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Productivity improvement in Korean rice farming: parametric and non-parametric analysis†

Oh Sang Kwon and Hyunok Lee*

The published empirical literature on frontier production functions is dominated by two broadly defined estimation approaches – parametric and non-parametric. Using panel data on Korean rice production, parametric and non-parametric production frontiers are estimated and compared with estimated productivity. The non-parametric approach employs two alternative measures based on the Malmquist index and the Luenberger indicator, while the parametric approach is closely related to the time-variant efficiency model. Productivity measures differ considerably between these approaches. It is discovered that measures of efficiency change are more sensitive to the choice of the model than are measures of technical change. Both approaches reveal that the main sources of growth in Korean rice farming have been technical change and productivity improvements in regions of the country that have been associated with low efficiency.

1. Introduction

Since the pioneering work of Farrell (1957), a large amount of literature has been published on the measurement of frontier production functions and productive efficiency. Within the common concept of a frontier production function, the empirical literature that focuses on frontier production has used two broadly defined approaches – the non-parametric programming approach, commonly referred to as data envelopment analysis (Charnes *et al.* 1978); and the parametric stochastic approach (Aigner *et al.* 1977).

The two alternative approaches have different strengths and weaknesses. The essential differences largely reflect the different maintained assumptions used

* Oh Sang Kwon is an associate professor at the School of Agricultural Economics and Rural Development, Seoul National University, Seoul, Korea. Hyunok Lee is a research economist at the Department of Agricultural and Resource Economics, University of California, Davis.

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in estimating the frontiers. The main strength of the statistical approach stems from the fact that the frontier is stochastic, and this allows the effects of noise to be separated from the effects of inefficiency. However, the statistical approach is parametric – it requires the specification of a functional form. This implies that structural restrictions are imposed, and the effects of misspecification of functional form might be confounded with inefficiency.[1] The reverse is true for the non-parametric approach. The non-parametric approach is free from the misspecification of functional form and other restrictions, but it does not account for statistical noise and is therefore vulnerable to outliers. Some progress has been achieved in overcoming the disadvantages of each approach, but the essential differences largely remain, and the empirical performance of each approach has continued to be of interest to the users of the frontier framework (Ferrier and Lovell 1990; Sharma *et al.* 1997; Fulginiti and Perrin 1998).

In the present paper, we use Korean rice panel data and both parametric and non-parametric frontier methods to estimate productivity changes for rice production in Korea. The application of the frontier framework to the Korean situation is motivated by our personal observation of Korean rice farms and evidence that farms might exhibit differences in their productivity.[2] Using panel data over the period of 1993–1997, we estimate parametric and non-parametric production frontiers and compare the results on productivity measures obtained from both approaches. More specifically, we employ a parametric model that is closely related to Battese and Coelli's (1992) time-variant efficiency model. For non-parametric models we employ two alternative measures based on the Malmquist index approach in the

[1] The underlying assumption of the statistical approach that the firm-specific level of inefficiency is uncorrelated with input levels may be unwarranted. Furthermore, one of difficulties with the statistical framework arises with the modelling of multi-output technology. While non-parametric methods easily accommodate multi-output technology, it is not easy to model multi-output technology in the statistical framework (particularly, in the primal approach).

[2] The fact that one even attempts to measure relative efficiency reflects a basic premise that firms may operate at different efficiencies. That is, using the same input mix, two firms produce different output levels or two firms use different input levels to produce the same output. This raises an interesting point that is not addressed in the neoclassical theory of the firm. The question becomes, why the optimizing behaviour of the firm does not lead to output maximization given a set of inputs. Under the neoclassical framework, one obvious explanation would be missing variables such as unobserved constraints or unmeasured input quality (such as managerial ability). In light of this, inefficiency may be a measure of our ignorance, that is, our inability to collect all the relevant information. In the present study, the notion of 'efficiency' is based only on input–output relationships observed from the data.

spirit of Caves *et al.* (1982) and further developed by Färe *et al.* (1994) and the Luenberger indicator approach recently developed by Chambers (Chambers *et al.* 1996; Chambers 2002).

While the primary objective of the present paper is to compare empirical performance of productivity outcomes between parametric and non-parametric approaches, another important aim is to shed some light on Korean rice productivity, an issue studied little in the past. Korea has long been a significant importer of wheat and feed grains, and more recently, it has become a growing market for beef and selected horticultural crops (Sumner *et al.* 1999). The exception, until recently, has been rice. The country's previous border policy inspired little research on rice productivity, particularly outside Korea. Research on Korean rice productivity contributes in two ways. First, as border restrictions have been relaxed, there has been growing interest in the Korean market among world market observers, and productivity is an important element in understanding the outlook for the Korean market. Second, until now, public policy in Korean agriculture has been focused on boosting rural income with little attention to productivity. Assessing the unexplored productivity potential is an important component of evaluating the future path of productivity. The previous regime of autarky and considerable government intervention helped marginal farmers remain in business. A more open market would be expected to induce some marginal farmers to retire from rice farming, which means that average current productivity would be misleading as an assessment of the productivity potential. This underscores the relevance of frontier methods.

The present paper is organised as follows. We first provide an analytical framework for estimating various productivity measures. Then, to provide context to our analysis, section three briefly describes rice farming in Korea and discusses the data used. We then present estimation procedures in section four. The estimated results are presented and discussed in section five. Conclusions are drawn in the final section.

2. Theoretical framework

As a first step to the representation of productivity change, we begin with the notion of total factor productivity (TFP). Let rice output $y \in \Re_+$ be produced using an input vector $\boldsymbol{x} \in \Re_+^N$. The rate of change in TFP represents the rate of change in productivity and is measured using the following Divisia index:

$$\dot{TFP} = \frac{d \ln y}{dt} - \sum_{n=1}^{N} s_n \frac{d \ln x_n}{dt}, \tag{1}$$

where x_n and s_n are the quantity and cost share of the n*th* input, respectively. Since the production data are collected for discrete years, the rate of productivity change is approximated with the following Törnqvist index:

$$T\dot{F}P = \ln y^{t+1} - \ln y^{t} - \sum_{n=1}^{N} \frac{1}{2}(s_n^{t+1} + s_n^{t})(\ln x_n^{t+1} - \ln x_n^{t}). \tag{2}$$

If data on the quantities and prices of all inputs and outputs are available, the rate of productivity change in equation (2) may be measured directly. However, the index in equation (2) does not explain the sources of productivity change.

Caves *et al.* (1982) introduced an output-based Malmquist index of productivity change as a measure of productivity growth. They defined the Malmquist index of change in output productivity as the geometric mean of two Malmquist indexes of output productivity:[3]

$$M^{t,t+1} = \left[\frac{D_o^{t}(\boldsymbol{x}^{t+1}, y^{t+1})}{D_o^{t}(\boldsymbol{x}^{t}, y^{t})}\frac{D_o^{t+1}(\boldsymbol{x}^{t+1}, y^{t+1})}{D_o^{t+1}(\boldsymbol{x}^{t}, y^{t})}\right]^{1/2}. \tag{3}$$

In equation (3) the function $D_o^t(\boldsymbol{x}^t, y^t)$ is the output distance function for year t, which is defined as the ratio of observed output to the maximum output producible with given technology and input vectors (Shephard 1970; Färe 1988).[4] The superscripts of the distance functions represent the reference technology indexed by year. Thus, $D_o^t(\boldsymbol{x}^{t+1}, y^{t+1})$, for instance, is the value of the output distance function evaluated at the input–output of year $t + 1$ using the technology of year t.

Färe *et al.* (1994) has suggested using a Malmquist index to decompose productivity change between two years into technical and efficiency changes:

$$M^{t,t+1} = \frac{D_o^{t+1}(\boldsymbol{x}^{t+1}, y^{t+1})}{D_o^{t}(\boldsymbol{x}^{t}, y^{t})}\left[\frac{D_o^{t}(\boldsymbol{x}^{t+1}, y^{t+1})}{D_o^{t+1}(\boldsymbol{x}^{t+1}, y^{t+1})}\frac{D_o^{t}(\boldsymbol{x}^{t}, y^{t})}{D_o^{t+1}(\boldsymbol{x}^{t}, y^{t})}\right]^{1/2}. \tag{4}$$

In equation (4), the first ratio represents the change in technical efficiency between the two years ($\mathrm{TEC_{Malm}}$) while the bracketed term represents

[3] Caves *et al.* have identified several conditions under which the Malmquist index is identical to the Törnqvist index.

[4] Following Shephard (1970) and Färe (1988), the output distance function is defined at t as $D_o^t(x^t, y^t) = \inf\{\theta > 0 : (\boldsymbol{x}^t, y^t/\theta) \in T^t\}$, where T^t is the production technology in the tth year consisting of all feasible input/output vectors.

technical change (TC_{Malm}) between the two years. That is, the expression in equation (4) allows us to decompose productivity growth into changes in technical efficiency over time (a measure of individuals catching up toward the frontier) and changes in the reference technology (i.e., shifts in frontier over time).

More recently, Chambers *et al*. (1996) and Chambers (2002) suggested an alternative non-parametric technique of measuring the total productivity change based on the directional distance function. The directional output distance function is defined as:

$$\vec{D}_o^t(\boldsymbol{x}^t, y^t; g) = \sup\{\beta \in R: (\boldsymbol{x}^t, y^t + \beta g) \in T^t\}, g \in R_+, g \neq 0, \tag{5}$$

where T^t is the production technology in year t consisting of all feasible input and output vectors, and g represents the direction in which y is expanded.[5] The directional output distance function represents the maximal translation of the output in the direction of g within T. At $g = y$, the relationship between the directional output distance function and the Shephard output distance function is obvious (Chambers *et al*. 1996):

$$\vec{D}_o^t(\boldsymbol{x}^t, y^t; y^t) = 1/D_o^t(\boldsymbol{x}^t, y^t) - 1. \tag{6}$$

Given that g can take other values, the Shephard output distance function is a special case of the directional output distance function.

Following Chambers *et al*. (1996), the Luenberger productivity indicator for periods t and $t + 1$ evaluated at $g = y$ is defined as:

$$L^{t,t+1} = \frac{1}{2}\{\vec{D}_o^{t+1}(\boldsymbol{x}^t, y^t; y^t) - \vec{D}_o^{t+1}(\boldsymbol{x}^{t+1}, y^{t+1}; y^{t+1}) + \vec{D}_o^t(\boldsymbol{x}^t, y^t; y^t) - \vec{D}_o^t(\boldsymbol{x}^{t+1}, y^{t+1}; y^{t+1})\}, \tag{7}$$

where the cross-period directional distance function, for example, $\vec{D}_o^t(\boldsymbol{x}^{t+1}, y^{t+1}; y^{t+1})$ is the maximal translation of output in the direction of y^{t+1}, using the technology of year t. As was shown in Chambers *et al*. (1996), the Luenberger productivity indicator can be additively decomposed into a rate of technical efficiency change (TEC_{Luen}) and a rate of technical change (TC_{Luen}),

[5] Note that directional distance functions are more general than expressed in equation (5). A vector of output can easily replace our single output, and ($\boldsymbol{x}$, y) both can be expanded in the directions of (g_x, g_y). In the present paper, we consider the case of a directional output distance function with $g_x = 0$. (For more information and intuition, see Chambers *et al.* (1996)). Furthermore, it is worth mentioning that an alternative formulation for the Luenberger distance function can be provided using the Farrell proportional distance introduced by Briec (1997). Briec provided the conditions under which the Farrell proportional distance is identical to the directional distance introduced by Chambers *et al.* (1996).

$$TEC_{Luen} = \vec{D}_o^t(\mathbf{x^t}, y^t; y^t) - \vec{D}_o^{t+1}(\mathbf{x^{t+1}}, y^{t+1}; y^{t+1}) \tag{8}$$

$$TC_{Luen} = \frac{1}{2}\{\vec{D}_o^{t+1}(\mathbf{x^t}, y^{t+1}; y^{t+1}) - \vec{D}_o^t(\mathbf{x^{t+1}}, y^{t+1}; y^{t+1}) + \vec{D}_o^{t+1}(\mathbf{x^t}, y^t; y^t) - \vec{D}_o^t(\mathbf{x^t}, y^t; y^t)\}.$$

Note that this additive decomposition property is particularly useful in our present study because the parametric model that follows also generates additive decomposition results, and the consistent additive format makes our comparison more relevant.[6]

In the estimation of distance functions required to generate Malmquist indexes and Luenberger indicators, we impose constant returns to scale (CRS). The empirical application does not necessitate the CRS assumption (Färe *et al.* 1994; Färe *et al.* 2001).[7] However, in our estimation, the CRS restriction guarantees that the values of cross-period distance functions, for instance, $D_o^t(\mathbf{x^{t+1}}, y^{t+1})$, are obtained for all individual observations.

Parametric methods have also been used to estimate productivity changes. Nishimizu and Page (1982), Bauer (1990), and Kumbhakar and Lovell (2000) have suggested several parametric ways to decompose productivity change. As a necessary step, one must assume functional forms for the production frontier and the distribution of disturbances. The ability to cope with stochastic elements comes at the cost of restrictions on the shape of the frontier.

As an initial step in developing the parametric approach, represent the production technology with the following function:

$$y = f(\mathbf{x}, t)\exp(-u), \tag{9}$$

where $f(\mathbf{x}, t)$ is a production frontier and $\exp(-u)$ is the value of the output distance function, which is less than or equal to one. Thus, $\exp(-u)$ is often represented as the efficiency score, that is, the efficiency of transforming inputs into output. If technical efficiency changes over time, then u is assumed to be dependent on time. When a functional form for $f(\mathbf{x}, t)$ is specified, the rate of change in y is represented by the following:

$$\frac{d\ln y}{dt} = \sum_{n=1}^{N} \frac{\partial f(\mathbf{x}, t)}{\partial x_n}\frac{x_n}{f(\mathbf{x}, t)}\frac{d\ln x_n}{dt} + \frac{\partial \ln f(\mathbf{x}, t)}{\partial t} - \frac{du}{dt}. \tag{10}$$

[6] The Luenberger indicator was suggested by a reviewer who noted that it is particularly useful in our context. In the present study the Luenberger distance function is estimated using non-parametric methods. However, it is useful to note that various Luenberger indexes can be also estimated within the parametric framework. For example, the quadratic approximation of the Luenberger distance function is introduced by Chambers (2001).

[7] Färe *et al.* (1994, 2001) show the calculation of the scale effect with no CRS restriction.

Define $\varepsilon_n = [\partial f(\boldsymbol{x}, t)/\partial x_n]/[x_n/f(\boldsymbol{x}, t)]$ as the elasticity of output with respect to the n*th* input. Then, the rate of productivity change is expressed as:

$$T\dot{F}P = \sum_{n=1}^{N} (\varepsilon_n - s_n)\frac{d\ln x_n}{dt} + \frac{\partial \ln f(\boldsymbol{x}, t)}{\partial t} - \frac{du}{dt}. \tag{11}$$

With the scale elasticity defined as $\varepsilon = \sum_{n=1}^{N} \varepsilon_n$, the rate of productivity change is then finally decomposed into (Kumbhakar and Lovell 2000):

$$T\dot{F}P = (\varepsilon - 1)\sum_{n=1}^{N} \frac{\varepsilon_n}{\varepsilon}\frac{d\ln x_n}{dt} + \sum_{n=1}^{N}\left(\frac{\varepsilon_n}{\varepsilon} - s_n\right)\frac{d\ln x_n}{dt} + \frac{\partial \ln f(\boldsymbol{x}, t)}{\partial t} - \frac{du}{dt} \tag{12}$$

$$= \mathrm{SEC}_{\mathrm{Para}} + \mathrm{AEC}_{\mathrm{Para}} + \mathrm{TC}_{\mathrm{Para}} + \mathrm{TEC}_{\mathrm{Para}}.$$

The first term ($\mathrm{SEC}_{\mathrm{Para}}$) on the right-hand side of (12) represents the effect of scale efficiency. It implies that if the production technology exhibits increasing (decreasing) returns to scale, that is, $\varepsilon > 1$ ($\varepsilon < 1$), an increase (decrease) in input use contributes to productivity. The second term ($\mathrm{AEC}_{\mathrm{Para}}$) represents the effect on productivity of a change in allocative efficiency. The third term ($\mathrm{TC}_{\mathrm{Para}}$) measures the effect on TFP of a shift in the production frontier (i.e., the rate of technical change). The last term ($\mathrm{TEC}_{\mathrm{Para}}$) measures the effect on TFP of a change in technical efficiency. The sum of these four components is the total change in productivity. All four terms in equation (12) can be identified if a production frontier $f(\boldsymbol{x}, t)$ is estimated and the value of u is identified based on the estimation results.[8]

3. Background and data

3.1 Background

As with many other Asian countries, rice is by far the most important crop in Korea. It accounts for more than 40 per cent of the country's cropland,

[8] To be consistent with the discrete form of the data, the components of the TFP in equation (12) are accordingly transformed into:

$$T\dot{F}P = \bar{f}^t - (u^{t+1} - u^t) + (\bar{\varepsilon} - 1)\sum_{n=1}^{N} \frac{\bar{\varepsilon}_n}{\bar{\varepsilon}}(\ln x_n^{t+1} - \ln x_n^t) + \sum_{n=1}^{N}\left(\frac{\bar{\varepsilon}_n}{\bar{\varepsilon}} - \bar{s}_n\right)(\ln x_n^{t+1} - \ln x_n^t)$$

where $\bar{f}^t = 1/2\{[\partial \ln f(\boldsymbol{x}, t)/\partial t\gamma] + [\partial \ln f(\boldsymbol{x}, t+1)/\partial t\gamma]\}$, $\bar{\varepsilon}_n = 1/2(\varepsilon_n^t + \varepsilon_n^{t+1})$, $\bar{\varepsilon} = \sum_{n=1}^{N} \bar{\varepsilon}_n$ and $\bar{s}_n = 1/2(s_n^t + s_n^{t+1})$.

generates about 50 per cent of total crop revenue (30% of total agricultural gross domestic product), and is cultivated on about 80 per cent of crop farms (Korean Ministry of Agriculture and Forestry 2002). With nine per cent of the country's total population still in farming, the importance of rice in the country's agriculture and economy is evident.

Such dominance of rice in crop agriculture in Korea had been maintained through the country's strict trade policy.[9] However, the minimum access provisions of the Uruguay Round Agriculture Agreement required Korea to import rice, beginning with one per cent of base-period domestic consumption in 1995 to four per cent in 2004. Minimum access quantities and the way imports have been managed mean that there has not yet been any measurable impact of market opening on the domestic market. But, it is obvious to Korean farmers that the changing domestic and world policy environment will in future require them to pay increasing attention to productivity issues.

Over the last several decades, Korean rice productivity growth has been sluggish, with year-to-year fluctuations. To provide an historical perspective on Korean rice production, figure 1 depicts total factor productivity growth over the last three-and-a-half decades (1966–2002) using the Törnqvist index formulation (the supporting data are presented in appendix 1).[10] The rates of total factor productivity have been fluctuating around zero, with no distinct growth path over time. We calculated cumulative productivity over this period and found it to be 35 per cent, which translates into an average one per cent annual growth rate.

3.2 Data

The models developed in the previous section are applied to panel data spanning a 5-year period, 1993–1997. The data are obtained from the special rice farmer survey administered by the Korean Ministry of Agriculture and Forestry. The survey collects rice-specific production data from 1026

[9] Until 1995, Korea had maintained a strict ban on rice imports, except for emergencies (in 1981, a severe drought year, Korea imported a substantial amount of rice). However, the markets for other commodities such as corn, soybeans, or wheat have been relatively open. For example, domestic production of wheat accounts for less than one per cent of total consumption.

[10] Data used for this calculation are aggregated time series data, with the same input groups used in the rest of the present study (see the data section).

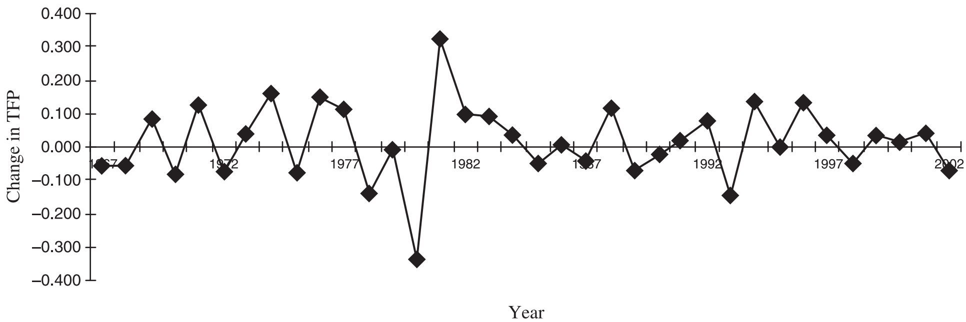

Figure 1 Rate of change in total factor productivity (TFP; 1967–2002).

Data source: Various issues of *Annual Report on the Farm Household Economy Survey*, Ministry of Agriculture and Forestry.

randomly selected farms over the 5-year period, 1993–1997, the maximum period for which the Ministry continues the same panel.[11]

Our data set contains observations on one output and six input variables. The output of rice is unhusked rice measured in kilograms. The input data are aggregated into six categories: (i) land, (ii) labour, (iii) capital, (iv) fertiliser, (v) pesticide and (vi) other inputs. The data collected on inputs are largely in value terms rather than quantities, except for land and labour. Land includes the area planted to rice, and labour measured in hours includes own and hired labour. The remaining inputs are measured in value terms. In particular, the capital input includes the average estimated replacement cost of structures, machinery depreciation, repairs, and leased farm equipment, and the other input category includes expenditures on seed, water, electricity and fuel. The capital, fertiliser and pesticide expenditure data are deflated using respective input-specific purchasing price indices, and the other input category is deflated using overall purchasing price indices of farm households.[12] Use of expenditure input data is a concern. When input prices vary systematically (changing in real terms), our data in value terms would systematically bias the estimation results. That is, prices lower than

[11] We have a relatively short time period for our panel data. However, to our knowledge, few frontier production studies in agriculture have been conducted using such a large sample. An exception is Huang and Kalirajan (1997). Using a stochastic varying parameter frontier approach, Huang and Kalirajan, in their study of Chinese grain production, used annual household survey data of 1000 grain farmers covering the years 1993–1995.

[12] We used national level input-specific deflators; unfortunately less aggregated (at the regional level) deflators were not available.

Table 1 Descriptive statistics of output and inputs†

	Rice (y)	Land (x_A)	Labor (x_L)	Capital (x_C)	Fertiliser (x_F)	Pesticides (x_P)	Others (x_O)
Mean value per farm household							
1993	7 775	0.97	314	500	190	274	91
1994	8 704	1.15	295	539	229	251	101
1995	8 366	1.20	281	544	222	260	98
1996	9 541	1.24	266	557	230	286	107
1997	9 887	1.29	255	562	221	321	109
Kyounggi	10 698	1.51	261	737	267	319	108
Kangwon	7 658	1.14	335	466	345	231	114
North Chungchong	7 549	0.97	273	440	207	223	98
South Chungchong	11 442	1.50	341	608	247	351	116
North Choolla	11 416	1.45	328	743	224	405	109
South Choolla	7 238	0.86	269	466	169	262	106
North Kyoungsang	7 348	0.85	242	435	152	200	91
South Kyoungsang	5 691	0.83	197	319	131	179	61
All year/province mean	8 855	1.17	282	540	218	278	101
Standard deviation	7 339	1.75	210	449	404	251	111
Input use per unit of output							
1993	1000 kg	0.125	40.4	64.3	24.4	35.2	11.7
1994	1000 kg	0.132	33.9	61.9	26.3	28.8	11.6
1995	1000 kg	0.143	33.6	65.0	26.5	31.1	11.7
1996	1000 kg	0.13	27.9	58.4	24.1	30.0	11.2
1997	1000 kg	0.13	25.8	56.8	22.4	32.5	11.0
Kyounggi	1000 kg	0.141	24.4	68.9	25.0	29.8	10.1
Kangwon	1000 kg	0.149	43.7	60.9	45.1	30.2	14.9
North Chungchong	1000 kg	0.128	36.2	58.3	27.4	29.5	13.0
South Chungchong	1000 kg	0.131	29.8	53.1	21.6	30.7	10.1
North Choolla	1000 kg	0.127	28.7	65.1	19.6	35.5	9.5
South Choolla	1000 kg	0.119	37.2	64.4	23.3	36.2	14.6
North Kyoungsang	1000 kg	0.116	32.9	59.2	20.7	27.2	12.4
South Kyoungsang	1000 kg	0.146	34.6	56.1	23.0	31.5	10.7

†Units are kilogram for rice, hectare for land, hour for labour and 1000 won for the rest of the inputs.

national prices result in the overestimation of efficiency. However, given that only material inputs are measured in value terms (excluding inputs such as labour and land that might exhibit significant regional differences) and input specific price trends are removed, we believe that the magnitude of estimation bias would be small.

The descriptive statistics for inputs and output are summarised in table 1. We present mean values per farm household by year as well as by province (regional unit used in our results section). Consistent with our output distance function approach, table 1 also provides input values per unit of output (1000 kg). These figures indicate that, except for labour, for this 5-year period input use per unit of output did not change much. Labor use per unit of output declined and this happened with no increase in capital or material input use.

Finally, our data also confirm that rice farms in Korea are small, with the average land holding of slightly over one hectare per household for the sample. Of the total farms, 93% had a land holding of less than 2 hectares, and another 5% had a land holding of between 2 and 3 hectares. One empirical implication of this characteristic relates to the CRS restriction on the non-parametric productivity calculations. One rationalisation for the CRS assumption in empirical estimation is that technology that is recoverable from the data involves only the local technology. The fact that farms in our sample can be characterised with a similar scale of operation (i.e., all are small) means we are less concerned about our CRS assumption. Simply put, over the range of the great majority of our observations the finding of a small and economically unimportant scale effect might not be surprising, as scale does not vary much over the observations.

4. Estimation procedures and stochastic frontier function estimation

4.1 Procedures for non-parametric estimation

The first step in non-parametric estimation is to estimate the relevant output distance functions. The inverse of the Shepard output distance function with respect to the ith firm's input and output bundle ($\boldsymbol{x}^{i,t}$, $y^{i,t}$), referenced to the year t technology, can be calculated using the following linear program:

$$
\begin{aligned}
&[D_o^t(\boldsymbol{x}^{i,t}, y^{i,t})]^{-1} = \max \tau \\
&\text{s.t.} \quad \tau y^{i,t} \leq \sum_{j=1}^{J} z_j y^{j,t} \\
&\qquad x_n^{i,t} \geq \sum_{j=1}^{J} z_j x_n^{j,t} \qquad n = 1, \ldots, N \\
&\qquad z_j \in R_+ \qquad\qquad j = 1, \ldots, J.
\end{aligned}
\tag{13}
$$

The maximised value of the objective function in the above problem measures the output-based technical efficiency of the ith firm at year t. The linear program used to calculate the directional output distance function can be similarly formulated following the definition provided in equation (5):

$$\vec{D}_0^t(\boldsymbol{x}^{i,t}, y^{i,t}; y^{i,t}) = \max \beta$$
$$\text{s.t.} \quad (1+\beta) y^{i,t} \le \sum_{j=1}^{J} z_j y^{j,t}$$
$$x_n^{i,t} \ge \sum_{j=1}^{J} z_j x_n^{j,t} \quad n = 1, \ldots, N$$
$$z_j \in R_+ \qquad j = 1, \ldots, J. \tag{14}$$

Note that the optimised value of the directional output distance function, β, equals $\tau - 1$ (see equation 6). Values of the distance function and directional distance function associated with period $t + 1$ are calculated using the linear programming problems (13) and (14) above, but with t being replaced by $t + 1$. The cross-period output distance functions are computed in a similar way with a slight modification of the above programs. We do not provide the programs here, but for example, $D_o^t(\boldsymbol{x}^{i,t+1}, y^{i,t+1})$ or $\vec{D}_o^t(\boldsymbol{x}^{i,t+1}, y^{i,t+1}; y^{i,t+1})$ can be computed by replacing $(\boldsymbol{x}^{i,t}, y^{i,t})$ with $(\boldsymbol{x}^{i,t+1}, y^{i,t+1})$ in the above problems, and finally the computation of $D_o^{t+1}(\boldsymbol{x}^{i,t}, y^{i,t})$ or $\vec{D}_o^{t+1}(\boldsymbol{x}^{i,t}, y^{i,t}; y^{i,t})$ can be carried out by solving for $D_o^t(\boldsymbol{x}^{i,t+1}, y^{i,t+1})$ or $\vec{D}_o^t(\boldsymbol{x}^{i,t+1}, y^{i,t+1}; y^{i,t+1})$ with the t and $t + 1$ superscripts being transposed. Our study uses a GAMS program (version 2.50A) to calculate distance function values.

4.2 Procedures for parametric estimation

To obtain the parametric decomposition of productivity change as in equation (12), a functional form for the stochastic production frontier has to be chosen. Ideally, the functional form should be flexible and computationally straightforward. For these properties, we have chosen the translog function that has been adopted widely in frontier studies (Kumbhakar 1994; Grosskopf *et al.* 1997; Fuentes *et al.* 2001) with time-varying technical efficiency:[13]

$$\ln y^{i,t} = \alpha_0 + \sum_n \alpha_n \ln x_n^{i,t} + \alpha_t t + \frac{1}{2} \sum_n \sum_{n'} \beta_{nn'} \ln x_n^{i,t} \ln x_{n'}^{i,t}$$
$$+ \sum_n \beta_{nt} \ln x_n^{i,t} t + \frac{1}{2} \beta_{tt} t^2 + v^{i,t} - u^{i,t} \tag{15}$$

[13] Pitt and Lee (1981) and Battese and Coelli (1995) have suggested a time-invariant random effect panel model of a stochastic frontier, where technical efficiency u^i is constant over time. However, because a time-invariant model cannot identify the contribution of efficiency change to productivity change, we did not adopt their model in our present study.

where $\beta_{nn'} = \beta_{n'n}$, $v^{i,t}$ is the two-sided noise component following an *iid* normal distribution with zero mean and variance σ_v^2, and $u^{i,t}$ represents the technical (in)efficiency of the i*th* producer in year t.

Allowing $u^{i,t}$ to vary over both producers and time periods, Battese and Coelli (1992) proposed the following specification of $u^{i,t}$:

$$u^{i,t} = \{\exp[-\eta(t-5)]\}u^i \tag{16}$$

where the u^i are assumed to be independent and identically distributed non-negative truncations of the N(μ, σ^2) distribution suggested by Stevenson (1980). Therefore $u^{i,t}$ decreases, remains constant or increases over time if $\eta > 0$, $\eta = 0$, or $\eta < 0$. If producers improve their level of technical efficiency, then η is positive. The advantage of the Battese and Coelli (1992) model in equation (16) is that it allows technical efficiency to change over time by adding just one more parameter, η, to be estimated. A shortcoming of the model is that it restricts technical efficiency to be monotonically increasing or decreasing over time. Cornwell *et al.* (1990), Kumbhakar (1990), and Lee and Schmidt (1993) have suggested several models where technical efficiency does not necessarily change monotonically over time. However, those more general models contain more parameters to be estimated than the model suggested in equation (16). Given the relatively short time span of our data, a more general model is not considered in our present study.[14] The maximum likelihood estimation of model (15) with the specification in (16) provides estimators for the α's and β's and the variance parameters σ^2 and $\gamma(=\sigma^2/(\sigma_v^2+\sigma^2))$. The estimation was conducted using the program STATA (8.0).

4.3 Estimated stochastic frontier function

Parametric productivity measures are based on the estimated parameters of the stochastic frontier function (15), and so a brief discussion of these estimates and their statistical properties precedes our comparative analysis of productivity indices that follows in the next section. The parameter estimates are presented in table 2 and several observations stand out. First, the variance parameters, σ^2 and γ, are significantly different from zero. This provides statistical confirmation of our presumption that there are differences in technical efficiency among farmers. Moreover, the share of this one-sided error in total variance (γ) is approximately 57 per cent. Second, μ, the mode of the truncated normal distribution, is significantly different from zero, providing statistical evidence that the distribution of the random

[14] Some of those more flexible models have never been estimated empirically.

Table 2 Parameter estimates of the stochastic frontier†

Parameter	Estimate	t-value	Parameter	Estimate	t-value
α_0	3.955	17.89	β_{CF}	−0.020	−2.73
α_A	0.247	3.92	β_{CP}	−0.016	−1.32
α_L	0.415	5.17	β_{CO}	−0.011	−0.95
α_C	0.176	2.77	β_{FF}	0.005	1.40
α_F	0.043	1.31	β_{FP}	−0.008	−1.19
α_P	0.014	0.24	β_{OF}	0.008	1.48
α_O	−0.003	−0.05	β_{PP}	0.098	7.06
α_t	0.150	7.19	β_{PO}	0.0004	0.04
β_{AA}	−0.025	−2.41	β_{OO}	−0.024	−2.16
β_{AL}	0.044	2.72	β_{At}	−0.021	−5.24
β_{AC}	−0.040	−3.11	β_{Lt}	0.025	5.33
β_{AF}	0.010	1.75	β_{Ct}	−0.014	−3.72
β_{AP}	−0.013	−1.10	β_{Ft}	−0.002	−0.60
β_{AO}	0.022	1.89	β_{Pt}	−0.010	−2.45
β_{LL}	−0.092	−3.53	β_{Ot}	0.006	1.83
β_{LC}	0.020	1.19	β_{tt}	−0.007	−2.58
β_{LF}	0.008	1.02	σ^2	0.056	14.00
β_{LP}	−0.036	−2.43	γ	0.573	19.10
β_{LO}	0.042	3.40	μ	0.217	6.91
β_{CC}	0.057	4.26	η	0.075	6.33

† $\gamma = \sigma^2/(\sigma_v^2 + \sigma^2)$, ln L = 1287.579.

variable, u^i, has a non-zero mean and is truncated below zero. Third, and most importantly, η is significant and positive. This implies that technical efficiency is time-varying and improves over time. The statistical significance of all of the parameters, σ^2, γ and η, reinforces the view that technical efficiency affects productivity.

5. Comparison of parametric and non-parametric productivity measures

Given that our procedures generate large sets of results (obtained from each of 5130 observations over 5 years), it is necessary to summarise the results to facilitate the presentation. To this end, we sort the estimates by time period and by geographical area, and present the mean values. Our regional aggregation corresponds to the provinces of the Korean peninsula (figure 2). These provinces are administrative units, but each province also tends to have its own characteristic of rice terrain. Although investigating regional patterns of productivity is not our main goal, the investigation at a less aggregated, regional level enables us to explore what might have been unobserved in the national numbers in our comparison analysis. Below, we begin with the analysis of technical efficiency, and then proceed to discuss productivity and decomposition results.

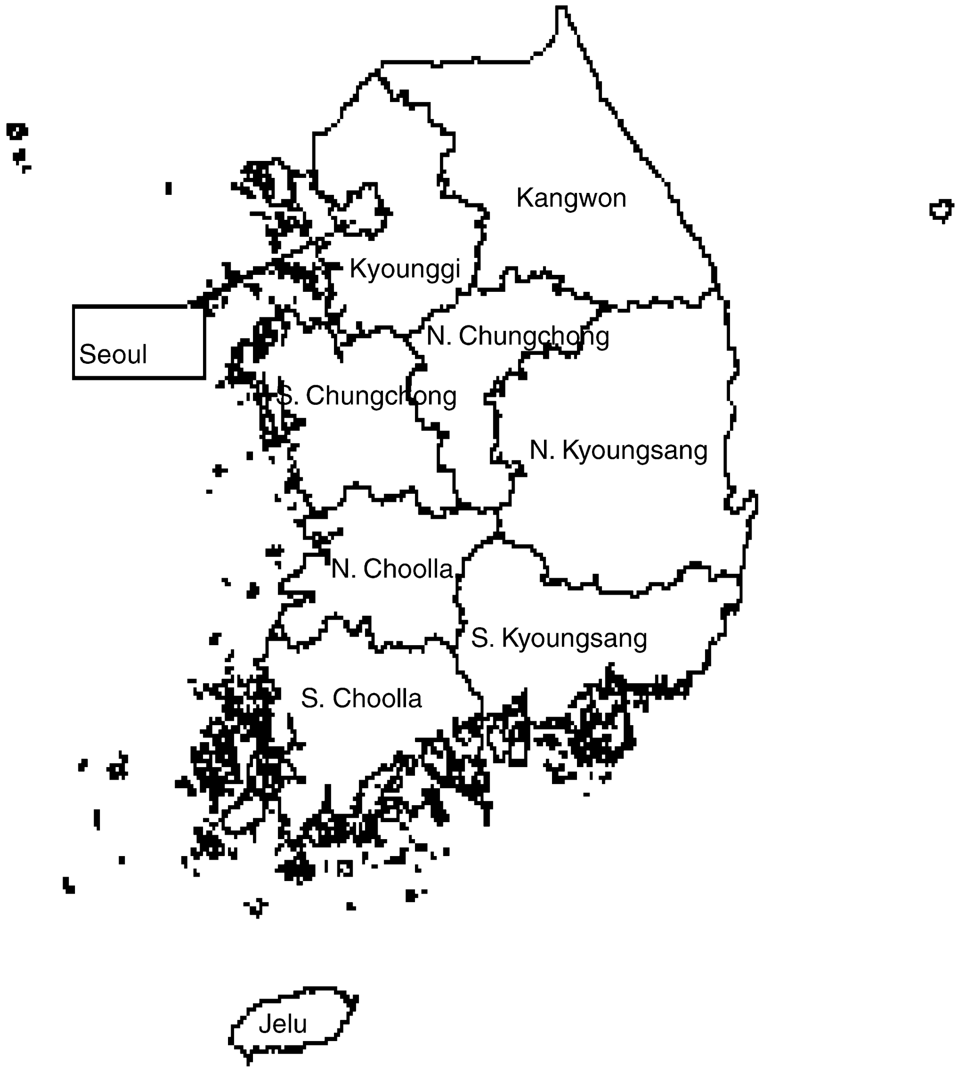

Figure 2 Provinces in South Korea.

5.1 Comparison of technical efficiency scores

Solving the linear program (13) yields Farrell's technical efficiency scores, a component of the productivity index calculation. The equivalent parametric scores are obtained by estimating exp(–u). Our estimates of the parametric efficiency scores are obtained using Battese and Coelli's (1992) formula for deriving the expected value of the efficiency scores. Table 3 presents mean efficiency scores by province and by year, which can be interpreted as the

Table 3 Mean technical efficiency scores

Province		Year 1993	1994	1995	1996	1997	All years
Kyounggi (148)[†]	Non-parametric	0.84	0.79	0.69	0.75	0.76	0.77
	Parametric	0.79	0.80	0.81	0.83	0.84	0.81
Kangwon (105)	Non-parametric	0.52	0.70	0.60	0.68	0.70	0.64
	Parametric	0.61	0.63	0.65	0.67	0.69	0.65
North Chungchong (120)	Non-parametric	0.74	0.74	0.70	0.72	0.69	0.72
	Parametric	0.71	0.72	0.74	0.75	0.77	0.74
South Chungchong (156)	Non-parametric	0.80	0.77	0.68	0.75	0.78	0.76
	Parametric	0.77	0.79	0.80	0.81	0.82	0.80
North Choolla (138)	Non-parametric	0.84	0.77	0.69	0.66	0.64	0.72
	Parametric	0.75	0.77	0.78	0.80	0.81	0.78
South Choolla (118)	Non-parametric	0.65	0.66	0.61	0.67	0.64	0.65
	Parametric	0.66	0.68	0.70	0.71	0.73	0.70
North Kyoungsang (124)	Non-parametric	0.62	0.79	0.74	0.76	0.77	0.74
	Parametric	0.71	0.73	0.75	0.76	0.78	0.75
South Kyoungsang (117)	Non-parametric	0.67	0.77	0.74	0.75	0.72	0.73
	Parametric	0.73	0.74	0.76	0.77	0.79	0.76
All regions (1026)	Non-parametric	0.72	0.75	0.68	0.72	0.71	0.72
	Parametric	0.72	0.74	0.75	0.77	0.78	0.75

[†]Numbers in parentheses are observation numbers.

average performance of each province relative to the national frontier in a given period.

Compared to the non-parametric approach, parametric estimation tends to produce higher efficiency scores. This is not surprising given that the non-parametric method attributes any deviation from the frontier to inefficiency, whereas the parametric method recognises the stochastic component in constructing the frontier. Furthermore, this tendency is more pronounced in the later years, and this is likely the consequence of the specification of the time variant one-sided error term, which in our case suggests increasing technical efficiency with time (the positive value of η). Year-to-year non-parametric fluctuations indicate that 1995 was an unusual year, experiencing a dip in the country's average efficiency score, which coincides with the report of crop damage by floods in that year. Even though non-parametric efficiency scores fluctuate from year to year, the overall means for each province from both approaches (last column of table 3) indicate that Kangwon, well known for its mountainous terrain, is consistently one of the least efficient regions, and Kyounggi, known for high quality rice, is found to be the most efficient region.

Given the fact that the non-parametric method does not allow stochastic terms and imposes less structural restrictions, non-parametric efficiency scores are expected to show fewer systematic patterns over the years than parametric scores. We now ask a related question: is there any relationship between the level of variation and the level of efficiency? In other words, would a more efficient individual show less variation in efficiency ranking over years? To investigate this issue, we examined the five-year efficiency scores of the selected individuals from three groups labelled as high, average and low efficiency.[15] For each individual, we calculated the coefficient of variation (CV) using the individual's 5-year scores to investigate the level of variation over 5 years. The mean CV of the groups, each consisting of 50 observations, were 0.21 for the low efficiency group, 0.16 for the mid efficiency group and 0.08 for the high efficiency group, indicating that efficient farmers tend to stay efficient over time. This cursory examination suggests a potentially important possibility – an individual's efficiency extends to an ability to cope with exogenous shocks such as weather.

One last inquiry regarding efficiency scores deals with the cross-sectional distribution of efficiency. Figure 3 plots the distributions of efficiency scores for three selected years. We constructed these distributions using the kernel method.[16] For all 3 years, parametric efficiency distributions seem to conform to a certain distributional pattern with the distribution shifting to the right with time (positive η). Non-parametric efficiency distributions show no conformity in distributional patterns. These distributions, in general, have wide spreads and have relatively high density clusters near the efficiency score of one. It is also interesting to note that these high densities form another mode in the distribution.

5.2 Comparison of productivity indexes and decomposition

We present three sets of productivity indexes in table 4, two non-parametric indexes, the Malmquist index and the Luenberger indicator, and one parametric productivity index. A Malmquist index of less than 1.0 indicates a decline in performance over time and a value greater than 1.0 indicates an improvement. Correspondingly, a positive or negative Luenberger indicator indicates improvement or decline. Comparing the two non-parametric

[15] The sample observations are ranked by the individual's 5-year average efficiency score. We then select 5 per cent of the sample (50 observations) from each of the top, middle and bottom of the ranking. The 5-year average scores range from 0.397 to 0.532 for the low-efficiency group (ranks 1 through 50), from 0.709 to 0.721 for the mid-efficiency group (ranks 489 through 538), and from 0.912 to 1 for the high-efficiency group (ranks 977 through 1026).

[16] We used the Epanechnikov kernel and the Silverman's (1986) optimal widow width for kernel density estimation.

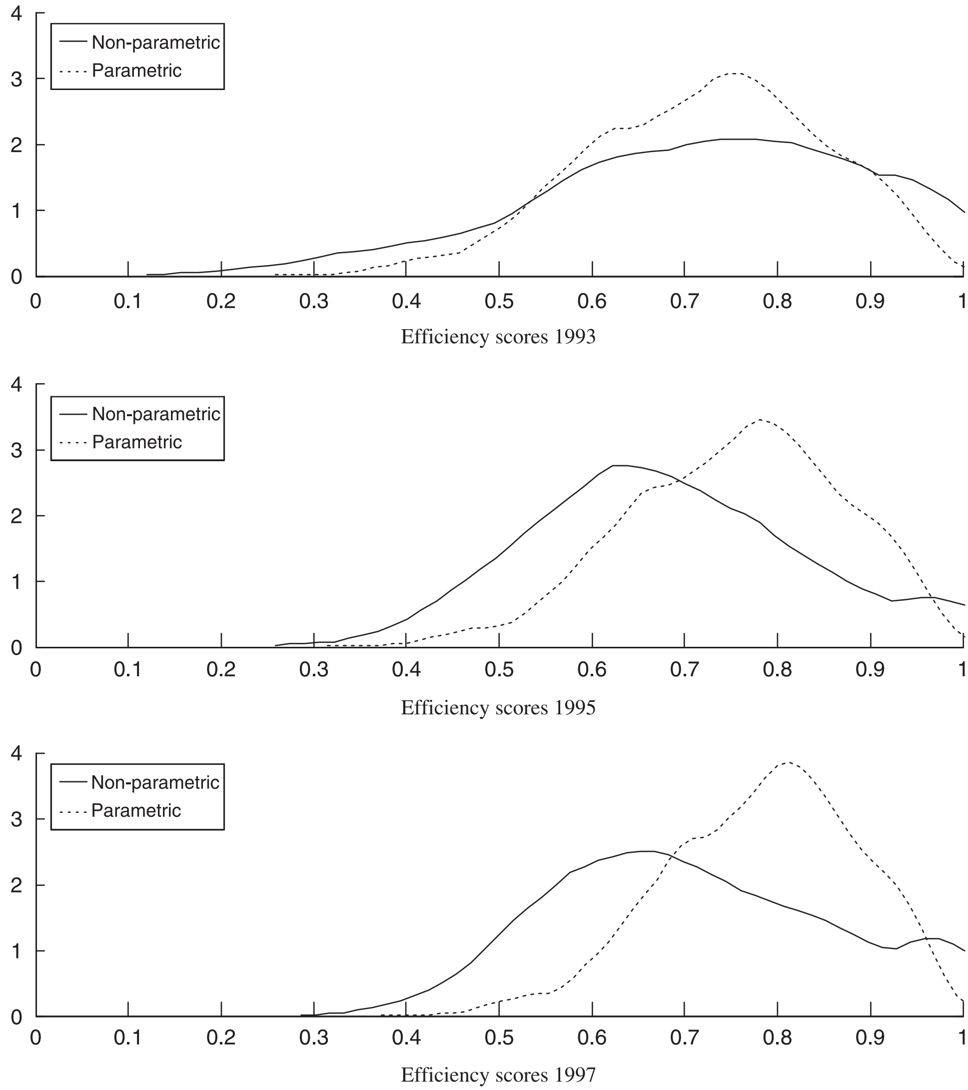

Figure 3 Distributions of efficiency scores for selected years.

productivity indexes, we notice that productivity growth at the annual and regional levels have been positive, with the exception of the Luenberger indicator for the period 1994–1995. Decomposition results for this period provide some insight on this conflicting result concerning net growth. Both Malmquist and Luenberger decompositions indicate that this period was characterised by productivity changes in both directions, an increase caused by the shift of the frontier and a decline as a result of decreased

Table 4 Non-parametric and parametric productivity indices and decomposition

	Non-parametric approach						Parametric approach			
	Malmquist index			Luenberger indicator						
		Decomposition			Decomposition			Decomposition		
	Malmquist index	TEC_{Malm}	TC_{Malm}	Luenberger indicator	TEC_{Luen}	TC_{Luen}	Rate of productivity	AEC_{Para}	TEC_{Para}	TC_{Para}
Year mean for all provinces										
1993–1994	1.24	1.107	1.116	0.265	0.125	0.14	0.084	0.0009	0.025	0.058
1994–1995	1.017	0.924	1.102	–0.014	–0.152	0.139	0.074	0.0021	0.023	0.049
1995–1996	1.166	1.079	1.08	0.195	0.09	0.105	0.089	0.027	0.021	0.04
1996–1997	1.031	1.002	1.031	0.018	–0.025	0.043	0.068	0.017	0.02	0.03
Provincial mean for all years										
Kyounggi	1.077	0.992	1.086	0.064	–0.038	0.102	0.059	0.011	0.016	0.038
Kangwon	1.253	1.156	1.083	0.307	0.189	0.118	0.101	0.013	0.034	0.054
North Chungchong	1.096	1.005	1.087	0.086	–0.023	0.109	0.089	0.014	0.024	0.051
South Chungchong	1.095	1.011	1.082	0.089	–0.013	0.103	0.076	0.018	0.018	0.04
North Choolla	1.024	0.946	1.085	0.016	–0.097	0.113	0.061	0.007	0.019	0.034
South Choolla	1.09	1.008	1.083	0.106	–0.018	0.123	0.084	0.008	0.028	0.048
North Kyoungsang	1.189	1.1	1.077	0.194	0.098	0.096	0.086	0.012	0.023	0.052
South Kyoungsang	1.126	1.044	1.074	0.122	0.032	0.09	0.084	0.012	0.022	0.05
All province & all year mean	1.114	1.028	1.082	0.116	0.009	0.107	0.079	0.012	0.022	0.044

technical efficiency. and the difference in the magnitude of these changes results in opposite net growth. Overall decomposition results indicate that growth as a result of technical change (TC) is always positive for both Malmquist and Luenberger indexes, but results on technical efficiency change (TEC) show mixed signs. Despite these obvious differences, the two non-parametric approaches yield consistent productivity rankings over provinces, and both confirm that technical change is the major growth component.

Parametric productivity rates are also presented in table 4. Overall, parametric rates tend to show less variation over the years and across provinces – a result directly linked to what we observed for efficiency scores. Note that the parametric decomposition has two additional efficiency components, allocative efficiency and scale efficiency. The rates of scale efficiency are all very small (all are below |0.001|) and are not reported in table 4.[17] The rates of change in allocative efficiency are modest. Judging from the all-province mean in the bottom row, allocative efficiency contributes approximately 15 per cent to overall growth in the country for the period analysed.

The comparison of parametric results with the Luenberger non-parametric results is particularly relevant given that Luenberger and parametric decompositions are both in additive form. Substantial differences exist between the parametric and Luenberger rates. These differences, however, seem more pronounced with the results by year than the results by region, which is attributable in part to the parametric restriction of the monotonic η. Using the rates provided in table 4, we calculated the cumulative productivity rates, 0.517 for the Luenberger rate and 0.354 for the parametric rate. These values are clearly high for productivity growth realised over only 5 years. However, it is important to bear in mind that these rates are based on productivity in 1993, a year marked by unusually low productivity (figure 1).[18]

Decomposition results also differ substantially. Even though considerable differences in magnitude exist, both parametric and non-parametric approaches indicate that technical change plays a substantial role in overall growth.[19] From the all-year averages, the shares of technical change in total growth are 92 per cent and 56 per cent for the Luenberger and parametric methods, respectively. The shares for technical efficiency change are 8 per cent and 28 per cent.

[17] Note that because of the CRS assumption, our non-parametric models have no component for scale efficiency (i.e., the change in scale efficiency is zero).

[18] We are indebted to a reviewer on this point.

[19] The existence of technical change can be parametrically investigated by testing $\partial \ln f(\boldsymbol{x},t)/\partial t = 0$, that is, $\alpha_t = \beta_{nt} = \beta_{tt} = 0$ in equation (15). We tested these parametric restrictions, and strongly rejected no technical change (P-value = 0.0004).

Despite these differences, some very similar results emerge from an examination of provincial rates. Kangwon, one of the least efficient provinces, experienced the fastest rate of productivity growth, while Kyounggi and North Choolla, two of the relatively efficient provinces, showed the lowest rates of productivity growth. Interestingly, these provinces identified with the fastest and slowest rates are both related to unusually high and low rates of technical efficiency change.

6. Conclusions

In the present research we applied non-parametric and parametric models to a sample of panel data of Korean rice production for the period of 1993–1997. We estimated productivity growth using the Malmquist index, Luenberger productivity indicator and parametric approaches. Our productivity measures are decomposed into several sources of growth including efficiency change (the portion attributable to individuals' 'catching up' with the frontier) and technical change (the portion attributable to the shift in the frontier). Various measures of productivity growth and decomposition results are compared and some implications about the models and results are drawn.

There are differences in our empirical results between the parametric and non-parametric models. First, the non-parametric results tend to fluctuate widely in both longitudinal and cross-sectional dimensions. This is clearly the consequence of the assumption on the stochastic component, something which may be intensified for agricultural data. Second, even though considerable differences in results exist between the two approaches, the longitudinal results (year means) seem to be farther apart than the cross-sectional results (provincial means). This tendency is clearly observed in table 4. We attribute this tendency to the monotonic property of the one-side error term in the parametric model. That is, the magnitude and sign of the parameter η determine the changes in the efficiency scores over time. Even though we found η to be positive and statistically significant, the assumption of technical efficiency improving over time for all individuals is indeed restrictive.[20] Third, examining the components relating to the shift in the frontier (TC) and efficiency change (TEC), technical change turned out to be a more important source of growth in the non-parametric models. Nevertheless, some similar patterns in the parametric and non-parametric

[20] Note that the specification of our parametric model is relatively less restrictive given our model uses a flexible function form (compared to the Cobb–Douglas model that is more commonly used), and it is also common to assume a time-invariant η in many panel data studies.

results are observed for the technical change component, whereas no such patterns seem to exist for the efficiency change component. This may indicate that the difference in TFP results between the two approaches is because of the efficiency change term. More generally, the measure of efficiency change may be more sensitive to the choice of the model than the measure of technical change.

Needless to say, empirical results are always dictated by the data used. It is vital to understand the data in interpreting the results. As suggested earlier, our data tended to fluctuate considerably, beginning and ending with historic low and high productivity years (measured by the Törnqvist total factor productivity index). This implies that our productivity measures are based on a low productivity year and our results must be interpreted in this context. A 5-year period of panel data is relatively short to draw any convincing results on productivity growth. It is unlikely that high productivity growth calculated in the present study can be sustained – rather, it is confined to our specific data period.

Despite the caution required in interpreting the results, we can draw some general conclusions about Korean rice productivity for the period examined. Both approaches find the shift in the frontier plays an important role as a source of productivity growth, suggesting that technological adoption may be a vitally important source for overall productivity growth. The provincial growth rates also indicate that the least efficient province (Kangwon) experienced the highest rate of productivity growth and North Choolla and Kyounggi, two of the most efficient provinces, exhibited the lowest rate of productivity growth. These all suggest that, for the period under analysis, the shift in the Korean rice production frontier has been a steadier source of productivity growth than the improvement in catching up with the frontier. Moreover, this growth has been achieved through productivity improvements in regions of the country that had been associated with low efficiency.

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Appendix 1

Törnqvist total factor productivity (1967–2002)

Year	Rate of change in TFP	TFP[†]	Year	Rate of change in TFP	TFP[†]
1967	–0.055	0.945	1985	–0.051	1.155
1968	–0.059	0.889	1986	0.010	1.166
1969	0.084	0.964	1987	–0.041	1.119
1970	–0.087	0.880	1988	0.121	1.255
1971	0.125	0.990	1989	–0.071	1.166
1972	–0.078	0.913	1990	–0.028	1.134
1973	0.050	0.959	1991	0.021	1.158
1974	0.165	1.117	1992	0.074	1.244
1975	–0.076	1.032	1993	–0.148	1.060
1976	0.144	1.181	1994	0.132	1.200
1977	0.110	1.311	1995	–0.003	1.197
1978	–0.144	1.122	1996	0.135	1.359
1979	–0.006	1.115	1997	0.032	1.402
1980	–0.334	0.743	1998	–0.048	1.335
1981	0.321	0.981	1999	0.032	1.377
1982	0.097	1.076	2000	0.014	1.396
1983	0.092	1.176	2001	0.045	1.459
1984	0.035	1.217	2002	–0.071	1.355

[†]The total factor productivity values (TFP) are based on 1966 (1966 = 1).