korea.

The panel data used do not include prices of inputs and outputs.[1] It is difficult to obtain appropriate price variations across farms for significant econometric parameter estimates. Therefore, this study focuses on productivity growth measurement using primal method that does not require price data.[2] For allowing a statistical noise from measurement error and unexpected shocks and statistical inference of production parameters, a primal parametric approach is explored.

This study makes use of the most comprehensive Korean farm level data available for the period 1998 to 2002 to analyze the productivity growth with panel data on multiple crops over the five years, from 1998 to 2002. Panel data provide more reliable evidence on Korean farms' performance because the data enable us to track the performance of each producer through a sequence of time periods. Furthermore, such analysis using Korean farm level data can be compared to similar analyses of data from other countries to look for commonalities and differences.

Previous studies show that the panel data of identical farms over the five years indicates that very small variations of technical efficiency over time(e.g., Kwon and Lee, 2004). Thus, this paper will not deal with technical

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1 Note that dual approach requires price data on inputs and outputs. Although the dual and primal approaches for measuring productivity change provide the same implications for product structure by duality principles, each approach has different limitations and advantages for empirical implementation. When the data are generated by competitive farms, useful variations of the prices often do not exist even though there are different prices among farms. Especially in the case of inputs, farmers usually keep records of total expenditures for the whole farm but rarely keep records on the purchasing prices of individual inputs. Furthermore, for farmers who buy and sell in the same market, recorded price variations may reflect differences in quality, volume discounts or other factors not accounted for in the model. In such cases, using price data may result in biased estimates.

2 There are also some disadvantages to the dual approach. Mundlak(2001) states that in empirical dual analysis, model specification requires special attention. The translog dual functions, for instance, have difficulty in universally satisfying regularity conditions such as monotonicity and curvature(concavity) conditions. The estimated technology is thus inconsistent with the basic premises of the model.

efficiency change contributing on productivity change, but non-frontier primal measure of productivity change in the context of multi-output production technology.[3] The fact that the non-frontier parametric approach reduces the reliance on questionable assumptions and approximations employed in the frontier-based productivity measures is addressed by Felthoven and Paul(2004).[4] Especially, when differences in efficiency are attributable to different regulatory, environmental, and resource conditions that are not independently identified, the potential problem due to unavailable data of these factors may be exacerbated in the frontier model. This study thus develops a transformation function framework that is less affected when such information is lacking. It also does not require making potentially inappropriate distributional assumptions about the form of the one-sided inefficiency error that are necessary for specifying a stochastic frontier model.

To measure productivity change using the primal parametric approach in the context of multi-output production technology, one must first specify multi-output production technology, which is based on either non-frontier model or frontier model. According to the specification of multi-output production technology, a functional form to represent the production relationships is chosen and its coefficients are econometrically estimated. Finally, one calculates related production parameters with estimated coefficients in order to carry out the decomposition of productivity change.

II. Specification of Multi-output Primal Production Technology

Note that the choice of an appropriate model for measuring productivity change in the context of multi-output production analysis is important.

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[3] The approach contrasts with stochastic frontier econometric techniques that explain deviations from best-practice productivity with a two-part error term including a statistical noise from measurement error and a technical inefficiency arising from farms not reaching the production frontier boundary, and with nonparametric or deterministic econometric frontier approaches that limit statistical inference.

[4] For instance, the fixed proportions assumptions of output combination common in the multi-output frontier models can be avoided in transformation function.

Production parameters estimated with different specifications may be sensitive to specification choices. The model differences could potentially cause considerable disparity in the performance implications ultimately derived from the empirical analysis.

Economists have developed several estimation approaches for the estimation of primal multiproduct production technology. Each approach has its strength and weakness: 1) the estimation of separate production functions for each output using allocated input data for each output, 2) the estimation of the model representing one output as a function of the remaining outputs and inputs, 3) the estimation of a distance function. Each approach has pros and cons, and the choice of the appropriate approach depends on the availability of data and model assumptions.

The first approach for estimating a primal multiproduct production function is to estimate separate production functions for each output, taking as arguments the amount of inputs specifically used for producing outputs. Accordingly, this approach requires the information of allocated inputs for the production of each output. Just et al.,(1983) developed a method to measure nonjoint production technologies using fixed but allocable inputs. This kind of production function assumes the separability or nonjointness of technology. Thus, they claim that it is the better approach for attaining tractability for multiproduct production function estimation. They suggest a method estimating production functions when allocations of inputs are unobserved by extracting the input allocation to the individual crops by utilizing the first order conditions for profit maximization. This method is applied to estimate multiproduct production functions using panel data for 1977-80 of 70 individual farmers in southern Israel. This approach requires the records of which inputs were used for which crops. Without information regarding allocations of at least an input among outputs, it is not possible to determine directly the effect of changing input use on the production among products. In most situations, however, such detailed data are unavailable. Thus, the estimation of individual production functions for each crop in a multioutput system is usually obstructed by lack of data.

The second approach for expressing the multiproduct production technology is to represent explicitly one output as a function of the remaining outputs and inputs. The specification is well-known as a transformation function.

This approach permits the possibility of complementarities between every pair of outputs, so it does not require strict assumptions of separability. However, asymmetric representation of outputs is one of the problems in this approach. That is, the empirical results of estimation may change according to the output chosen as the dependent variable. Another problem of this approach is that the empirical equation does not have any theoretical justification for regularity conditions on the output relationships(Orea et al., 2003).

The third approach for representing a primal multiproduct production technology is to estimate a distance function(Lovell et al., 1994). Distance function is alternative representation to describe the production technology. The distance function represents distance from the frontier. Most of previous studies estimate multi-output distance function within the frontier framework, which can be applied in either a stochastic frontier or a nonparametric frontier(e.g., Paul et al., 2000). One specifies input distance function and output distance function. An input distance function characteristics the production technology by looking at a minimal proportional contraction of the input vector, given an output vector, whereas an output distance function represents a maximal proportional expansion of the output vector, given an input vector (Coelli et al., 1999, pp.62).

For empirical implementation, the distance function is usually transformed through normalization by one output(or one input) in order to impose directly the homogeneity condition on the output(or input) distance function. Estimation of the ratio form of the distance function raises a problem. Since this model examines how an output variable expands holding output composition constant, this specification imposes perfect complementarities of outputs. However, if cross terms for ratios are incorporated in the model, this problem can be solved to some extent. Another problem with ratio form of normalization relates to endogeneity. The endogeneity issue is that dependent variable appears on the right side as the denominator of ratios in the model.

This study employs the second approach to represent a multi-output production technology, which is an appropriate approach for the non-frontier parametric multi-output production framework.

III. Analytical Framework

The multi-output production technology is characterized with a transformation function of the form $\tilde{F}(y, x; t) = 0$, where x, y, and t represent input vector, out put vector, and a time shifter to capture technical change, respectively. To make the implicit form operational for productivity measurements, one alternative is to characterize the production of one output as a shift variable for the production function expressed in terms of the other output, in the case of two outputs. Such a multi-output production function may be specified as: $y_1 = f\ (y_2, x; t)$ or $y_2 = g\ (y_1, x; t)$.

To investigate whether the production technology by the output chosen changes, the model selection by a non-nested hypothesis is tested as Vong (1989) suggested. The specification of the test formula for the null hypothesis, $f(y_2 \mid x_i, t) = g(y_1 \mid x_i, t)$, is as the followings.

(1) $T_{LR} = \dfrac{LR}{N^{-1/2}\varpi} \rightarrow normal(0,1)$,

here, $\varpi^2 = \dfrac{1}{N}\sum_{i=1}^{N}\left(\ln \dfrac{f(y_2 \mid x_i, t)}{g(y_1 \mid x_i, t)}\right)^2 - \left(\dfrac{1}{N}\sum_{i=1}^{N}\ln \dfrac{f(y_2 \mid x_i, t)}{g(y_1 \mid x_i, t)}\right)^2$.

Any arbitrary output, say y_1, given x and the rest of output y_2, can be expressed as (Diewert, 1973)[5]:

(2) $\tilde{F}(y, x; t) = 0 \Leftrightarrow y_1 = F(y_2, x; t)$.[6]

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5 By the implicit function theorem, if $F(y_2, x; t)$ is continuously differentiable and has non-zero first derivatives with respect to one of its arguments, $F(y_2, x; t)$ may be specified with this argument on the left-hand side of the equation and the other arguments on the right-hand side(Felthoven and Paul, 2004).

6 For $F(y_2, x; t)$ to be well behaved, the transformation function must satisfy a standard set of regularity conditions: (a) Non-negative condition, i.e., $F(y_2, x; t)$ over the range of data, (b) non-decreasing in inputs, $\frac{\partial F(y_2, x; t)}{\partial x_k} = MP_{y_1, x_k} \geq 0$, (c) non-increasing in outputs, $\frac{\partial F(y_2, x; t)}{\partial y_m} = MRPT_{y_1, y_m} \leq 0$, and (d) concavity. The last condition requires that the matrix of second order partial derivatives of $F(y_2, x; t)$ is negative semi-definite.

Taking the log of all variables and differentiating the latter expression in (2) with respect to time, t, leads to

$$(3)\quad \frac{d\ln y_1}{dt} = \sum_{m=2}^{M}\left(\frac{\partial F(.)}{\partial \ln y_m}\right)\frac{d\ln y_m}{dt} + \sum_{k=1}^{K}\left(\frac{\partial F(.)}{\partial \ln x_k}\right)\frac{d\ln x_k}{dt} + \frac{\partial F(.)}{\partial t}$$

Given the formulation above, the productivity change over time can be expressed as:

$$(4)\quad \begin{aligned} &\frac{\partial F(.)}{\partial t} = \frac{d\ln y_1}{dt} - \sum_{m=2}^{M}\left(\frac{\partial F(.)}{\partial \ln y_m}\right)\frac{d\ln y_m}{dt} - \sum_{k=1}^{K}\left(\frac{\partial F(.)}{\partial \ln x_k}\right)\frac{d\ln x_k}{dt} \\ &\Rightarrow \frac{\partial \ln y_1}{\partial t} = \frac{d\ln y_1}{dt} - \sum_{m=2}^{M}\left(\frac{\partial \ln y_1}{\partial \ln y_m}\right)\frac{d\ln y_m}{dt} - \sum_{k=1}^{K}\left(\frac{\partial \ln y_1}{\partial \ln x_k}\right)\frac{d\ln x_k}{dt}\ . \end{aligned}$$

Define $\varepsilon_{y_1,y_m} = \frac{\partial \ln y_1}{\partial \ln y_m}$ and $\varepsilon_{y_1,x_k} = \frac{\partial \ln y_1}{\partial \ln x_k}$, while expressing (4) with output elasticities:

$$(5)\quad \frac{\partial \ln y_1}{\partial t} = \frac{d\ln y_1}{dt} - \sum_{m=2}^{M}\varepsilon_{y_1,y_m}\frac{d\ln y_m}{dt} - \sum_{k=1}^{K}\varepsilon_{y_1,x_k}\frac{d\ln x_k}{dt}\ .$$

The percentage change in output with respect to a change in t represents productivity growth in that it accounts for changes in output between time periods that are not directly attributable to changes in output composition and input use.[7] The two terms can be disentangled from changes in productivity. The changes in output and input variable are weighted by output substitution effects and the productive contributions of input variables to output, respectively.

Interpreting such a productivity growth representation as technical change implicitly assumes that all productive determinates are captured within the functional specification. Thus, if one incorrectly assumes that the components of y_2, x, and t represent all factors affecting production of y_1, or imposes

[7] The change in productivity is defined as the rate of growth of an output y_1, holding other outputs and inputs constant in the transformation production function.

other inappropriate assumptions about the production technology or markets, this approach may yield erroneous results.

To compute the components of (5), $\frac{d \ln y_m}{dt}$ and $\frac{d \ln x_k}{dt}$ terms can simply be measured from the data, but the output elasticities (i.e., ε_{y_1,y_m} and ε_{y_1,x_k}) are not directly observable. These elasticities can be computed by estimating a parametric transformation function with a specified functional form.

IV. Data and Variables

This study relies primarily upon farm-level data, compiled by the Korea National Statistical Office in a national farm survey for the period 1998 through 2002. The survey classified and reported statistics for approximately 2,900 randomly selected farm households, spanning nine provinces. The data tracked farm households with the same farm identification number through the five years of observation (1998~2002) to make a balanced panel data set. The resulting panel data set contains statistics for 2,450 farms across eight provinces.[8]

For each farm household, data are aggregated into two outputs and four inputs. The outputs are rice and non-rice crops(including vegetables, fruits, and other crops)[9]. The inputs are land, labor, capital, and other inputs. The number of outputs and inputs aggregated is decided by considering the trade-off between modeling more technical details by applying more inputs and outputs(and adding the risk of multicollinearity and many zero observations) on the one hand and aggregating the inputs and outputs(and sacrificing potentially useful information) on the other(Brummer et al., 2002).

Land and labor are measured by quantities. Land is planted area and includes three types of cropland: paddy, upland, and orchard. Paddy refers to

8 The data used in this article exclude Jeju province (an island off the south coast of the peninsula). Less than one percent of farms in Jeju province - 0.007% - produce rice. This study also excludes livestock farms which tend to be specialized operations in Korea.

9 Since rice is planted in more than 50 percent of cropland and generates about 50 percent of total crop revenue in the panel data, it is important to focus special attention on rice.

land primarily used for flood-irrigated rice, and upland area is other annual cropland. Labor is hours spent on farm work and includes both family labor and hired labor. Capital and other inputs are measured in value terms. Capital includes the average estimated replacement cost of structures, machinery depreciation, repairs, and leased farm equipment. Other inputs include expenditures on fertilizers, pesticides, fuel, electricity, seeds, and miscellaneous operating expenses.

The data collected on outputs and some inputs are in value terms rather than quantities. When output and input prices vary systematically over the period(changing in real terms) and across space, the data in value terms will systematically bias the estimation results due to inflation and quality differences; under reasonably competitive market conditions, price variation is likely to include quality differences(Kwon and Lee, 2004). Such bias can be kept to a minimum by removing output and input specific price trends. National level output and input-specific deflators were used to rescale those outputs and inputs that are collected in value terms, with 1998 being the base year. In this way, outputs and inputs become implicit quantities.[10]

TABLE 1. Summary Statistics for Aggregate Outputs and Inputs

	Rice (1,000won)	Non-rice crops (1,000won)	Land (ha)	Labor (hour)	Capital (1,000won)	Other inputs (1,000won)
All	7,558	8,964	1.06	1,038	3,616	4,104
	(9,085)	(14,051)	(1.03)	(813)	(3,885)	(4,860)
1998	7,034	8,194	1.04	1,050	3,178	3,822
1999	7,490	9,194	1.06	1,068	3,413	4,240
2000	7,469	9,467	1.06	1,045	3,626	4,253
2001	8,264	9,366	1.07	1,037	3,830	4,226
2002	7,533	8,600	1.09	991	4,034	3,981

Note: Standard deviations are in parenthesis.
Non-rice crops denote all crops such as vegetables, fruits, and other crops except rice.

10 Most of the previous studies using the Farm Economy Survey, compiled by the Korea National Statistical Office in a national farm survey, have dealt with input and output value terms as this paper did(i.e., Kwon and Lee, 2004)

Descriptive statistics for the two outputs and four inputs are summarized in Table 1, including mean per farm household by year. The data confirm that farms in Korea are small, with an average landholding of 1.06 hectares per farm in the sample. The average farm has a part-time operator with about 1,000 total hours of labor used, including all family and hired labor. Labor use declined over the sample period, while usage of capital and cultivated land per farm increased steadily.

V. Empirical Implementation

For empirical implementation, a functional form for the multi-output transformation function first has to be chosen. This study employs the generalized linear transformation function suggested by Diewert(1973), which extends a linear functional form by allowing a full set of interactions among arguments in the function. In the context of panel information, individual *i*'s production of y_2 given x vector and y_1 is expressed as:

$$
\begin{aligned}
& F_i^t(y_1, x; t) = y_{i2}^t = \alpha_0 + 2\alpha_y (y_{i1}^t)^{1/2} + \beta_1 y_{i1}^t + 2\sum_{k=1}^{4} \alpha_k (x_{ik}^t)^{1/2} \\
(6) \quad & + \sum_{k=1}^{4}\sum_{l=1}^{4} \beta_{kl} (x_{ik}^t)^{1/2} (x_{il}^t)^{1/2} + 2\sum_{k=1}^{4} \beta_{yk} (x_{ik}^t)^{1/2} (y_{i1}^t)^{1/2} + 2\alpha_t t^{1/2} \ , \\
& + \beta_{tt} t + 2\sum_{k=1}^{4} \beta_{tk} (x_{ik}^t)^{1/2} t^{1/2} + 2\beta_{yt} (y_{i1}^t)^{1/2} t^{1/2} + u_i^t
\end{aligned}
$$

where F_i^t denotes the transformation function measure, t indexes time, u_i^t is the disturbance term, and y_i^t is a vector of outputs (y_{i1}^t=non-rice crops; y_{i2}^t =rice). The outputs included in the right hand side of equation (6) exclude y_2. x_i^t is a vector of inputs (x_{i1}^t=land, x_{i2}^t=labor, x_{i3}^t=capital, x_{i4}^t=other inputs).

For estimation, the disturbance term is assumed to decompose into two error components: $u_i^t = v_i + \varepsilon_{it}$. The error term v_i accounts for the farm fixed effects of the *i*th farm. Farm fixed effects include all unobserved farm specific components that may vary across farms. The last term ε_{it} represents the random error component. The fixed effects model reduces omitted variables bias by controlling for unobserved farm fixed effects(Baltagi, 2001), which also reduces simultaneous equations bias to the extent that the unobserved components(such as managerial ability and individual specific constraints) affect both production and input use. Mundlak(1978) asserts under certain simplifying assumptions, the fixed effects model(the within estimator or covariance analysis) controls for simultaneity caused by endogenous input use.

Within the specification in (6), the production parameters needed to measure the components of productivity growth discussed earlier can be obtained using the following equations.

(7a) $$\varepsilon_{y_2,y_1} = (\alpha_y y_1^{-1/2} + \beta_1 + \sum_{k=1}^{4} \beta_{k1} x_k^{1/2} y_1^{-1/2} + \beta_{yt} t^{1/2} y_1^{1/2})(\frac{y_1}{y_2}).$$

(7b) $$\varepsilon_{y_2,x_k} = (\alpha_k x_k^{-1/2} + \sum_{l=1}^{4} \beta_{kl} x_l^{1/2} x_k^{-1/2} + \beta_{yk} y_1^{1/2} x_k^{-1/2} + \beta_{tk} t^{1/2} x_k^{-1/2})(\frac{x_k}{y_2}), \; k=1,\ 2,\ 3,\ 4.$$

(7c) $$\varepsilon_{y_2,t} = (\alpha_t t^{-1/2} + \beta_{tt} + \sum_{k=1}^{4} \beta_{tk} x_k^{1/2} t^{-1/2} + \beta_{yt} y_1^{1/2} t^{-1/2})(\frac{t}{y_2}).$$

Finally, even estimation results do not change by the choice of the output, the choice of y_2 is crucial for the estimation, and depends on the data and research focus. This study chooses rice as y_2, given the importance of rice in Korean agriculture.

VI. Estimation Results

Initially, the Vong's test for the model selection of a transformation function form finds that there is no difference between the two models, $y_1 = f\,(y_2, x; t)$ vs. $y_2 = g\,(y_1, x; t)$, so it does not matter which output is chosen to represent the multi-output production technology(see Table 2). This study explores $y_1 = f\,(y_2, x; t)$ as a form of the transformation function.

TABLE 2. Result of the non-nested hypothesis for the selection of functional form

Null hypothesis	T_{LR}	p-value
$y_1 = f\ (y_2, x; t)$ vs. $y_2 = g\ (y_1, x; t)$	-0.127	0.899

The validity of the specification for the fixed farm effects model is then examined. Testing the joint significance of individual farm dummies indicates that the null hypothesis, of no distinct individual effects, is rejected at the 5 percent significance level. Most coefficients from the estimation of the transformation function (6) are significant in Table 3.

Table 4 presents the average rates of productivity growth, calculated using estimated coefficients of the transformation function. Given that the estimation procedures generate a large subset of productivity growth rates for each of the 2,450 farms, it is necessary to summarize the results to facilitate presentation. To this end, several categories distinguish the average productivity growth rates by time period, farm size, farm operator's age, and major crop.[11] The value in each category presents the average productivity growth rate for those farms within that category. T-tests for testing the null hypothesis that the sample mean is identical zero are performed. Note that productivity growth in the transformation model is measured as the net change in rice production, after eliminating substitution effects between rice and non-rice crops and the scale effects of inputs. Also, positive or negative rates of productivity growth indicate improvement in or decline of productivity, respectively.

The average rate of growth, evaluated over all provinces and years, is 0.0216, which implies that productivity increased 2.16% during the period 1998~2002. Average productivity growth, at the annual level, indicates that the average rate of productivity growth was highest between 1998 and 1999 and lowest between 2001 and 2002. Technical change between 2001 and 2002 in

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11 Farm size, measured by hectares of farmland operated, is separated into five categories: 0-0.5ha, 0.5-1.0ha, 1.0-2.0ha, 2.0-3.0ha, and above 3.0ha. Farm operator's age is divided by years into the following groups: less than 40, 40-54, 55-64, and above 65. Major crop produced is separated into two groups by share of crop receipts: rice dominant farms(i.e., farms with share of rice receipts greater than 50% of total gross farm receipts) and non-rice dominant farms(i.e., farms with share of non-rice receipts greater than 50% of total gross farm).

dicates a negative change. This result must be interpreted in the context that the productivity measure between 2001 and 2002 is based on a high yield year of 2001 and a poor harvest year of 2002 by a bad weather condition.

TABLE 3. Parameter estimates of the generalized transformation function

Parameter	Estimate	Standard error
α_0	-2244.56	679*
α_y	22.38	2.56*
α_1	55.43	34***
α_2	-10.83	12.97***
α_3	4.67	3.70
α_4	5.59	4.63
α_t	669.36	269*
β_1	0.02	0.01**
β_{11}	33.29	2.34*
β_{12}	3.10	0.73*
β_{13}	-0.18	0.25
β_{14}	0.83	0.23*
β_{22}	-0.16	0.37
β_{23}	-0.22	0.10**
β_{24}	-0.06	0.10**
β_{33}	-0.01	0.03
β_{34}	-0.03	0.04**
β_{44}	-0.19	0.05*
β_{y1}	-1.67	0.13*
β_{y2}	-0.08	0.05**
β_{y3}	0.07	0.02*
β_{y4}	0.01	0.02
β_{tt}	-884.82	157*
β_{yt}	-7.52	0.88*
β_{t1}	98.83	9.23*
β_{t2}	14.00	3.96*
β_{t3}	-0.26	1.48
β_{t4}	4.00	1.84**
σ_v	4,709*	
σ_e	2,733*	

Note: $F(27,9773)= 203$
*, **, and *** indicate significant at the 1%, 5% and 10% level, respectively.

TABLE 4. Productivity growth rates from the estimation of transformation function

	Productivity growth rates
Mean for all provinces and years	0.0216
Year mean for all provinces	
1998-1999	0.0582
1999-2000	0.0178
2000-2001	0.0076
2001-2002	-0.0999
Means by farm size category	
0-0.5 ha	0.0208
0.5-1.0 ha	0.0214
1.0-2.0 ha	0.0114
2.0-3.0 ha	0.0307
Above 3.0ha	0.0367
Means by farm operator's age category	
Less 40 years	0.0328
40-54 years	0.0282
55-64 years	0.0182
65-69 years	0.0057
Above 70 years	0.0034
Means by major crop	
Rice dominant farms	0.0364
Non-rice dominant farms	-0.0046

Note: Farm size, measured by hectares of farmland operated, is separated into five categories: 0-0.5ha, 0.5-1.0ha, 1.0-2.0ha, 2.0-3.0ha, and above 3.0ha. Farm operator's age is divided by years into the following groups: less than 40, 40-54, 55-64, and above 65. Major crop produced is separated into two groups by share of crop receipts: rice dominant farms(i.e., farms with share of rice receipts greater than 50% of total gross farm receipts) and non-rice dominant farms (i.e., farms with share of non-rice receipts greater than 50% of total gross farm).

Note that productivity change in the non-frontier production technology compounds aggregate shocks such as those due to weather variations with true technological change. Since it is difficult to construct annual weather data into a variable and the decomposition of the technical change seems to deviate from the mainstream of the paper, I will not split the weather effect from the technical change. Such decomposition of the technical change will be left as a further study.

The average growth rate of farms with farmland operated of more than 3.0ha has the highest growth rate, due to this class having the greatest scale effect.

While farm operators above 70 years of age showed the smallest rate of average productivity growth, operators less than 40 years of age displayed the highest rate of average growth. Farm operator's age affects the ability of farms to learn and absorb new information, thus the farms operated by a younger farm operator contribute more to productivity growth.

Finally, the average productivity growth rate of rice dominant farms (with shares of rice receipts making up more than 50 percent of total gross farm receipts) is higher than that of non-rice dominant farms. Rice dominant farms have especially received benefits from government policies associated with farm consolidation, since most of policies in this area have focused on fostering large rice farms. Among farms producing rice and non-rice crops, rice dominant farms make up 63 percent in the sample. To indirectly evaluate policy effects related to farm consolidation, farms producing both rice and non-rice crops are separated into rice dominant farms and non-rice dominant farms. Farm growth of rice-dominant farms thus increased productivity growth, implying there was a positive return on policies which focused on expanding the landholdings of rice-specialized farms.

VII. Conclusion Remarks

Despite the caution required in interpreting the results, this study can draw some general conclusions about Korean agricultural productivity for the period examined. The technical change plays an important role as an origin of productivity growth in Korean agriculture during 1998~2002, suggesting that technological progress is a vital source of overall productivity improvement during the study period. Larger farms of above 3.0ha experienced the fastest productivity growth attributed to the greatest rate of scale effect, which suggests farm consolidation is one source of the average productivity growth. The results also indicate higher rates of average productivity growth for younger farmers.

This paper aims to provide information about the productivity change during 1998~2002 in the context of multi-output production technology in Korean agriculture. The empirical evidence that the technology progress has acted as an important factor for productivity improvement during the study period, implies the necessity of a sustainable R&D investment on Korean agriculture to improve productivity. Also, as farmer is younger and as farm size is larger, the productivity change is higher. Many studies have already identified public R&D as a primary source of measured growth in agricultural productivity with large social benefits. Accordingly, efficient allocation method of R&D toward enhancing agricultural productivity and increase of R&D expenditures need to be considered.

Future studies may attempt to build on this research by including more detailed weather data, public-sector R&D expenditures, and government policy as determinants affecting the technical change.

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