The Spillover Effects of R&D Investment on the Performance of Individual Firms in Food Manufacturing Industry

by

Donghwan An

and

Sangjun Lee*

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* Donghwan An and Sangjun Lee are Assistant Professor and PhD student, Department of Agricultural Economics and Rural Development, College of Agriculture and Life Sciences, Seoul National University, Seoul, Korea, 151-742 (dha@snu.ac.kr, +82-2-880-4729). This work was supported by Seoul National University.

I. Introduction

There has been increasing recognition that the size of R&D investment in an industry affects the performance and location decision of individual firms through the various types of spillover effects (Jaffe et al., 1993; Henderson et al., 1995; Kim & Lee, 2001; Berliant et al. 2002). However, the literature on the spillover effects of the concentration of industry-specific R&D investment on the performance of individual firms remains sparse from the perspective of empirical context.

The recent increase of micro-level data accessibility has contributed to the development of productivity measures and this line of research (Färe et al., 1994; Ericson et al., 1995; Pavcnik, 2002). The reliable estimates of firm's performances with micro-level data would shed light on the important industrial economic issues such as R&D spillovers, industrial policy and growth strategy.

This study intends to investigate the performance of food processing industry in Korea and the spillover effects associated with the externalities of R&D investment in this industry using firm-level data from the perspective of both industry and space.[1] This study specifically tries to shed some light on both the spatial and industrial spillover effects of R&D investment on the performance of individual firms.

Food manufacturing industry is fundamentally connected both with agricultural production, and consumption demand.[2] Particularly, in Korea, the investigation of R&D spillover effects on the

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[1] There are several empirical analyses in this line of research. But relatively little attention has been paid to the industrial economic issues, especially to those concerning to food processing industry (e.g. Henderson et al., 2001; Kim, 2002; Lee, 2000; Lee and Zang, 1998; Koo and Kim, 1999).

[2] About 188 thousand persons are employed in food manufacturing firms in 2003, which explains 0.8% and 6.9% of total national employment and manufacturing sector employment, respectively. Food manufacturing industry produced about 2.3% of GDP and 8.7% of the value-added of manufacturing industry in 2003. The inter-industry employment multiplier of food manufacturing industry is 0.3374 which is ranked

firms' performance in this industry is of interest in two reasons. First, as one of the major importers of agricultural products, the overall performance of food manufacturing firms is particularly of interest in the context of competitiveness in world market. Second, in Korea, promoting the food processing sector that uses local farm products as inputs has been an important rural development policy measure to increase the farm income and improve the rural economy. So, this study could provide useful information to see whether the policy to stimulate R&D investment in food processing industry is helpful for rural economy or not. This study attempts to provide useful information on these issues by developing an empirical framework of measuring and identifying these spillover effects of R&D investment both at the industry and regional level.

The structure of this paper is as follows. The next section provides estimation models and discusses data used in this study. The following section presents estimation results and implications. Finally, concluding remarks are presented.

II. Empirical Model

We employ a two-step approach that uses a frontier production function approach and a regression model sequentially. In the first step, we employ a non-parametric approach commonly referred to as data envelopment analysis (DEA). Specifically, to represent the production technology, the directional distance function, a version of Luenberger shortage function is estimated. In the frontier literature, the difference in productivity or performance of firms is termed "inefficiency." In the second step, we use a Tobit model in which we regress our inefficiency

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to be 6-th among 14 sub-industries in manufacturing sector. Food manufacturing industry in Korea processes large proportion of domestic products of primary industrial sectors; 42.6% of agricultural product, 90.3% of livestock product, 6.5% of forestry product, and 42.9% of fishery product (Bank of Korea, 2003).

measures on the various factors influencing the performance of individual firms including the R&D investment measures of individual firm-, industry-, and regional level.

1. Measuring productivity

This paper employs the nonparametric approach, i.e., DEA technique, which does not require any assumption on the functional form of production technology and error terms.[3] In particular, this study estimates the directional distance function, a version of Luenberger's shortage function (Luenberger, 1992, 1995) rather than Shephard's input or output distance function. While Shephard's input and output distance functions are respectively dual to the cost function and the revenue function, the directional distance function is dual to the profit function (Chambers et al., 1998). Shephard's input (output) distance function measures the largest `radial contraction' of an input vector (the largest `radial expansion' of an output vector) with each remaining technically feasible (Chambers et al., 1998). That is, Shephard's distance function is defined by either contracting inputs or expanding outputs while satisfying feasibility conditions. However, the directional distance function is defined by simultaneously contracting inputs and expanding outputs. Therefore, the directional distance function is more general than Shephard's input or output distance function (Chambers et al., 1998; Färe et al., 2000).

The directional distance function approach has been increasingly used for the empirical productivity analysis. Chambers et al. (1996b) used directional distance function approach to measure productivity growth in APEC countries. More recently, Färe et al. (2001) used this framework for analyzing the productivity of manufacturing industry in the presence of undesirable

[3] Unlike the parametric stochastic frontier approach (Aigner et al., 1977), however, the nonparametric approach does not take into account random factors affecting inputs and outputs due to its deterministic characteristics.

outputs (air pollution), which is originally suggested by Chung et al. (1997). An et al. (2004) was the first contribution that estimated directional distance function application in Korea, which analyzed productivity dynamics of manufacturing industry for the local government level.

Consider a production technology producing a M-vector of outputs, $y \in R_{+}^{M}$, by using a N-vector of inputs, $x \in R_{+}^{N}$. Using netput notation, where outputs are positive and inputs are taken to be negative, let a closed set $F \subset R_{-}^{N} \times R_{+}^{M}$ represent the production possibility set. That is, $(-x, y) \in F$ means that outputs y can be produced from inputs x. Then, Luenberger's shortage function is defined as

$$\begin{aligned} S(x, y, g_x, g_y) &= \min_{\beta}\{\beta : (-x - \beta g_x, y - \beta g_y) \in F\} \quad \text{for some } \beta \\ &= +\infty \quad \text{otherwise}, \end{aligned} \tag{1}$$

where $g_x \in R_{+}^{N}$ and $g_y \in R_{+}^{M}$ are nonzero directional (reference) vectors representing the direction in which the netput vector $(-x, y)$ is expanded. This measures how far the point (x, y) is from the frontier technology, expressed in units of the reference input bundle g_x and output bundle g_y.

Following Chambers et al. (1996a), the directional distance function as a variation of Luenberger's shortage function can be defined as

$$\vec{D}(x, y : g_x, g_y) = \sup\{\theta : (x - \theta g_x, y + \theta g_x) \in F\}. \tag{2}$$

Here, the vector g_x and g_y represent the directions in which the input vector x is contracted and the output vector y is expanded, respectively. This function also measures the distance in a pre-assigned direction to the frontier technology. According to Luenberger's shortage function approach, this distance can be interpreted as a shortage of (x, y) to reach the frontier, while it can be interpreted as an efficiency measure using the directional distance function approach.

Under freely disposability of inputs and outputs, the directional distance function in equation (2) can completely depict the production technology and is dual to the profit function (Chambers, et al., 1998). If and only if (x, y) is feasible, the directional distance function is nonnegative, i.e. $\vec{D}(x, y : g_x, g_y) \geq 0$. And the directional distance function completely generalizes Shephard's input or output distance function. Recall that Shephard's input and output distance functions are defined as $D_i = \sup_\theta\{\theta > 0 : (x/\theta, y) \in F\}$ and $D_o = \inf_\theta\{\theta > 0 : (x, y/\theta) \in F\}$, respectively. If we take $g_y = 0$ and $g_x = x$ in equation (2), then the directional distance function can be represented by Shephard's input distance function, i.e., $\vec{D}(x, y : x, 0) = 1 - 1/D_i(x, y)$. Second, if we take $g_x = 0$ and $g_y = y$ in equation (2), then the directional distance function can be represented by Shephard's output distance function, i.e., $\vec{D}(x, y : 0, y) = 1/D_o(x, y) - 1$.

The shortage function and the directional distance function defined above can be estimated econometrically. However, econometric estimation requires assumptions on the functional form and the distribution of error terms. On the contrary, a nonparametric programming approach can be used to estimate $S(x, y, g_x, g_y)$ or $\vec{D}(x, y : g_x, g_y)$ without such assumptions.

Consider a set of observations on K firms, (x^k, y^k), $k = 1, \ldots, K$. Assume that the set F is convex and that the technology exhibits free disposal. When there is no assumption on the return to scale of the technology (variable return to scale: VRS), a nonparametric representation of the technology is

$$F_{VRS} = \{(-x, y) : \sum_{k=1}^{K} \lambda^k x^k \le x,\ \sum_{k=1}^{K} \lambda^k y^k \ge y,\ \sum_{k=1}^{K} \lambda^k = 1,\ \ \lambda^k \ge 0,\ k = 1,...,K\}. \qquad (3)$$

Then, a nonparametric estimate of the shortage function under VRS for k-th firm is

$$\begin{aligned} S_{VRS}^k(x^k, y^k, g_x^k, g_y^k) = \min_{\beta,\lambda}\{\beta : & \sum_{k=1}^{K} \lambda^k x^k \le x^k + \beta g_x^k, \\ & \sum_{k=1}^{K} \lambda^k y^k \ge y^k - \beta g_y^k, \\ & \sum_{k=1}^{K} \lambda^k = 1, \\ & \lambda^k \ge 0,\ k = 1,...,K \quad \}. \end{aligned} \qquad (4)$$

And the directional distance function can be estimated by solving the following linear programming problems in equation (5). Here, the value of θ is a measure of "(technical) inefficiency," which represents the inability to produce maximum output given production resources and technology and, hence, the productivity (or performance) gab compared with the most efficient production unit.

$$\begin{aligned} \vec{D}(x^k, y^k : g_x^k, g_y^k) = \max_{\theta,\lambda} \theta & \\ s.t. \quad & \sum_{k=1}^{K} \lambda^k x^k \le x^k - \theta g_x^k, \\ & \sum_{k=1}^{K} \lambda^k y^k \ge y^k + \theta g_y^k, \\ & \sum_{k=1}^{K} \lambda^k = 1, \\ & \lambda^k \ge 0,\ k = 1,...,K \end{aligned} \qquad (5)$$

2. Factors influencing productivity differences

The second step of our study focuses on the factors affecting on the performance of regional manufacturing industry. Since the distribution of our productivity measure is truncated at zero

($\theta \geq 0$), a Tobit or censored regression model (Tobin, 1958) is employed. Additionally, the panel structure of our data also enables us to focus on random individual effects. To account for these, we specify our empirical model for characterizing the factors affecting productivity measure as follows:

$$\begin{aligned} &\theta_{kt} = \delta' W_{kt} + v_k + \varepsilon_{kt}, \ \text{ if } \ \delta' W_{kt} + v_k + \varepsilon_{kt} > 0 \\ &\theta_{kt} = 0, \ \text{otherwise} \end{aligned} \quad , \tag{6}$$

where δ is a $l \times 1$ vector of unknown parameters. W_{kt} is a $l \times 1$ vector of explanatory variables at t and ε_{kt} is the error term which is assumed to be independent of W_{kt} and i.i.d. over time (t) and across individuals (k). Individual-specific effects are captured by v_k.

Under the assumption that the term capturing individual effects v_k is randomly distributed with a density function $g(v)$, the likelihood function of censored data is of the form

$$\prod_{k=1}^{K} \int [\prod_{\theta_{kt}=0} F(-\delta' W_{kt} - v_k) \prod_{\theta_{kt}>0} F(\theta_{kt} - \delta' W_{kt} - v_k)] g(v_k) dv_k \,, \tag{7}$$

where $f(\cdot)$ denotes the density function of ε_{kt} and $F(a) = \int_{-\infty}^{a} f(\varepsilon) d\varepsilon$. Note that maximizing (7) yields consistent and asymptotically normally distributed estimators of δ when *K* or *T* or both tend to infinity. We assume that v_k is i.i.d. $N(0, \sigma_v^2)$ and ε_{kt} is i.i.d. $N(0, \sigma_\varepsilon^2)$.

III. Data

1. Input and Output Variables

We used the Korea Information Service (KIS) database of firm-level financial statements, which consists of balance sheet, income statement and statement of manufacturing costs. This data set includes most of listed firms and external auditing companies in Korea. We used a panel dataset of 214~741 food processing firms for the period of 1990-2003 (i.e. total 6,364 observations).

Input and output variables are constructed as follows using the database. First, we used value added as an output measure. Value added is composed of a firm's ordinary income, employment costs, net interests expanses, rent, tax and dues and depreciation. Here, net interests expanses consist of corporate bonds interest, interest expanses and interest return in the income statement. The value added is evaluated at 2000 constant prices deflated by producer price index of food processing industry. Second, total employees are used as labor inputs. Third, each firm's tangible asset including land is used as capital inputs.[4] The tangible asset is also evaluated at 2000 prices deflated by GDP deflator. Summary statistics for the input and output variables are provided in the Table 1.

2. Variables Influencing Productivity

We consider three groups of factors that are expected to influence the performance of individual firms; the characteristics of individual firm, the characteristics of region where the firm is located, and the R&D stock measures.

[4] Unfortunately, flow measure of capital input is not available. Many studies in this line of research have utilized tangible fixed assets as capital stock, e.g. Henderson et al. (2001), Kim (2002), Lee (2000), Lee and Zang (1998), Koo and Kim (1999), etc. And here, land indicates the land and buildings that firms are carrying only for their operation.

First, we include capital-labor ratio and firm size of individual firms to take into account the characteristics of individual firm. As the size variables, we used the size of firms' sales in a year.

Second, we include the regional population to capture agglomeration effects. We also include the length of road per capita (ROAD) to capture the effect of public infrastructure on the performance of individual firm.

Third, we consider various measures of R&D stock to capture the effects of R&D on the performance of individual firms and the R&D spillover effects; individual firm's R&D stock, own industry R&D stock (intra-industry spillover), other industry R&D stock (inter-industry spillover), regional R&D stock (intra-regional spillover), and other region's R&D stock (inter-regional spillover). In particular, we used a gravity equation to construct other region' R&D stock to take into account the spatial spillover effects of R&D investment. We used $w_{ij} = G_i G_j / r_{ij}^2$ as weight to make the weighted sum of other region's R&D stock. Here, G_i and G_j are total employment size of region *i*, *j* and r_{ij} is the distance between two regions. Therefore, the equation above gives greater (smaller) value if the total employment (distance) of each region increases. Summary statistics for the input and output variables are also shown in the Table 1.

IV. Estimation Results

1. Technical efficiency

To solve linear programming problems in (5), we used each firm's observed inputs and outputs in that period as the direction g_x and g_y.[5] Note that the positive value of indicates the presence of technical inefficiency. The smaller the value of θ, the less inefficient, i.e., higher level of performance or productivity. The efficiency estimation results are provided in Table 2.

We grouped all firms into five sub-industry groups according to 3-digit SIC (Standard Industrial Classification) code. The overall mean of technical efficiency during the sample period is 0.7519. This indicates that, on average, the netputs of firms could have been increased by 0.7519 times observed netput level if frontier technology had been available. As shown in the table, this high inefficiency in food processing industry seems to reflect current market structure. Since Korean food processing industry consists of many small fringes that has poor operating condition, the overall efficiency level is estimated to be low.[6] Especially, this low efficiency is prominent during financial crisis period in Korea (1998~2000). Comparing annual investment growth in the industry between early and late 90's, this drastic efficiency decline is due to low investment followed by demand decline during financial crisis.[7]

Beverage industry (D155) shows relatively better performance than other industries. However, it shows higher fluctuation in efficiency level. Since beverage industry is dominated by a few large firms that have better performances than small and medium ones, it has higher efficiency level than others. However, the higher fluctuation in this industry indicates that large firms are affected by economic environment more than others. Similarly, Processing of meat, fishes, fruits, vegetables

[5] It is known that the direction vector equal to the value of the observation provides a link and symmetry with the traditional distance functions defined in the directions of the observed input or output mix for each observation (Färe and Grosskopf, 2000).

[6] Lee et al. (2005) showed that Korean food processing industry has lower productivity especially in small and medium enterprises than large ones.

[7] Following The Agriculture, Fisheries and Livestock News (2004), annual growth rate in plant and equipment investment in food processing industry was 3.0% in early 90's. However, it was decreased by 37.9% in 1998.

and oil and fats (D151) and other food products industry (D154) fall below average in technical efficiency. Also, these two sub-industries are dominated by many small fringes compared to beverage industry.

2. Factors Influencing Technical Efficiency

Table 3 provides the estimation results of the regression model in which the technical inefficiency measures are dependent variables, specifically a Tobit model with individual-specific random effects. Most of the variables are estimated to have expected signs and highly significant.

First, two variables capturing the characteristics of individual firms have expected signs and are statistically significant. To control for size effects, this paper includes the size of firm's sales in value terms. We found that there exist a significant size effect. That is, bigger firms perform better than small ones. We also found a significant positive relationship between capital-labor ratio and technical efficiency. This represents that firms with higher capital intensity in production perform better.

Second, two regional variables are included to capture the effects of region-specific variables; population size and transportation infrastructure. The size of regional population is positively related with firms' performance. This implies that regional population is a surrogate of agglomeration factor for this industry. However, the negative sign of transportation infrastructure variable is counter intuitive.

We included not only firm's own R&D measure but several R&D measures to investigate the spillover effects both from industrial and special perspectives. The estimation result shows a firm's own R&D investment has positive effect on its efficiency. Considering a partial effect, a billion increases in R&D investment would improve its technical efficiency by 0.0189.

We found that there exist significant positive R&D spillover effects on firm's performance. This implies the existence of both intra-industry and inter-industry R&D spillover effects. Also, the estimation result shows that the intra-industry R&D spillover effects are bigger than inter-industry R&D spillover effects. This indicates that the industry R&D spillover effects are industry-specific rather than inter-industrial.

Finally, we found some empirical evidences of spatial R&D spillovers. Our estimation result shows inter-regional R&D spillover effects are positive and significant. However, intra-regional R&D spillover effects turn out to be positive but not to be significant. Spatial spillover also seems to be intra-regional rather than inter-regional.

V. Summary and Concluding Remark

Using the firm-level micro panel data, this analysis has investigated the performance of Korean food processing industry during the period of 1990~2003, especially focusing on the spillover effects of R&D investment. We incorporate the measures of R&D investment both at the industry and regional level into our framework and test whether these spillover effects are significant or not. For doing this, this paper employs two-step approach using a nonparametric DEA approach based on a directional distance function and a Tobit model sequentially.

The findings of our analysis are as follows; (i) there exists considerable performance gap in food processing firms; (ii) bigger firms perform better than small ones; (iii) firms with higher capital intensity in production perform better; (iv) the size of regional population is positively related with firms' performance; (v) a firm's own R&D investment has positive effect on its efficiency; (vi) there exist significant positive intra-industry and inter-industry R&D spillover effects; (vii) inter-regional R&D spillover effects are positive and significant, and intra-regional

R&D spillover effects are positive but not significant; (viii) the industry R&D spillover effects are industry-specific rather than inter-industrial and the spatial R&D spillover also seems to be intra-regional rather than inter-regional.

Finally, this study can be extended in several ways. First, technological distance measures such as patent data can be put into consideration. In that these measures technological proximity between firms, we can have more reliable estimates of R&D spillover effects. Secondly, other manufacturing industries can be considered as a spillover pool. Therefore, the boundary of our study can be extended whole manufacturing sector.

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Table 1. Summary Statistics of Output and Inputs

Variables		Mean	Std.Dev.	Min	Max
Output	Value added (Million Won)[1)]	7,610	28,648	0.037	460,000
Input	Labor (persons)	240	646	1	6,654
	Capital (Million Won) [2)]	19,577	87,333	0.141	1,480,000
Factors Influencing Productivity	Sales (Million Won)	44,726	146,626	0.240	2,410,000
	Firm's R&D Stock (Million Won)	95	711	0	28,074
	Own Industry R&D Stock (Million Won)	10,976	12,624	810	55,100
	Other industries' R&D Stock (Million Won)	6,179,729	3,943,787	1,176,416	13,805,730
	Regional R&D Stock (Million Won)	452	1704	0	33,800
	Weighted Sum of R&D Stock for Other Regions	3,049	10,213	0.006	109,018
	Population (1,000 person)	269	191	22	1,083
	Road (km/person)	413	192	20	1,235

Note: 1) ordinary income + employment costs + rent + tax and dues + depreciation + net interest expanses,
(net interest expanses = corporate bonds interest + interest expanses - interest returns)
2) tangible asset

Table2. Changes in Technical Efficiency by Subindustry

Year	Industries					All
	D151	D152	D153	D154	D155	
1990	0.7602	0.6542	0.6677	0.7065	0.5382	0.6822
1991	0.6907	0.6567	0.6247	0.7213	0.4964	0.6566
1992	0.6554	0.6014	0.6602	0.7020	0.4372	0.6317
1993	0.6940	0.5020	0.6435	0.6920	0.3676	0.6239
1994	0.7535	0.6385	0.6748	0.7398	0.5740	0.7023
1995	0.6997	0.5963	0.5799	0.6870	0.4679	0.6451
1996	0.6850	0.5891	0.5717	0.6512	0.3976	0.6217
1997	0.8713	0.9004	0.8295	0.8641	0.8557	0.8625
1998	0.8802	0.9422	0.8427	0.8900	0.8908	0.8804
1999	0.8784	0.9097	0.8059	0.8880	0.8452	0.8682
2000	0.8358	0.8168	0.7736	0.8450	0.8134	0.8257
2001	0.8007	0.8017	0.7311	0.8212	0.7570	0.7912
2002	0.8653	0.8885	0.8491	0.8645	0.8631	0.8630
2003	0.9045	0.7764	0.8555	0.8865	0.7483	0.8717
mean	0.7839 (0.0852)	0.7339 (0.1393)	0.7222 (0.0990)	0.7828 (0.0865)	0.6466 (0.1881)	0.7519 (0.1040)

Note: 1) D151 denotes production, processing and preserving of meat, fishes, fruit, vegetables, and oils and fats, D152, manufacture of dairy products and ice cream, D153, manufacture of grain mill products, starches and starch products, and prepared animal feeds, D154, manufacture of other food products, and finally D155, manufacture of beverages, respectively.

2) The numbers in the parenthesis are standard deviations.

Table 3. Estimation Results of Technical Efficiency Model

Variables (dependent variable = θ_{it})	Parameters	(s.e.)
Firm Size (Sales)	-0.0001902	(.0000321) *
Capital Labor Ratio	-9.53E-08	(1.67e-08) *
Population Size	-0.0000561	(.0000259) **
Road per Capita	0.0000586	(.000022) *
Firm's R&D stock	-0.0188821	(.0068338) *
Industry R&D stock	-0.0010674	(.0002912) *
Other industries' R&D stock	-5.05E-06	(1.23e-06) *
Regional R&D stock	-0.0022688	(.0018103)
Weighted Sum of R&D Stock for Other Regions	-7.46E-10	(3.78e-10) **
time	0.0300594	(.001378) *
const	-59.23294	(2.744942) *
$\sigma^2{}_u$	0.1677907	(.0040879) *
$\sigma^2{}_\varepsilon$	0.1485961	(.0015257) *
Number of Observation	6,364	
Log-likelihood	1637. 8	

Note: Standard errors of coefficients are in parentheses. * significant at 1%. ** Significant at 5%.