WHAT DRIVES THE PRODUCTIVITY CHANGE OF THE KOREAN FOOD PROCESSING INDUSTRY?: A STOCHASTIC FRONTIER ANALYSIS USING FIRM-LEVEL PANEL DATA, 2001-2009*

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Keywords
food processing industry, productivity growth, panel data, stochastic frontier production function

Abstract
This article conducts an analysis on changes in productivity in Korean major food processing industries (meat processing industry, milk processing industry, and pickle industry) with the financial data over the five years from 2001 to 2009. Measurements are obtained from the estimation of a stochastic production function. The results find that technical change and allocative efficiency have led significant productivity changes in the three industries. Especially, pickle industry experienced a higher rate of productivity growth by a greater rate of technical change and allocative efficiency. Accordingly, the technical progress and efficient resource allocation resulting from greater investment in R&D and stable supply of raw materials are required for enhancement of productivity in the Korean food processing industry.

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* This research was extracted from "Mid/long-term food industry development strategies for creation of value added in agriculture and fishery (3/5th year)"(Choi Ji-Hyeon et al. Korea Rural Economic Institute, 2011).

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I. INTRODUCTION

The food processing industry is widely recognized as an important industry in Korea for having a huge potential to uplift the agricultural economy, create large-scale processed food manufacturing and food chain facilities, and generate employment and export earnings. Food processing industries provide a bridge between farm and industry, accelerating agricultural development through the creation of backward linkages – supply of credit, inputs and other production enhancement services – and forward linkages – processing and marketing (Kumar and Basu, 2008).

The growth of these industries induces the increase of agricultural production and the creation of employment opportunities, thereby improving the economic condition of the farmers. In addition, processing activities generate more demand on the farm sector for agricultural products which are suitable for processing.

The agricultural sector also contributes to the development of the food processing industry by supplying it with high-quality agricultural products, while the food processing industry uses as much domestic food products as possible to increase the value added of agricultural products and farm incomes so as to maintain a symbiotic relationship. Strengthening the linkage between the domestic agricultural sector and the food processing industry is thus necessary to expand the demand for domestic agricultural products and promote their consumption. Linking the two industries together will also reaffirm the role of agriculture in the nation and enhance the cultural heritage of Korea (Kim et al., 2008).

While the total production and the value added of the food processing industry have risen steadily, lackluster changes in industrial structure reduced the growth of the industry compared to others. The share of the value added of the food processing industry in relation to the whole agricultural industry fell to 2.1% in 2009 from 2.5% in 1991. Although the production and sales of processed foods have increased steadily since the 1990s, production per business has remained stagnant since 2000, showing little change in the past several years. The food processing industry is also largely made up of small enterprises, with 92.9% of the companies with less than 10 employees in 2009, but the sale of the companies with over 100 employees accounted for 71.9% of total sale (Choi et al., 2011).

Productivity growth is now an important topic in the Korean food processing industry, particularly in that the food industry acts as the driving force for the growth of agriculture and is directly linked with food security. The growth of the food processing industry is expected to increase agricultural growth given that the current government's policies aim to expand the demand for domestic agricultural products for food processing. Productivity gains have been regarded as the best way for the Korean food processing industry to develop further and compete with imports, and considerable public efforts such as R&D investment have thus been devoted to improving the productivity (Lee et al., 2008; Choi et al., 2011).

In order to better understand the recent performance of these efforts, this paper analyzes the productivity growth in major food processing industries (meat processing industry, milk processing industry, and pickle industry) with firm-level panel data over the ten years from 2001 to 2009. Panel data provide more reliable evidence on Korean food processing enterprises' performance because the data enable us to track the performance of each company through a sequence of time periods.

This study especially focuses on meat, milk, and pickle (including kimchi) industries among the food processing industries. Those industries are representative food processing industries in Korea, occupying 24% of the total number of food processing enterprises. The number of employees of the three industries accounted for 32% of the total number of employees in food processing industries in 2009. The share of the value of those three industries in the total food processing industry was 32% in 2009.

Those three industries have a small-scale industrial structure and show the characteristics of having a relatively large share of raw material cost. The meat processing industry has a market structure of an oligopoly as the market concentration ratio of top 3 corporations and next 7 corporations reaches as much as 30% and 43% respectively in 2009. The market size of the milk processing industry maintains an oligopoly with the top 4 corporations taking an 80% market share alone. The market share of top 3 corporations in the pickle industry is not so high at 14.9%, but the packed kimchi market has an oligopoly structure as the market concentration ratio of large corporations is more than 70% (Choi et al., 2011).

Choi et al.(2011) contend that the food categories such as processed livestock products, milk and kimchi are able to contribute to boosting farm income by enlarging the consumption of processed food if proper quality control and supply systems were established. The results of a survey conducted on food processors and consumers indicated that the meat processing, milk processing, and fruit and vegetable processing businesses should be capable of expanding productivity and the value added in the agricultural industry. Therefore, we intend to study these businesses in this paper.

There are very few studies for productivity growth of the food processing industry in Korea, especially in the context of the analysis of firm-level panel data. While several empirical studies have measured the productivity growth of the Korean food processing industry, these studies have used exclusively disaggregated data that are lacking in the sample representativeness. For example, Lee(2005) investigated the performances of foreign invested and domestic firms in the Korean food processing industry over the period 1990-2003, using the dataset of 114-249 firms provided by KIS(Korea Investors Service, Inc.). An and Lee(2006) used the same KIS dataset and analyzed the production efficiencies and the R&D spillover effects on the performance of 214-741 food processing firms.

On the other hand, this paper uses the balanced panel dataset of 6,421 firms obtained from the raw data of the National Manufacturer Survey from 2001 to 2009, compiled by the Statistics Korea. The data include all food processing firms in Korea and the firms represent the five-digit standard industrial classification. An et al.(2003) also used the same data to measure production efficiency and explained its determinants for manufacturing industries, but utilized the aggregated level data of two-digit industrial classification.

This paper applies a panel data production frontier model to measure productivity growth of food processing firms. Specifically, this study estimates a stochastic frontier function to accommodate output and input within the frontier framework.[1] Panel data frontier models allow the measurement of firm and time specific indices of technical efficiency changes, that is, technical efficiency is allowed to vary across firms and through time for each firm. Furthermore,

1 Since our panel data do not include prices, productivity growth is measured using a primal parametric method that does not require price data. Kwon and Lee(2004) apply both parametric and nonparametric production frontier models to estimate the productivity change in Korean rice farming.

stochastic frontier econometric techniques 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 firms not reaching the production frontier boundary. This contrasts with conventional econometric approaches that fit a function through the data assuming a normal error distribution, and with nonparametric or deterministic econometric frontier approaches that limit statistical inference (Paul et al., 2000; Kang, 2006).

The methodology used to measure productivity growth and its components is derived from several sources; Nishimizu and Page(1982) initiated the decomposition of TFP(Total Factor Productivity) into technical progress and technical efficiency change and Kumbhakar and Lovell (2000) and Kumbhakar (2000) provide an analytical framework for estimation and decomposition of TFP growth into technical progress, changes in technical efficiency, changes in allocative efficiency, and scale effects. Battese and Coelli(1992) activated an estimation of the stochastic frontier production function for panel data to derive the four factors of TFP growth. Kim and Han(2001) applied a stochastic frontier production model to the non-IT manufacturing industries (SIC 2 digit 31, 32, 34, 35, 36, 37, AND 38) of Korea to decompose TFP growth into technical progress, changes in technical efficiency, changes in allocative efficiency, and scale effects. Han(2005) estimated the TFP growth in the non-IT manufacturing industries of Korea and decomposed the sources of TFP growth into technical change and technical efficiency using the balanced panel data of 358 firms during 1986-2000.

This paper also provides evidence about importance of sources leading overall productivity growth and heterogeneous adjustments of Korean food processing firms based on the production technology available to firms. As well as measurement of productivity growth rates of firms, productivity growth is decomposed as technical change, technical efficiency change, allocative efficiency, and scale effects.

II. ANALYTICAL FRAMEWORK

A frontier production function $y_{it}(x,t)$ is defined as:

$$y_{it}(x,t) = f(x_{it},t)\exp(-u_{it}),\ \text{for all}\ i = 1,...,N\ \text{and}\ t = 1,...,T, \tag{1}$$

where y_{it} represents the feasible set of output that can be produced with the input vector x, given external production determinant t. Time t facilitates the calculation of technical change. The $\exp(-u)$ is the random disturbance with variations over time, which is less than or equal to one. The exponential $-u$ is therefore often represented as the technical efficiency score, i.e., the efficiency of transforming inputs into output. Here, u is assumed to be dependent on time if technical efficiency changes over time.

The production frontier $y_{it}(x,t)$ is totally differentiated with respect to time t, then the rate of change in y is represented by the following:

$$\frac{d\ln y}{dt} = \sum_{k=1}^{K} \frac{\partial f(x,t)}{\partial x_k} \frac{x_k}{f(x,t)} \frac{d\ln x_k}{dt} + \frac{d\ln f(x,t)}{dt} - \frac{du}{dt} \tag{2}$$

The rate of change in TFP ($\dot{TFP}$) represents the rate of change in productivity and is measured by the following:

$$\dot{TFP} = \frac{d\ln TFP}{dt} = \frac{d\ln y}{dt} - \sum_{k=1}^{K} S_k \frac{d\ln x_k}{dt} \tag{3}$$

where S_k denotes the observed cost share of input x_k.
Summing up (2) and (3) leads to the rate of productivity change as:

$$\dot{TFP} = \sum_{k=1}^{K} (\varepsilon_{x_k} - S_k) \frac{d\ln x_k}{dt} + \frac{\partial \ln f(x,t)}{\partial t} - \frac{du}{dt}, \tag{4}$$

where $\frac{d\ln x_k}{dt}$ indicates the growth rate of x_k, $\frac{\partial \ln f(x,t)}{\partial \ln x_k}$ denotes as ε_{x_k}.

With the scale elasticity denoted as $\varepsilon(=\sum_{k=1}^{K}\varepsilon_{x_k})$, the decomposition formula of the productivity growth is represented by the following[2]:

$$\dot{TFP} = (\varepsilon - 1)\sum_{k=1}^{K}\frac{\varepsilon_{x_k}}{\varepsilon}\frac{d\ln x_k}{dt} + \sum_{k=1}^{K}\left(\frac{\varepsilon_{x_k}}{\varepsilon} - S_k\right)\frac{d\ln x_k}{dt} + \frac{\partial \ln f(x,t)}{\partial t} - \frac{du}{dt} \tag{5}$$

Equation (5) for TFP growth decomposes observable productivity growth into a scale efficiency (SE=$(\varepsilon - 1)\sum_{k=1}^{K}\frac{\varepsilon_{x_k}}{\varepsilon}\frac{d\ln x_k}{dt}$), a change in allocative efficiency (a AE= $\sum_{k=1}^{K}\left(\frac{\varepsilon_{x_k}}{\varepsilon} - S_k\right)\frac{d\ln x_k}{dt}$), technical change effect (TC= $\frac{\partial \ln f(x,t)}{\partial t}$), and a technical inefficiency change (TE=$\frac{du}{dt}$). The sum of these four components is the total change in productivity.[3] These calculations are based on the coefficients resulting from the estimation of a specified parametric production model.

III. DATA AND VARIABLES

This study relies primarily upon a balance panel data set of individual firm-level data, obtained from the raw data of the National Manufacturer Survey for the period 2001 through 2009. The Korean Ministry of Statistics classified and

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2 For the detail, see Kumbhakar and Lovell(2000, p. 285), and Kwon and Lee(2004, pp. 328-329).

3 Since cost information for each input is available in the panel data used, the allocative inefficiency components can be calculated empirically.

reported financial statistics for all manufacturing firms each year. The data tracked firms with the same firm identification number through ten years of observation (2001-2009) to make a balanced panel data set. The resulting panel data set contains statistics for 6,421 food processing firms (with over 10 employees), classified by the five-digit industrial classification.

For each firm, data are aggregated into one output and four inputs. The output is the value of gross output. The inputs are labor, capital, raw material and other inputs.

Labor is total labor cost that consists of annual cost of hired employees and unpaid family workers. The value for family labor is imputed at the average wage of hired employees. Capital, raw material, and other inputs are measured in value terms. The capital measured as a flow term includes depreciation cost, rent cost, and the opportunity cost of capital calculated by applying market interest rate to beginning year capital stock excluding the capital stock under construction.[4] Raw material is measured by expenditures on raw material. Other inputs include expenditures on fuel, electricity, seeds, repairs, and miscellaneous operating expenses. GDP deflators were used to rescale those outputs and inputs that are collected in value terms, with 2000 being the base year. In this way, outputs and inputs become implicit quantities.[5]

Descriptive statistics for output and inputs are summarized in Table 1, including mean value per firm by year and industry. In all food processing industries, capital use declined over the sample period, while usage of raw material per firm increased steadily. The data confirm that milk processing industry in Korea is relatively larger in scale than those of meat and pickle industries in terms of gross output value and input use.

4 The construction of capital input follows An et al.(2003).

5 In this paper, the data collected on output and inputs are in value terms rather than quantities. When output and input prices vary systematically over the period and across space, the data in value terms will bias the results due to inflation and quality differences (Kwon and Lee, 2004, p.331-332). However, price trends are removed by deflator, so the magnitude of estimation bias is expected to be reduced.

Table 1. Summary Statistics for Output and Inputs (Industries with over 10 employees)

Unit: million won

Year	Gross value of output(y)	Labor (x_1)	Capital (x_2)	Raw material (x_3)	Others (x_4)
			All industries		
2001	20,134	1,279	1,408	11,050	692
2002	20,696	1,311	1,228	11,381	711
2003	20,123	1,356	1,075	11,415	753
2004	21,083	1,327	870	11,547	733
2005	20,328	1,363	972	11,092	774
2006	19,264	1,333	980	10,587	775
2007	19,563	1,328	974	10,798	769
2008	20,338	1,223	921	11,946	721
2009	19,747	1,146	874	11,864	689
			Meat processing industry		
2001	11,701	1,010	449	7,574	221
2002	14,730	1,151	470	9,362	232
2003	14,795	1,309	613	9,979	299
2004	15,010	1,303	176	9,644	714
2005	15,520	1,245	490	10,574	636
2006	15,602	1,199	469	10,525	413
2007	16,477	1,256	473	11,554	333
2008	16,246	1,358	458	11,987	381
2009	21,458	1,081	508	12,059	285
			Milk processing industry		
2001	56,013	2,635	3,028	31,559	1,219
2002	56,298	2,738	2,785	31,032	1,235
2003	53,024	2,761	2,588	29,151	1,289
2004	56,047	2,665	1,716	28,791	1,130
2005	54,029	2,689	2,739	28,249	1,404
2006	53,578	2,798	1,621	27,295	1,217
2007	53,747	2,744	1,549	22,591	1,112
2008	57,382	2,435	1,844	29,933	1,693
2009	49,645	2,257	1,329	27,562	1,247
			Pickle processing industry		
2001	2,826	428	183	1,355	56
2002	3,563	539	260	1,656	101
2003	4,005	597	198	1,948	96
2004	3,944	642	187	1,902	74
2005	3,441	597	165	1,581	73
2006	3,522	608	310	1,765	75
2007	3,336	531	198	1,766	101
2008	3,251	457	222	1,594	96
2009	3,244	430	245	1,942	91

Note: The data of the industry with over 10 employees are reported solely, since 2007.

IV. EMPIRICAL IMPLEMENTATION

For empirical implementation, a functional form for the stochastic production function has to be chosen first. This study employs the translog functional form that has been adopted widely in frontier studies (Lovell et al., 1994; Grosskopf et al., 1997; Paul et al., 2000; Kwon and Lee, 2004). The translog function allows for a variety of possible production relationships including nonconstant returns to scale, non-homothetic production, and nonconstant elasticities of outputs and inputs.

A translog stochastic production function with one output and four inputs, and time t is specified as:

$$\begin{aligned} \ln y_{it}(x,t) &= \alpha_0 + \sum_{k=1}^{4}\beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{4}\sum_{j=1}^{4}\beta_{kj}\ln x_{kit}\ln x_{jit} \\ &+ \delta_0 t + \frac{1}{2}\delta_{11}t^2 + \sum_{k=1}^{4}\delta_{xk}\ln x_{kit}t + v_{it} - u_{it} \end{aligned} \quad , \tag{7}$$

where firms are indexed by subscript i and time is indexed by subscript t and $\beta_{kj} = \beta_{jk}$. y_{it} is an output, x_{kit} is a vector of inputs ($k=1$ for raw material, $k=2$ for labor, $k=3$ for capital, $k=4$ for other inputs). Time t allows for possible shifts of the frontier over time and may reflect technical change or other systematic change over time. The v_{it} is a random error term independently and identically distributed as $N(0,\sigma_v^2)$ (intended to capture events beyond the control of farmers), and u_{it} (intended to capture technical inefficiency in outputs) are assumed to vary over both firms and time periods. Battese and Coelli (1992) proposed the following specification of u_{it}.

$$u_{it} = \{\exp[-\eta(t-5)]\}u_i , \tag{8}$$

where the u_{it} are assumed to be independently distributed non-negative truncations of the $N(0,\sigma_u^2)$ distribution suggested by Stevenson (1980).

The maximum likelihood estimation of model (7) with the specification in (8) provides estimators for α, β, δ and variance parameters, σ_u^2 and σ_v^2.[6]

V. ESTIMATION RESULTS

Parameter Estimates and Output Elasticities

About 70 percent of the parameters in the frontier function are statistically significant at the ten percent level or higher in Table 2. The Wald-chi square test for significance of the regression rejects the null hypothesis that the coefficients of the explanatory variables are all zero at the one percent level. The variance parameter σ_u^2 which measures the relative importance of inefficiency is statistically significant at the one percent level. The other variance parameter σ_v^2 which indicates inherent randomness in production due to variations in weather and other conditions is statistically significant at the one percent level. The statistical significances of the two variance parameters confirm the importance of using the parametric stochastic approach to estimate the productivity growth of food processing firms.

6 There are three methods to represent a technical efficiency in the context of panel data: the fixed effects model, the random effects model, and maximum likelihood method (MLE). The three approaches impose different requirements on the data, and they have different properties. When independence of effects and regressors is a plausible assumption, MLE is generally more efficient than either fixed effects model or random effects model, since it exploits distributional information that the other two do not (Kumbhakar and Lovell, 2000, p.106).

Table 2. Parameter Estimates of the Stochastic Production Function

Variables	Coefficients	z-value
lnx1	0.3504	16.37***
lnx2	0.2181	6.03***
lnx3	0.1052	4.89***
lnx4	0.2522	11.1***
t	0.0680	6.05***
(lnx1)(lnx1)	0.1380	48.41***
(lnx1)(lnx2)	-0.0811	-14.93***
(lnx1)(lnx3)	-0.0189	-5.94***
(lnx1)(lnx4)	-0.0366	-10.97***
(lnx2)(lnx2)	0.1115	9.89***
(lnx2)(lnx3)	-0.0018	-0.34
(lnx2)(lnx4)	-0.0092	-1.71
(lnx3)(lnx3)	0.0238	5.37***
(lnx3)(lnx4)	-0.0032	-0.92
(lnx4)(lnx4)	0.0403	10.3***
(lnx1)t	-0.0005	-0.59
(lnx2)t	-0.0035	-2.11*
(lnx3)t	0.0002	0.13
(lnx4)t	0.0003	0.28
t^2	-0.0028	-2.95**
Constant	-3.4780	-19.17***
σ_u^2	0.0340	3.19***
σ_v^2	0.0377	2.71***
η	-0.0172	-2.15**
Log likelihood	652.8	
Wald chi2	60930.4	

Note: *, **, and *** indicate significance at the 1%, 5% and 10% level.

The coefficients of the production function itself are not useful for interpretation. Table 3 thus presents an overview of the technological properties of the estimated model based on the average output elasticities. The elasticities are the estimated frontier elasticity or the elasticity of best practice production with respect to the arguments in the function. The elasticities with respect to four inputs, time, and returns to scale can be obtained.

The very high elasticity of raw material (over 60%) reflects the large contribution of raw material to production (high returns to raw material) in food processing industry. Especially, the elasticity of raw material in meat processing industry is the highest in the three industries. At the sample mean in the three industries, constant returns to scale are realized (around 1.00).

Table 3. Average Production Elasticities

Variable	Average output elasticity	Standard error
	All industries	
Raw material	0.64	0.0019
Labor	0.21	0.0012
Capital	0.06	0.0003
Other inputs	0.09	0.0007
Returns to scale (RTS)	0.99	0.0001
	Meat processing industry	
Raw material	0.73	0.0088
Labor	0.19	0.0053
Capital	0.04	0.0018
Other inputs	0.05	0.0033
Returns to scale (RTS)	1.01	0.0010
	Milk processing industry	
Raw material	0.65	0.0134
Labor	0.20	0.0078
Capital	0.06	0.0019
Other inputs	0.09	0.0041
Returns to scale (RTS)	1.00	0.0013
	Pickle processing industry	
Raw material	0.60	0.0041
Labor	0.25	0.0027
Capital	0.06	0.0009
Other inputs	0.08	0.0016
Returns to scale (RTS)	1.00	0.0007

Note: The values are the elasticity of the production function with respect to the variables.

Productivity growth and its components

Using the estimated coefficients of the production function, production parameters needed to measure the components of productivity growth are calculated. Table 4 presents productivity growth rates calculated by estimation of the stochastic production function. A productivity index of positive or negative value indicates improvement or decline in productivity, respectively.

Productivity growth in the frontier model is decomposed into four sources of growth; technical efficiency change (TE) is attributable to improvements in individuals "catching up" with the frontier, technical change (TC) is attributable to a shift in the frontier, allocative efficiency (AE)[7] shows how far the firm is from the point of maximum profitability at given market prices, and scale effect (SE) reflects change in scale economies.

Given that estimation procedures generate a large subset of productivity growth rates for each of the 6,421 firms, it is necessary to summarize the results to facilitate presentation. To this end, several categories distinguish the average productivity growth rates by time period and major industries. Value in each category presents the average productivity growth rate for those firms within that category. T-tests for testing the null hypothesis that the sample mean is identical zero are performed.

For technical changes, allocative efficiency changes, and technical efficiency changes in all categories, the null hypotheses are all rejected at the one percent significance level, implying that the sample means are statistically different zero. However, the sample means for the scale efficiency changes in some categories are statistically not different zero.

Overall, productivity growth rates tend to show large variation over years.[8] This tendency may be attributable to the monotonic assumption on the

7 Technical efficiency measures show how efficiently the firm uses the available inputs to produce a given output. In other words, technical efficiency determines whether the firm achieves maximum output using a given bundle of factors of production, while allocative efficiency determines whether the factors of production are used in proportions that ensure maximum output at given market prices.

8 Note that empirical results are always dictated by the data used. It is important to understand the data in interpreting the results (Kwon and Lee, 2004). The data used tend to fluctuate considerably, beginning and ending with historic high and low productivity years. This implies that our productivity measures are based on a high pro-

time-variant parameter of the one-side error term in the frontier model (Kwon and Lee, 2004).

The average growth rate for all years in Korean food processing industry is about 3.70 percent. The productivity growth rates in all industries have been declining over time. The decomposition results provide some insights into net growth: technical change (TC) is larger than allocative efficiency change (AE) or technical efficiency change (TE) or the scale efficiency change (SE). Note that values of technical efficiency change and scale efficiency change in all categories are all smaller than those of technical change. Since this study uses the panel data of identical firms over the five years, the variations of technical efficiency and scale effect over time seem to be small.

At an annual level, productivity growth rates in Korean food processing industry were highest between 2001 and 2002, and lowest from 2007 to 2008. A substantial productivity decline, as seen in the decomposition, between 2007 and 2008 was due to negative allocative efficiency change overwhelming positive technical change and technical efficiency change.

The magnitude of such productivity changes thus resulted in smaller positive net growth. Interestingly, the fastest and slowest years of productivity growth correspond to the highest and lowest rates of technical change. A negative allocative efficiency change throughout the selected time periods hinder the productivity growth. Note that the term of technical change compounds aggregate productivity shocks such as those due to food processing technology advanced with R&D investments. Also, the negative allocative efficiency change implies that input prices do not match their market values of marginal products. Actually, allocative efficiency change in 2007-2008 indicates a negative change, resulting from a high price of the raw material occupying the highest cost in the period.

Productivity growth rates across the three industries differ substantially. The average growth rates show that the average productivity growth of pickle industry is greater than those of other two industries. This is due to the substantial roles of technical change and scale effect. The pickle (including kimchi) processing firms averagely have lower cost share of raw material than other two

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ductivity year and the results must be interpreted in this context. It is unlikely that low productivity growth calculated in this study can be sustained, and is rather related to the specific data period.

industries. Expansion of the production scale derived by increased demand may lead to increasing returns to scale.

Table 4. Productivity Growth Rates and Decompositions: Food Processing Industry

	TFP growth rates	Decomposition of TFP growth rates			
		Scale Efficiency Change (SE)	Allocative Efficiency Change (AE)	Technical Change(TC)	Technical Efficiency Change(TE)
All periods	0.0370	-0.0001	0.0011	0.0308	0.0052
2001-2002	0.0524	-0.0002	0.0064	0.0408	0.0054
2002-2003	0.0490	-0.0002	0.0061	0.0377	0.0054
2003-2004	0.0493	0.0002	0.0090	0.0348	0.0053
2004-2005	0.0264	-0.0006	-0.0103	0.0320	0.0053
2005-2006	0.0379	-0.0008	0.0042	0.0293	0.0052
2006-2007	0.0288	-0.0004	-0.0023	0.0264	0.0051
2007-2008	0.0258	0.0005	-0.0036	0.0238	0.0051
2008-2009	0.0265	0.0009	-0.0007	0.0213	0.0050

Figure 1. Productivity Growth Rates and Decompositions: Food Processing Industry

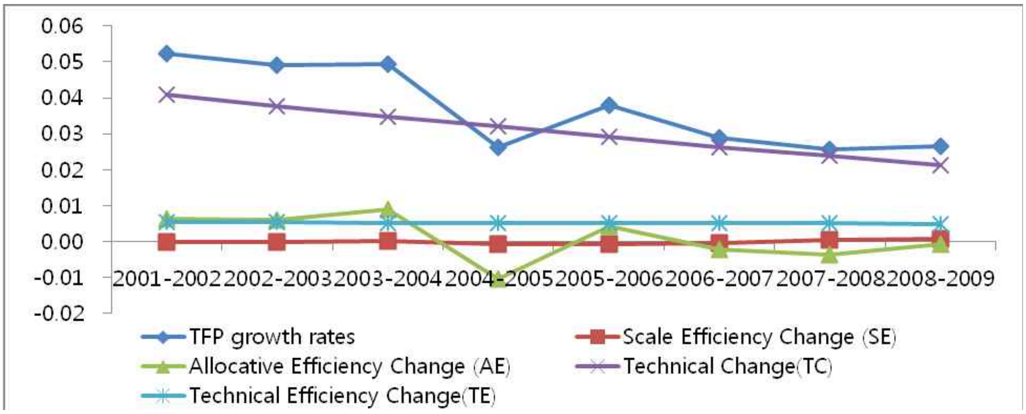

Table 5. Productivity Growth Rates and Decompositions: Meat Processing Industry

	TFP growth rates	Decomposition of TFP growth rates			
		Scale Efficiency Change (SE)	Allocative Efficiency Change (AE)	Technical Change(TC)	Technical Efficiency Change(TE)
All periods	0.0340	0.0003	-0.0001	0.0286	0.0052
2001-2002	0.0456	0.0039	-0.0026	0.0388	0.0055
2002-2003	0.0469	0.0008	0.0052	0.0355	0.0054
2003-2004	0.0516	-0.0003	0.0140	0.0326	0.0053
2004-2005	0.0194	-0.0006	-0.0153	0.0300	0.0053
2005-2006	0.0368	-0.0010	0.0054	0.0272	0.0052
2006-2007	0.0260	0.0002	-0.0035	0.0242	0.0051
2007-2008	0.0312	-0.0004	0.0052	0.0213	0.0051
2008-2009	0.0142	0.000010	-0.0097	0.0189	0.0050

Table 6. Productivity Growth Rates and Decompositions: Milk Processing Industry

	TFP growth rates	Decomposition of TFP growth rates			
		Scale Efficiency Change (SE)	Allocative Efficiency Change (AE)	Technical Change(TC)	Technical Efficiency Change(TE)
All periods	0.0359	-0.0002	0.0047	0.0262	0.0052
2001-2002	0.0503	-0.0004	0.0091	0.0362	0.0054
2002-2003	0.0486	-0.0014	0.0116	0.0330	0.0054
2003-2004	0.0375	-0.0004	0.0025	0.0301	0.0053
2004-2005	0.0402	0.0005	0.0068	0.0276	0.0053
2005-2006	0.0432	-0.0012	0.0148	0.0244	0.0052
2006-2007	0.0136	-0.0010	-0.0122	0.0217	0.0051
2007-2008	0.0249	0.0006	-0.0005	0.0197	0.0051
2008-2009	0.0289	0.0014	0.0052	0.0173	0.0050

Table 7. Productivity Growth Rates and Decompositions: Pickle Processing Industry

	TFP growth rates	Decomposition of TFP growth rates			
		Scale Efficiency Change (SE)	Allocative Efficiency Change (AE)	Technical Change(TC)	Technical Efficiency Change(TE)
All periods	0.0366	0.0005	-0.0012	0.0321	0.0052
2001-2002	0.0473	0.0013	-0.0014	0.0420	0.0054
2002-2003	0.0545	0.0005	0.0098	0.0389	0.0053
2003-2004	0.0425	-0.0003	0.0016	0.0359	0.0053
2004-2005	0.0498	-0.0002	0.0115	0.0333	0.0052
2005-2006	0.0108	-0.0003	-0.0247	0.0307	0.0051
2006-2007	0.0405	0.0012	0.0062	0.0280	0.0051
2007-2008	0.0157	0.0001	-0.0149	0.0255	0.0050
2008-2009	0.0315	0.0014	0.0021	0.0231	0.0049

VI. SUMMARY AND CONCLUSION REMARKS

The purpose of this paper is to obtain a better understanding of productivity growth patterns and its components that have driven the productivity changes in Korean food processing industry. To achieve this empirical evidence, this study uses firm-level panel data from 2001 to 2009. This paper applies a panel data production frontier model to measure productivity growth of food processing firms. Specifically, this study estimates a stochastic frontier function to accommodate output and input within the frontier framework.

Despite the caution required in interpreting the results, the results indicate that technical change and allocative efficiency change played important role in productivity growth in Korean food processing industry. The fastest and slowest years of productivity growth correspond to the highest and lowest rates of technical change and allocative efficiency change.

Among meat, milk, pickle processing industries, pickle processing industry experienced a greater productivity growth attributed to a greater rate of technical change and scale effect, which suggests that the expansion of firm scale is one source of the average productivity growth.

Based on the empirical analysis, it can be concluded that technical innovation and efficient allocation of resources, which include such factors as greater investment in R&D and stable supply of raw materials, were most important for changes in productivity in Korean food processing industry during 2001-2009.

This paper has broken a new ground with respect to understanding the factors expediting productivity growth in the Korean food processing industry. Some important questions related to the productivity growth and its components have been left for future work. This study was hampered by lack of data such as R&D investment, firm characteristics, and so on. Future research might attempt to answer the following questions: "How do changes in R&D investment influence productivity growth in the Korea food processing industry?" and "How have firm characteristics affected the productivity growth?"

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Date Submitted: Sept. 18, 2012
Period of Review: Sept. 26, 2012～Mar. 20, 2013