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Technological diversification, R&D and innovation

A firm-level exploration of Korean manufacturing industry

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***Abstract*—This paper investigates the effects of technological diversification on R&D activity and innovation by using Korean firm-level data over the period between 2001 and 2009. We improved the conventional CDM model so that we can consider the relationship among R&D activities, innovation activities, and technological diversification. In order to examine this relationship we use of a large sample by merging different data sets including firms' financial statements, Korean Innovation Survey data, and patent application information, consisting of 5,861 firms. The empirical results imply a proportional relationship between various activities, as follows: i) technological diversification and R&D activities, ii) innovation output, measured by the number of patent applications, and R&D intensitiy. However, the relationship between innovation output and its technological diversification, measured as entropy, is found to be negative. Based on our empirical results we proposed policy implications especially considering differentiated innovation strategies across industrial sectors, firm's size and age.**

***Keywords*—Technological diversification; R&D; innovation; CDM model**

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I. Introduction

The ever-changing market environment is characterized by convergence and globalization. The convergence enabled firms to deliver a great variety of products and services. So, the more firms will need to enhance technological diversification to compete with their competitors in this market situation.

The effect of technology diversity and specialization on innovation has been a subject for debate in former literature; but relation evidences are ambiguous and mixed

[1][2][3] mentioned that technological diversification has negative sides. Diversity causes loss of economies of scale, because firm must share own limited resources for the diversification. And high transaction cost is also an issue. To handle many kinds of technology, firms need greater information and infrastructure.

However, in spite of negative side from diversity, technological diversified firms can have advantages in the markets. Positive side of diversity can be summarized briefly as follows: i) increasing technology cross-fertilization between different[4], ii) managing the risks from failure in the R&D projects[5] iii) preventing a negative lock-in effect.[6]

This paper updates former work on the link between diversification, research, and innovation. We will improved the conventional CDM model[7] considering technological diversification among R&D and innovation activities

We investigates the effects of technological diversification on R&D activity and innovation by using Korean firm-level innovation, financial and patent data

The empirical results imply a proportional relationship between various activities, as follows: i) technological diversification, measured as entropy, and R&D intensity, ii) innovation output, measured by the number of patent applications, and R&D intensity. However, the relationship between innovation output and its technological diversification is found to be negative.

II. Model and Data

A. *Model*

We modified the conventional CDM model. We dropped productivity part and considered technology diversification. Our model consists of two sub-models. First sub-model contains two equations for describing firm's R&D behavior. The first one is selection equation to specifying firm's R&D engagement. And second one is for firm's R&D intensity condition on firm's R&D engagement

To correct selectivity biases we estimate two equations systemically using the generalized Tobit model. If g^*_{it} is a latent(unobserved) R&D engagement variable and k^*_{it} is latent R&D intensity variable, first sub-model, R&D engagement equation and R&D intensity equation can be expressed as

The R&D engagement equation:

$$g_{it} = \beta_0 x^0_{it} + u^0_{it}$$

$$g_{it} = 1 \text{, If } g^*_{it} > 0 \text{. Otherwise } g_{it} = 0 \qquad (1)$$

The R&D intensity equation:

$$k_i \mid g_{it} > 0 = \beta_1 x^1_{it} + u^1_{it}$$

$$k_{it} = k_{it} \text{, If } k^*_{it} > 0 \text{. Otherwise } k_{it} = 0 \qquad (2)$$

Second sub-model is the innovation output equation

$$p_{it} = \gamma_1 k^*_{it} + \beta_2 x^2_{it} + u^2_{it} \qquad (3)$$

Where p_{it} is innovation output (knowledge) proxied by annual sum of patent applications, k^*_{it} is latent R&D intensity variable predicted from generalized Tobit model in the first sub-model. x^2_{it} is a vector of determinants of innovation output. Vector β_2 is corresponding unknown parameters. And u^2_{it} is an error term.

We estimate the innovation output equation as a negative binomial generalized linear model because of patents being observed as count data.

B. *Database*

We made use of a large sample by merging three kinds of databases between 2001 and 2009 for analyzing Korean manufacturing firms; firms' financial statements, Innovation Survey data and patent application information.

Firm's R&D activity related information like R&D expenditure and the number of R&D employees was extracted from the Korean Innovation Survey(KIS) data(2002, 2005, 2008, 2010). The Science and Technology Policy Institute has conducted this survey in Korea since 2002 following the OECD's Oslo manual.

We used two finance and firm information databases to extract the number of employees, firm's age, the Herfindahl index and industry classification. One of databases is the Korea Information Service-Value (KIS-VALUE) database from Korea Investors Service, Inc. The other is TS2000 database from Korea listed companies association. To make more accurate and abundant sample, two databases were considered together.

Lastly, we used The European Patent Office(EPO) Worldwide Patent Statistical Database version 4.31(11-10-2011) as main patents source. Like finance and firm information databases, we also consider patent information from KIS data to make accurate sample. Using patent application data, technology diversification index, which is entropy index in this paper, and annual sum of patent applications is calculated.

Our sample for the R&D equation consisted of 40,002 observations (34,992 censored and 5,010 observed). One for the innovation output equation consisted of 4,799 observations

C. *Variables and Measures*

We categorized variables into three groups: knowledge/innovation, technology diversification, and controls group. Knowledge/innovation variables are R&D engagement, R&D intensity , sum of patent. We defined R&D intensity as annual R&D expenditure per employee for R&D doing firms. Sum of patents means annual sum of patent applications which firm applied for each year (in log).

Technology diversification related variables are entropy index, sum of multi IPC(the International Patent Classification System) patents and multi IPC patent ratio. Entropy index and Herfindahl index are representative indices for measuring degree of technological diversification of the firm. This paper will use the entropy index as technology diversification measurement. because previous studies have show that entropy index is more effective than hergindahl index ([8],[9],[10])

Entropy index(ε_{it}) and Herfindahl index(H_{it}) [11] are defined as :

Entropy index :

$$\varepsilon_{it} = -\sum_{j=1}^{m_{it}} P_{ijt} \ln(P_{ijt}), \qquad (4)$$

Herfindahl index :

$$H_{it} = (1 - \sum_{j=1}^{m_{it}} P^2_{ijt}) \qquad (5)$$

P_{ijt} is firm i's the share of the technological field j over year t, it can be expressed as $Pijt = n_{ijt}/ N_{it.}$ m_i is the total number of IPC categories(technological field) into which firm i's patent applications are classified. n_{ij} is firm i's sum of patents classified as IPC code j over year t. N_{it} is sum of IPC codes appear in firm i's patents over year t.

Multi IPC patent means annual sum of patent application (in log). And Multi IPC patent ratio is the share of multi IPC patent applications in annual sum of patent application

We control industry, market concentration, firm's age, year and firm size . We use industry dummies variables classified according to two-digit KISC(korean standard industrial classification) codes for firm to control industry affiliation.

The Herfindahl index(HHI) is used as market concentration index and the number of employees is used as proxy variable of firm size

TABLE I. SUMMARY STATISTICS: MEAN (STD. ERROR.)

	R&D engagement equation	R&D intensity equation	R&D intensity equation
Variable	n=40002	n=6250	n=4799
R&D engagement(dummy)	0.13(0.00)		
R&D intensity(in log)		5.20(0.08)	8.20(0.03)
Predicted R&D intensity(in log)			7.49(0.01)
Number of R&D employees(in log)			2.77(0.02)
Number of employees(in log)	3.81(0.01)	4.97(0.02)	5.11(0.02)
Sum of patents	21.07(1.91)		
Entropy		0.57(0.01)	0.60(0.01)
Sum of Muli-IPC patents**(in log)		13.32(1.34)	0.25(0.03)
Mult-IPC patent ratio		0.53(0.01)	
Firm age(in log)	2.30(0.00)		2.68(0.01)
Industry HHI	0.09(0.00)	0.10(0.00)	0.10(0.00)

III. Empirical Results

A. *R&D and R&D intensity*

Table 2 and 3 present the results of the estimation of R&D engagement and intensity equations. The probability of R&D engagement increases with its age, competition pressures (industry HHI) and its size (Number of employees)

Firm size has negative effect on R&D intensity contrast to R&D engagement case. An industrial competition pressure, measured as HHI, is more important factor for the R&D engagement decisions than for R&D intensity.

Technological diversification, measured as entropy index, promotes R&D intensity. But estimator of Multi IPC patent variable gives a higher value to the diversity index for firm with less R&D intensity.

TABLE II. RESULT OF R&D ENGAGEMENT EQUATION:

Dep. Var	R&D engagement
	n=40002
Number of employees	0.426 (0.007)***
Industry HHI	0.789 (0.109)***
Firm age	0.074 (0.011)***

Note: Regression includes 23 industry and 14 year dummies
(***) indicate statistical significance at 1% levels, respectively

TABLE III. RESULT OF R&D INTENSITY EQUATION:

Dep. Var	R&D intensity
	n=6250
Number of employees	-0.144 (0.037)***
Industry HHI	0.188 (0.563)
Entropy	0.597 (0.040)***
Mult-IPC patent ratio	-0.147 (0.064)**
Sum of Muli-IPC patents	0.001 (0.000)***
sigma	1.643 (0.029)***
rho	0.310 (0.056)***
log-likelihood	-21861

Note: Regression includes 23 industry and 14 year dummies
(***) indicate statistical significance at 1% levels, respectively

B. *Innovation output*

To find the impact of technological diversification on innovation output, measured as sum of patents, we estimated equation (3). A positive value of the estimated coefficient of Predicted R&D intensity means firm has strong impact of R&D investment on innovation. However result show that firm's technological diversification give negative effect on innovation output. But innovation out for a firm increases whit its sum of Multi-IPC patents. Considering negative correlation between entropy and sum of Multi-IPC patents, it can be interpreted as technological diversification drop innovation performance but related diversification activity gives positive effect at a certain diversification degree. Results are consistent with many of previous empirical literatures about related diversification of firm ([12],[13],[14])

TABLE IV. RESULT OF THE INNOVATION OUTPUT EQUATION.

Dep. Var	Sum of patents
	n=6250
Predicted R&D intensity	7.020(0.097)***
Number of employees	1.113(0.016)***
Number of R&D employees	0.050(0.008)***
Entropy	-3.805(0.062)***
Sum of Multi-IPC patents	0.516(0.007)***
Firm age	-0.115(0.015)***
Industry HHI	-1.411(0.244)***
2xlog-likelihood	-22223.458

Note: Regressions include 23 industry and 14 year dummies
(***) indicate statistical significance at 1% levels, respectively.

IV. Conclusion

This paper investigated the determinants of R&D activity and innovation performance of Korean manufacturing firms.

We use four databases to construct more accurate and abundant sample. We take care of selectivity bias in R&D intensity equation by using the generalized Tobit model. And we use the predicted value for correcting both the selectivity and endogeneity biases of R&D intensity variable in the innovation output equation.

We confirmed trade-off between positive indirect effect and negative direct effect on innovation output of technological diversification. Similar to this, we

Industrial competition pressures, as measured by HHI, effect on R&D engagement and intensity positively but innovation out negatively.

In the future, we will refine the model to find determinants interacting with technological diversification on innovation system and firm's optimum point at technological diversification

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