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Analysis for R&D Organization Choice in Innovative Firms*

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We are interested in the behaviors of innovative manufacturing firms in choosing and implementing the organizational forms such as cooperative R&D. In this study, we examine the behavior of innovative firms regarding employment, R&D spending, or in-house or outsourcing(cooperation) by limited dependent variable model. We find the determinants of innovating firms for choosing the alternative methods of R&D: cooperative R&D, female employment, and specific department for R&D, etc. In special, R&D organization and firm size affect the magnitude of female employment. For the probability of product innovation, female employment is significant in the range of R&D spending more than $120 mil.

We also examined the determinants of cooperative R&D. From the results, we can find that special R&D team(department) affects employment pattern significantly. We also considered sample selection issue. This study may help government in which public experts seeks to enhance the productivity level of firms.

JEL Classification: E32, O30
Keywords: cooperative R&D, outsourcing, skill-biased technical change, individual heterogeneity of labor, R&D organization

1. INTRODUCTION

Many governments are interested in transforming into qualitative growth system in implementing economic growth policy such as increase in per capita income growth. We are interested in the questions as follows: First, do the firm characteristics of firms performing R&D are related with the magnitude of R&D spending? Second, what kind of factors affect the research form of organization specializing in R&D? Third, which factor is most important in deciding the type of cooperative R&D.

Aghion and Howitt (1998, 2009) analyzed the organizational forms of research. This study focuses on the spending for R&D. Meschi, Taymaz, and Vivarelli (2016) analyzed the employment of skilled and unskilled laborers and technological change. In this study, we apply these methods to the panel data of Korea (KIS) with regard to R&D structure of innovative firms.

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Fernandez-Villaverde (2001) considered complementary between (R&D) capital and skill level.[1)] Moon (2015) estimated the effect on total employment of knowledge-based service industry of sales increase. But he did not isolate the R&D labor employment.[2)] Belderbos, Carree and Lokshin (2004) used data on Dutch innovating firms in CIS survey (1996, 1998). They examined the effect of cooperative R&D on productivity growth. Their study is a theoretical one, and the objective of this study is to apply to real data for innovative firms.[3)]

Sakakibara (1997) provides capabilities heterogeneity of R&D consortia (cooperation) as a condition for competing motives: cost-sharing vs. skill-sharing.

Lee, Kim, and Zo (2017) find that the participation of large firms in firm-to-firm R&D cooperation affects overall ICT convergence in Korea.

In this study, we examine the determinants of specific forms in research organization seeking to success in product and process innovation of Korean firms using survey data of KIS (Korea Innovation Survey) data. For example, a firm may have some factors that affect the innovative behavior of the form or process of innovative action as inputs for creating new products determining whether cooperation is desirable.[4)] In addition, we also estimate the effects of female employment on the choice of R&D method such as cooperative R&D. We can also infer diverse factors affect the firm's choice depending on the characteristics. By this study, we can predict firms' behavior and may give policy implication to labor policy and STI policy implementation. Other motivation in this study is that beyond admitting the characteristics of firms, we need to focus on the structural changes in the choice of M form or U form with regard to kinds of the level or type of R&D activities by manufacturers. Aghion and Howitt (1997) analyzed the real and formal authority within organizations. They examined factors that affect real authority: overload, urgency of decision and reputation.

This paper is organized as follows: section 2 presents standard economic model. This section examine whether organizational forms such as cooperation or outsourcing affect the R&D spending and the probability of innovation. Then, we provide the basis for estimating the parameters and a concise interpretation of the behavior in Korean innovating firms among manufacturing industries through econometric model in section 2. In section 3, we briefly examine the factors affecting the "sentiment" for the importance among several research strategies.

In section 4, we examine specific issue of knowledge property protection by econometric method. Section 5 summarizes and concludes.

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1) A specific program such as reformation of income tax could be discussed by sophisticated econometric methods.

2) Hornstein, Krusell and Violante (2005) analyzed gender gap with regard to the effects of technical change on labor market inequalities.

3) Bloom, Canning, Fink, and Finlay (2009) argue that the increase in people's skill level during 1970s to 1990s, and explain why the gender gap closed.

4) With regard to the protection of research output, it was Ginarte and Park (1997) who investigated the length of protection and a country's income level.

2. RESEARCH FRAMEWORK

2.1. Cooperative R&D of Firms and R&D Organization

Usually, private firms set a research joint venture (RJV) to perform R&D cooperatively. US sometimes relax antitrust regulation for promoting innovation, and standard example is RJV.

D'Aspremont and Jacquemin (1988) shows that the equilibrium level of R&D input in cooperative R&D is less than that of fully merged firms. Most previous studies try empirical estimation, but they do not divide the drastic and nondrastic innovation.

In this section, we examine various aspects of cooperative R&D using KIS data. In special, we test several hypotheses with regard to cooperation such as RJVs. RJVs seek to maximize their joint profits. Without any spillovers, the cooperative R&D input level should be less than that of noncooperative R&D. This is because cooperating firms can reduce duplication. With some spillover effects between members, however, the level of cooperative R&D is larger than that of noncooperative R&D. This is because the firms can internalize the positive externalities.

Since we do not consider spillovers, we expect the R&D level will decrease under cooperation for the former reason. The implication of this fact is that STI policy promoting R&D coordination may happen to reduce total research effort in the economy. We examine the welfare effects of allowing competing firms for R&D cooperation.

In this section, we only consider the cooperative research effort in the pre-competition stage. That is, firms only cooperate their process innovation before actual production occurs. The case of cooperation in both R&D and production is examined in later section. Firms consider their decisions of how much R&D input to invest thinking of the output competition in oligopolistic market. If he or she puts too much input in R&D stage, then he encounters fierce competition in output market, since it decreases the price at which consumers are willing to pay due to overflow of final output from low-cost production technology. D'Asparamont and Jacquemin (1988) present VLSI, ESPIRIT and MCC as good examples. In this case, firms maximize joint profits at the second stage output market.

2.2. Schumpeterian Model

Aghion and Howitt (1998, 2009) provided the theory of general purpose technology (GPT).[5)] If we denote the number of innovations as $\varepsilon(\tau)$ and final output as y, the growth rate is: $\ln y(\tau+1) = \ln y(\tau) + \varepsilon(\tau)$, (AH 1998). Katz (1996) provided R&D cooperation model. There are n firms. If c_i denote marginal cost across firms, then $V^i[\boldsymbol{c}]$ means firm i's profits. He considered cost-sharing rules that depend on R&D effort, $r_1,\ r_2,\ \dots r_n$. If a firm enter cooperative R&D, total R&D expenditures are:

5) This model deals with R&D input as of labor.

$$s^k r_i + \frac{(1-s^k)}{(k-1)} \sum r_j \ , \tag{1}$$

k is the set of firms (cooperative R&D) and s^k is the share of cost.

Let z_i donate the effective R&D from which i benefits:

$$z_i(r) = r_i + \varphi \sum r_j \ , \tag{2}$$

$z_i(r)$ is the individual member firm and φ is spillovers.

If marginal cost is constant, each firm consider whether he enters cooperative R&D and how much share he pays costs. In later section, we estimate the coefficients and test the significance of factors affecting cooperative R&D following this logic.

Katz (1986) formulizes R&D joint venture on the basis of Schumpeterian framework. This study is interested in the determinants of R&D spending and joining cooperative R&D.

Next, we develop Schumpeterian model to examine the demand for skilled labor (R&D research sector employee by assumption). The firm (or economy) pass through 2 phases. GPT_i arrives at time t_i. During phase 1, n of labor is devoted to R&D. This process is explained in Aghion and Howitt (2009).

Aghion and Howitt (2009) explains skill premium by dividing skilled and unskilled labor in this model.[6] In this study, we regard non-R&D sector workers as relatively unskilled workers in innovative firms, but they have unobserved characteristics in the ratio of employment of representative firm that can be explained by methods of R&D organization such as internal own R&D spending. Our empirical study for testing these equations have to be based on simultaneous equations model. Since unskilled worker demand and innovation interacts each other, there is endogeneity problem. Main equation is the labor demand regression model. But we also estimate the marginal effect from employment share to the probability of innovation.[7] We can infer R&D organization and R&D labor demand for manufacturing sector at firm i as a function of wages or firm size (SIZE_i).

The marginal effect of firm size on manufacturing labor may be affected by the rate of (tax) subsidy from government.[8] Aghion and Howitt (1998) presented the bechmark model in Schumpeterian framework. It is known that capitalization effect from technical progress could create jobs in contrast to that from creative destruction effect.

Pissarides (1990), and Aghion and Howitt (1998) provided matching model (Romer, 2006). In matching function $m(1, \upsilon)$, 1 denotes normalized labor force, and υ total vacant jobs.[9] This

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6) In this section, skilled worker is assumed to only work in R&D sector.
7) In later study, we could revise manufacturing labor demand function slightly including the effects of government tax subsidy policy.
8) One of the additional econometric methods we consider in this study is sample selection model (Heckman, 1976).
9) $m'(\upsilon)>0$, $(m/\upsilon)'(\upsilon)<0$.

model could provide basic framework for the relationship between manufacturing worker and technical progress. But it would be difficult to apply to individual firm. This study reviews these previous theoretical studies and apply empirical tools to KIS data for examining the relationship between innovation and organizational characteristics such as cooperative R&D or female employment. Aghion and Tirole (1997) analyzed the allocation of formal authority and real authority. They examined the determinants of delegation of authority within organizations such as overload, lenient rules, urgency, etc.

3. DATA AND BASIC STATISTICS

Our data can be summarized as follows: First, we use 3500 cross section manufacturing firm-level data of KIS 2016-2020 (biannual) that have the same ID. Sometimes, we use only 4001 cross section manufacturing firm-level data of KIS 2018.

Korean Innovation Survey (KIS) is performed by government supported research institute, STEPI in Korea.

We mainly extend our analysis into KIS 2018-2020 panel data set. These firms chose one of innovative methods for producing new commodities. The survey data have characteristics of nonexperimental or observational data, so, the (response) value may be random.[10)] In each estimation equation, adjustable number of observations may differ from each other due to missing data and change of questionnaires. Cowling (2016) analyzed the SMEs in the UK, and arranged variables of data: innovation characteristics, firm characteristics, strategic planning and firm capabilities. So, variables KIS can be composed similar to those in Cowling (2016).

Table 1 to table 3 shows that the survey questions are similar to revealed preferred data for firm's choice of female employment and R&D activities. In appendix, we provide full questions. Figure 1 shows the main statistics for each question such as distribution for choices of the organization in R&D performance. Figure 1 shows that most firms surveyed perform innovative activities for themselves. We want to know whether these preferences are related with forms of R&D performance activities. The most frequent organizational form of partner is subsiduary of firms. Next, private downstream firms became main partner in R&D cooperation.

10) This means that sample selection bias could cause problem for estimates such as inconsistency.

Table 1 Variables Used

Employment	1 (MASTER)[11]: If respondent has MA degree 2 (RESEARCH, RDSPECIAL)[12] : Share of R&D labors (MANU = 1-RESEARCH): Share of manufacturing labors 3 (FEMALE, WOMAN): Share of female workers
Importance of Strategies: Product Innovation	1 COMMODITY: Drastic 2 COMMODITY2: Non Drastic
Innovator[13]	1 (OWN): Independent innovation 2 (COOPERATIVE): PRODUCTCO: Cooperative R&D in product innovation PROCESSCO: Cooperative R&D in process innovation 3 (DEVELOP): Revision of other firms' innovation 4 (OTHERR&D): Innovation by other firms
R&D Activities	1 (IN-HOUSE): Independent innovation 2 (COOPERATIVE): R&D cooperation 3 (Outsourcing): Outside innovation 4 (New Capital): Purchasing new machinery 5 (Patents): Purchasing IPR 6 (OJT): On the job training 7 (Marketing Research): Market research 8 (Design): Creation of new design 9 (Others): Other activities
Government Support	Importance of Subsidy on Taxation (Tax Credit, TAXC2[14]) 1 high 2 medium 3 low 4 no use.
R&D Costs	(Mil. Won, RD) 1 Share of Internal R&D Costs (INTERRD) 2 Share of External R&D Costs (OUTRD)
Protection for IPR	1 PATENT 2 PETTY (Patent)

Note: The letters in () is name of variables used in empirical analyses.
Source: KIS (Korea Innovation Survey) (2018).

Table 1-1 Variables Classification for Innovator(firm) Characteristics[15]

1 innovation characteristics	Product or service innovation (COMMODITY2: nondrastic), Process innovation (PROCESS), Completely new product or service innovation (COMMODITY: drastic), Completely new process innovation, R&D tax credit (TAXC2).
2 firm characteristics	Single site (COMPLEX), Family owned (GOVERN), Board size (SIZE, VENTURE). Private limited company (GOVERN, SIZE), Employment size band (MANU, RESEARCH), Age band, International sales, Growth orientation
3 strategic planning	Strategic planning, Planning index
4 firm capabilities	Capabilities Index

11) The words in () denote variables used in empirical study. FEMALE is a binary variable.
12) Research labor is denoted diversely sometimes as RESEARCH, RDSPECIAL, and RD LABOR, respectively.
13) Only for the respondents answered in Q8 as Yes.
14) We reversed the ordering of answers into ascending one by TAXC2.
15) Variables in Parentheses are similar to Cowling (2016) Classification for firm characteristics.

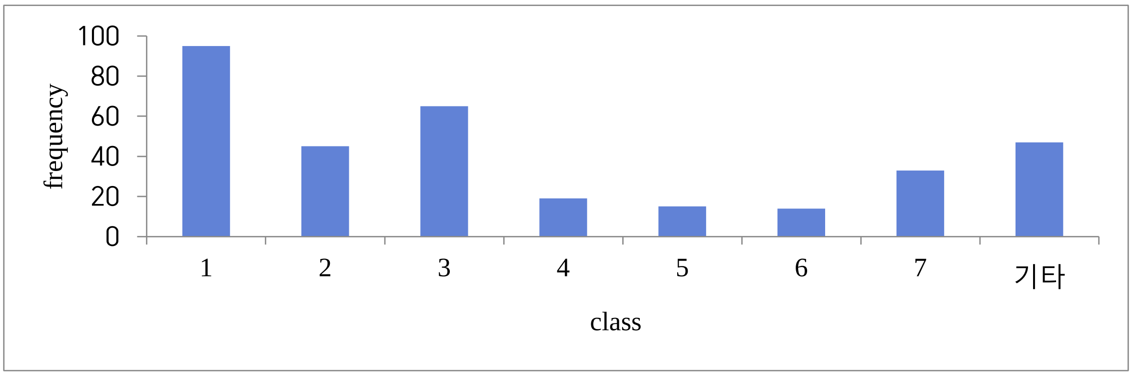
Table 2 Descriptive Statistics

Innovator	Own	Cooperative	Develop	OtherR&D
Mean	0.196571	0.046571	0.006286	0.006000
Std. Dev.	0.397462	0.210749	0.079044	0.077238

Table 3 Distribution of Organizational Forms of Innovation Partners

Organizational Forms of Innovation Partners (PARTNER)	1 subsidiary of firms 2 upstream suppliers 3 private downstream firms 4 public downstream firms 5 competitors 6 private service provider 7 university 8 public research institute 9 private research institute

Figure 1 Distribution of Choices for R&D Methods and Organizational Forms of R&D Cooperation



Basic statistics are summarized at the box in table A1.[16] Our study focuses on the success of innovation as a factor of main determinants of organizational forms of innovative firms.[17] We can recognize that the trend of time-specific R&D labor demand in firms using panel data from 2016 to 2018 exists. The wage variable used is monthly earnings across all jobs.

16) They show that share of reserach worker has incresed to 7.5% in 2018. And they show that the correlation with the frequency of innovation and holding share of Master's degree.

17) As the estimation equations show, these estimations have the potential problem of an endogeneity.

Table 4 Summary Statistics

Table 4-1 Employment – Characteristics of Firms[18)]

(%)	MASTER	RESEARCH (RDSPECIAL)	MANU	WOMAN	UNION
Mean	4.270286	7.546571	92.45342	25.09849	1.910571
Std. Dev.	9.990368	11.39866	11.39866	21.64766	0.285402

Table 4-2 R&D Organization – Characteristics of Firms

Descriptive Statistics for RDSPECIAL (%)
Included observations: 7416

YEAR	Mean	Std. Dev.	Obs.
2016	3.467594	7.562480	3916
2018	7.546571	11.39866	3500
All	5.392678	9.780301	7416

Table 4-3 Method (Activity) of R&D

	COOPERATE	EXTERNAL	INTERNALR
Mean	0.101143	0.092857	0.360286
Std. Dev.	0.301561	0.290274	0.480152

Table 4-4 Using Patent – Strategy of Firms

Descriptive Statistics for PATENT
Included observations: 7000

YEAR	Mean	Std. Dev.	Obs.
2018	0.315714	0.464866	3500
2020	0.028286	0.165812	3500
All	0.172000	0.377407	7000

Table 4-5 Tax Credit

Descriptive Statistics for TAXC(Q31)
Categorized by values of SIZE
Sample: 2016 2018

SIZE	Mean	Std. Dev.	Obs.
1 Large	2.279762	1.261714	168
2 Medium	2.230392	1.110938	3468
3 Small	1.884387	1.145698	2863
All	2.079243	1.143463	6499

Source: KIS (2016-2020).

18) The numbers in sub-title are mainly from 2018 Questionnaire.

Table 5 A Research Framework by Park (2019)

	Target
1- (success and failure)	Innovation success (COMMODITY=1) and failure (COMMODITY=0) contribution to sales (SALE) Y/N
2- (successful innovative firm) Characteristics: (R&D Activity)	R&D activity manners(Q17)

Table 5 shows research framework of Park (2019) that studied innovation behavior of successful firms by KIS panel data. She also modeled target and input variables in each stage (Module). She examined the causal relationship between each target variables.

In this study, we focus the effect of R&D sector forms of operations that are the characteristics of firms on R&D behavior instead. Each variable feedback with that of other stages. Table 6 shows the summary statistics with regard to the grades(sentiments) of relative importance of R&D strategies.

In this study, we examine the decision for choosing type of R&D activities of Korean manufacturing firms.[19] For example, a firm may do not R&D, but only buy patents of others or new intermediate goods.[20] And, this may be affected by the organization of employment.

We first use 3500 cross section firm-level data of KIS 2018 of Korea. Then, we extend panel data from 2016-2020 if necessary.[21] Firms (or an institutions) selected one type of R&D methods because he or she can have higher profit from this choice than any other alternatives. We have to notice that the survey data used in this study may have characteristics of non-experimental, that is random. Table 6 shows the basic statistics for innovative firms' choices.

Table 6 Importance of Strategies for Innovative Firms and Probability of Innovation and Average Probability of Product Innovation[22]

	PRICE competitiveness	PRODUCT new	CUSTOMER new	NEW improvement	SOLUTION for customers	COMMODITY (Drastic 0 or 1)	COMMODITY2 (NonDrastic 0 or 1)
Explanation	Lowering price relative that of competitors	Creating new kind of product	Capturing new group of customers	Improvement of previous commodity	Customer friendly strategy		
Mean	2.161143	2.352571	1.918286	1.852571	2.196571	0.112286	0.210286
Std. Dev.	0.832862	0.765229	0.865758	0.914762	0.886332	0.315763	0.407570

We want to know what factors of firms and institutions in Korean manufacturing industry lead

19) Park (2019) analyzed overall innovation behavior by a decision tree.
20) Koo et al. (2012) that investigated the choice of automobiles using TEMEP Household ICT/Energy Survey in 2006.
21) Using sophisticated estimation technique is difficult due to unavailability of statistical methods of SW package.
22) Hereafter, if the estimate is significant at 5%, 10%, then we denote **, *, respectively.

to choosing specific method and the characteristics of firms.[23)] We want further to know how these choices for R&D sector activities lead to the probability of success of product innovation and R&D labor demand.

4. EMPIRICAL ANALYSES USING ECONOMETRIC MODELS

4.1. Optimal Choice for R&D Activity

Basic econometric models for choice of R&D activity have a base on the random utility model.[24)] In our study, statistics of alternatives for R&D activities are shown in table 1. In general, applying OLS to binary choice data is not a good idea since though both OLS and Feasible GLS yield consistent estimators, and the latter produces more efficient estimator.[25)] Our study may be summarized as several hypotheses that may be tested.

For estimating the choice behavior of innovative firms for product innovation alternatives, we need to note the fact that the probability of choosing a specified share of female labor and a spe cific method of innovation can be affected by firms' characteristics.[26)] Table 1 summarized th equestions and answers related to choosing strategic variables and innovation outcomes.[27)]

The reason for analyzing this choice is that R&D process is closely related with demand for female labor.[28)] There are two approaches that treat binary choice model, regression approach and latent regression (index function model). If we use logistic or normal distribution, then these are logit or probit models. There is close relation between two estimates (Amemiya, 1961).

Meschi, Taymaz and Vivarelli (2016) analyzed the relationship between the employment of skilled and unskilled laborers and technological change. We can apply this method to the panel data of Korea (KIS). The results provide rich implications for the wage and employment policy in Korean R&D labor market. In later sections, we examine the determinants such as the share of R&D workers for choosing various forms of R&D activities.

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23) We can see that from description data table, the type of choosing to adopt specific activities such as cooperation, in-house or outsourcing, in which external R&D(outsourcing) has relatively high frequency.

24) We can consider utility as ordinal profits in which the ordering is important. Nakosteen-Zimmer (1980).

25) Shortcomings of simple LPM (linear probability model) model may be: First, heterogeneity problem, which leads to inefficient estimator or misleading standard error. Second, estimated dependent variable can be inconsistent with the concept of probability.

26) We can see that the size of household affects the probability of choosing brands, but this LPM has the problem of heteroscedasticity and unreasonable marginal effect implication.

27) We express firms' choices for specific method by the binary dependent variable.

28) We can set the probability of choosing patents as probit estimation.

Table 7 Questionnaire and Varibles Used (Characteristics of Firms)[29)]

2018 2020 Manufacturing ID	
Established year	HISTORY = 2020 - est year
Industry	IND
Corporate structure	GOVERN
Firm size	SIZE
Annual sales	SALE (2015, Mil. Won)

Product Innovation (1) Drastic	
Characteristics establish, governance, industry, sale, size, wt	
Failure	Success Then, by what method? (PARTNER)
	1 In-house 2 Cooperative 3 Outsourcing 4 New capital 5 Patents 6 OJT 7 Market research 8 Design 9 Others

4.2. Results from Discrete Variable Model for Innovation Using R&D Cooperation as a Regressor

Aghion and Howitt (1998) emphasized the role of R&D organization in innovation process. Table 8 shows the effect of cooperative research on the probability of nondrastic innovation, and it is positive significantly. The interaction term with R&D expenditure and female labor is significant at 10% level, so we can see that marginal effect depends on the R&D input spending or labor demand in innovative firms. That is, cost-sharing motive operates through magnitude of research input or employment of female labor. But (INTERNAL) and (COOPERATE) may be correlated, and there can be multicolinearity problem. So, in-house method seems to affect the probability of nondrastic innovation negatively. In addition, in the area of nondrastic innovation such as traditional manufacturing, technology adoption or cross-licensing may be more appropriate than research by in-house. Goodness of fit measure such as LR (likelihood ratio) is significant. In table 8, we added Granger causality test results. We can see that firms focusing in-house (INTERNALR) affect the probability of nondrastic product innovation (COMMODITY2). That is, firm characteristics such as the form of R&D activity seem to cause the firm to make a success in innovation. Product innovations are made mainly from R&D cooperation.

29) Other questions and variables in Questionnaire are in table of appendix.

Table 8 Nondrastic Innovation (KIS 2018)[30)]

Dependent variable: OMMODITY2		Dependent variable: OMMODITY2			
Method: ML-Binary Probit					
Sample (adjusted): 6 3500 (2018)		Sample:1 3500(2018)			
Variable	Coefficient Prob.	Variable	Coefficient Prob.		
C	0.062962 0.445	C	0.050572 0.5705		
INTERNALR	–0.178538 0.0500**	INTERNALR	–0.155858 0.1082		
COOPERATE	0.248049 0.0044**	COOPERATE	0.333317 0.0005**		
EXTERNAL	0.014229 0.8701	EXTERNAL	0.00301 0.9725		
RD* COOPERATE	2.66E-10 0.3006	WOMAN* COOPERATE	–0.012092 0.0905*		
		R-squared 0.007799		Mean dependent var	0.492053
Prob (L Rstatistic) 0.002777**		Prob (L Rstatistic) 0.003540**			
Obs with Dep=0 761	Total obs 1497	Obs with Dep=0 735	Total obs 1447		
Obs with Dep=1 736		Obs with Dep=1 712			

Table 8-1 Granger Causality Tests

Pairwise Granger Causality Tests
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
COMMODITY2 does not Granger Cause COOPERATE	726	0.00872	0.9256
COOPERATE does not Granger Cause COMMODITY2		1.70896	0.1915
COMMODITY2 does not Granger Cause INTERNALR	726	0.96560	0.3261
INTERNALR does not Granger Cause COMMODITY2		4.90986	0.0270**
COMMODITY2 does not Granger Cause COOPERATE*(RD)	726	0.67732	0.4108
COOPERATE*(RD) does not Granger Cause COMMODITY2		2.32391	0.1278
COMMODITY2 does not Granger Cause EXTERNAL	726	4.16125	0.0417**
EXTERNAL does not Granger Cause COMMODITY2		0.19959	0.6552

According to Sakakibara (1997), the size of participants in consortia is asssociate with motive for cooperation. So, we used size variable (SIZE) in the regression for research spending.

Table 9 shows that cooperation also increases the R&D expenditures significantly. Interaction term is not significant, but the results are omitted. Both pooled and fixed effects LS estimation the coefficient for cooperation as positive. In Table 9, the estimated coefficient for cooperation in product innovation increases R&D spending. In addition, R&D costs in outward innovation (OUTRD) can increase in the case of product innovation.

30) Hereafter, the estimation results have different numbers of sample. This is because we use different time period, or missing values exists. In addition, if the coefficient is significant at 10% and 5%, we denote * and **, respectively.

The relationship between patenting firms (apply or register) and their characteristics may have selection bias. In this case, estimator can be biased and inconsistent. We used Heckit model to this R&D spending equation. Finally, we estimated binary Probit model for estimation of coefficients of factors determining whether firms spend research costs or not. Many variables such as SIZE, and SALE showed positive effects on the probability significantly, but location or industry type affected negatively. We used TRD when research spending is positive as a dependent variable, and it has two values, 0 or 1. In addition, we performed pairwise Granger causality tests. We can see that almost all variables in the regression affect(cause) the amount of total R&D spending (TRD).

Table 9 Determinants of R&D Spending (Fixed Effects Model)

Dependent Variable: OUTRD Method: Panel Least Squares				Dependent Variable: RD			
Sample: 2018 2020				Sample: 2018 2020			
Variable	Coefficient Prob.			Variable	Coefficient Prob.		
C	7.157018 0.1542			C	29290272 0.0000**		
SIZE	1 0.0000**			SIZE	0.999889 0.0000**		
PRODUCTCO	9.479741 0.0574*			COMPLEX	−434966.4 0.9146		
PROCESSCO	-6.885178 0.0874*			SALE	0.49986 0.0000**		
Cross-section fixed (dummy variables)							
R-squared	1	Mean dependent var	3455736	R-squared	0.912214	Mean dependent var	35032358
Prob (F-statistic)	0.000000**			Prob (F-statistic)	0.000000**		
Redundant Fixed Effects Tests				Redundant Fixed Effects Tests			
Effects Test	Statistic Prob.			Effects Test	Statistic Prob.		
Cross sectionF	3.584665 0.0000**			Cross sectionF	3.670562 0.0000**		
Cross-section Chi-square	5057.908458 0.0000**			Cross-section Chi-square	7778.077418 0.0000**		

Dependent Variable: LOG(RD) Panel Least Squares		Dependent Variable: LOG(TOTALRD) ML Heckman Selection	
Variable	Coefficient Prob.	Variable	Coefficient Prob.
		Response Equation - LOG(RD)	
C	2.583612 0.0000**	C	2.268817 0.0000**
PATENT10	1.168757 0.0000**	PATENT10	1.138308 0.0000**
LOG(SIZE)	0.654047 0.0000**	LOG(SIZE)	0.76778 0.0000**
COMPLEX	0.486226 0.0000**	COMPLEX2	0.129999 0.0004**
LOG(SALE1)	0.180919	LOG(SALE1)	0.121874

	0.0000**		0.0000**
PRODUCTCO20	0.323364 0.0000**		Selection Equation - TRD
		C	0.021968 0.8048
		VENTURE	0.517112 0.0000**
Prob(F-statistic): 0.000000** Dependent Variable: TRD (RD>0) Method: ML - Binary Probit		Log likelihood	-4836.07

Table 9-1 Granger Causality Tests

Pairwise Granger Causality Tests
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
TOTALRD does not Granger Cause PATENT	1086	7.31722	0.0069**
PATENT does not Granger Cause TOTALRD		7.76862	0.0054**
TOTALRD does not Granger Cause SIZE	1086	0.02079	0.8854
SIZE does not Granger Cause TOTALRD		21.0695	5.E-06**
TOTALRD does not Granger Cause COMPLEX	1086	3.25522	0.0715*
COMPLEX does not Granger Cause TOTALRD		7.71654	0.0056**
TOTALRD does not Granger Cause SALE	1086	4.52740	0.0336**
SALE does not Granger Cause TOTALRD		4.61068	0.0320**

Sakakibara (1997) summarized 2 competing motives as cost-sharing vs. skill-sharing. In Schumpeterian growth model, low-skill workers work only in manufacturing sector. Sakakibara (1997) set the hypothesis that whether cooperative R&D affects R&D spending depends on the incentives of participating firms. That is, skill-sharing motivation increases spending, but cost-sharing one decreases it. If we use panel data so that we can control individual heterogeneity, we can find that R&D cooperation in product innovation increases spending (skill-sharing, PRODUCTCO $\rightarrow$OUTRD), but cooperation in process innovation decreases spending (cost-sharing, PROCESSCO $\rightarrow$OUTRD). Sakakibara (1997) emphasized that the role of R&D capability heterogeneity important. This may be the motive for R&D cooperation.

Finally, the size and magnitude of sales affects R&D spending positively as coincided with our intuition. Whether the firm is located in industry complex affects the R&D expenditures positively. Table 9 shows that external costs in R&D (OUTRD) are affected by both product and process cooperation. As coincided with intuition, cooperative R&D in external product innovation activity increases outward R&D costs (OUTRD). F-test shows that individual-specific constants are significantly different from zero. As in table 9, if we measure R&D input by number of persons, this relationship is not significant.

Discrete threshold regression assumes (m+1) regimes. In general, nonlinear LS is adopted for estimating the parameters of the discrete threshold regression:[31)]

$$y_t = X_t^{'}\beta + Z_t^{'}\delta_j + e_t \ .$$

This revised model from original one is smooth transition regression.

$$y_t = X_t^{'}\alpha + \sum 1_j\left(s_t, c, \gamma\right) Z_t^{'}\delta_j + e_t \ . \tag{3}$$

The basis for this estimation can be referred to Hansen (2001) and Perron (2000).[32)] Table 10 presents the implication of cost-sharing motive of cooperative R&D, has is, external R&D activity is performed when R&D spending is high. Table 10 shows the effect of firms characteristics on R&D spending using Threshold Regression (TR). The other terms than firm governance, size and method of using external knowledge need to be examined whether these affect R&D expenditure significantly. Table 10 in Discrete Threshold Regression specification presents the implication that although insignificant at low levels of R&D, cost-sharing motive works. But, at high levels of expenditures, cooperation increases R&D spending. We also consider a standard LPM variable model with *N* persons and *m* potential breaks (possibly *m*+1 regimes). The estimated common factor for determining threshold is the level of R&D expenditures.

In the case of R&D intensity(labor), cooperative R&D significantly reduces it (labor demand or cost).

Table 10 Discrete Threshold Regression

Dependent Variable: LOG(RD) 2018
Method: Discrete Threshold Regression

Variable	Coefficient Prob.	Variable	Coefficient Prob.
RD < 72 - 218 obs		574 ≤ RD < 2590 - 325 obs	
C	4.373324 0.0012**	C	7.137014 0.0000**
COOPERATE	0.115336 0.7773	COOPERATE	–0.101006 0.7185
GOVERN	–0.350763 0.5370	GOVERN	0.151802 0.5835
SIZE	–0.243905 0.4115	SIZE	–0.170104 0.5090
EXTERNAL	–0.157671 0.6799	EXTERNAL	0.158500 0.6301
72 ≤ RD < 574 - 690 obs		2590 ≤ RD - 217 obs	
C	5.467091 0.0000**	C	1.760997 0.0820**
COOPERATE	–0.033215 0.8860	COOPERATE	0.777873 0.0278**
GOVERN	0.181044 0.5885	GOVERN	0.058570 0.8824

31) Discrete TR is a form of nonlinear regression similar to piecewise linear regression and regime switching. The applications are Threshold Autoregression (TAR) and self-exciting TAR (Hansen, 2011; Potter, 2003).

32) Discrete threshold regression (TR) assumes (*m*+1) regimes. (Hansen, 2011; Potter, 2003).

SIZE	–0.151564 0.3562	SIZE	4.201237 0.0000**
EXTERNAL	0.088048 0.6895	EXTERNAL	1.422160 0.0005**
F-statistic	229.7633	Durbin-Watson stat	1.490200
Prob(F-statistic)	0.000000**		

Sakakibara (1997) classified the motive of cooperative R&D into cost-sharing and skill-sharing. Spence (1984) argues that positive externalities make firms to underinvest in R&D. But, if cooperation increases the spillover parameter φ, then cooperative - R&D such as RJVs make the R&D expenditure increase. Sakakibara (1997) emphasizes that cost-sharing motivation decreases R&D spending. Nielsen, von Hellens and Trauth (2003) address the themes regarding Australian women in IT. They provided the explanation that socio-cultural factors affected the women IT profession.

As we saw, table 9 shows that the R&D spending is decreasing function of cooperation. This shows that Korean manufacturing firms have relatively strong cost-sharing motive.[33)]

Table 11 shows that the odds of success in innovation is increasing function of cooperation. In addition, the interaction term of R&D spending has negative insignificant coefficient estimate. This also shows that Korean manufacturing firms have aspects in skill-sharing motive. Table 11 shows that the odds of success in innovation is decreasing function of cooperation. This shows cost-sharing motive.

The effects of female labor (WOMAN) are not significant. This complements the hypothesis by Nielsen, von Hellens and Trauth (2003). They examined open-ended interview with regard to IT industry, but KIS did not excluded other manufacturing industry. They emphasized the importance of additional study for this theme (with regard to skill-biased technical change). The results of causality tests shows that size of innovative firms cause it to increase the probability of drastic product innovation.

Table 11 Probability of Product Innovation

Dependent Variable: COMMODITY Method ML – Binary Probit			
Variable	Coefficient Prob.	Variable	Coefficient Prob.
C	–0.826347 0.0000**	C	–1.66332 0.0000**
COOPERATE	0.203333 0.0287**	COOPERATE	–0.08185 0.5508
COOPERATE*RD	–2.93E-10 0.2884	COOPERATE* WOMAN	–0.004188 0.2878
GOVERN*(10^6)	3.07E-07 0.0040**	WOMAN	0.010623 0.1395
SIZE*(10^6)	–2.97E-07 0.0000**	(GOVERN)*10^6	3.15E-07 0.0032**

33) Cotter, Hermsen, and Vanneman (2001) analyzed the effects of R&D labor on the different gender LFP (labor force participation) behaviors.

			(SIZE)*10^6		2.83E-07 0.0000**
EXTERNAL		−0.04197 0.6592	EXTERNAL		0.035616 0.7084
Prob (LR statistic)	0.000021**		Prob (LR statistic)	0.000011**	
Obs with Dep=0	1071	1450	Obs with Dep=0	1071	1450
Obs with Dep=1	379		Obs with Dep=1	379	

Table 11-1 Granger Causality Tests

Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
COMMODITY does not Granger Cause INTERNALR	726	0.14379	0.7047
INTERNALR does not Granger Cause COMMODITY		1.45659	0.2279
COMMODITY does not Granger Cause COOPERATE	726	2.86470	0.0910*
COOPERATE does not Granger Cause COMMODITY		0.66632	0.4146
COMMODITY does not Granger Cause SIZE	3499	16.0754	6.E-05**
SIZE does not Granger Cause COMMODITY		5.65806	0.0174**
COMMODITY does not Granger Cause EXTERNAL	726	0.17241	0.6781
EXTERNAL does not Granger Cause COMMODITY		0.14296	0.7055
COMMODITY does not Granger Cause GOVERN	3499	3.10281	0.0782*
GOVERN does not Granger Cause COMMODITY		0.00405	0.9493
COMMODITY does not Granger Cause WOMAN	3489	0.93247	0.3343
WOMAN does not Granger Cause COMMODITY		2.44495	0.1180
COMMODITY does not Granger Cause WOMAN*COOPERATE	724	0.36443	0.5462
WOMAN*COOPERATE does not Granger Cause COMMODITY		0.23006	0.6316

Sakakibara (1997) classified the motive of cooperative R&D and incorporate them into questionnaire for firms. Table 12 shows the comparison of implications for incentive in joining cooperative R&D. Overall, participants in consortia in Japan took importance on skill-sharing motive such as gaining complementary knowledge. Contrary, Korean manufacturing firms emphasize the cost-sharing aspects of co-R&D. In addition, the motive of Korean firms focused on product improvement or upgrading (in raising quality innovation).

Table 12 shows that the incentive for Improvement is strongest for joining cooperative R&D. Table 12 also emphasizes that cost-sharing motivation decreases R&D spending, so we can conclude that firms have a strong incentive to upgrade quality efficiently by cooperation.

Table 12 Korean vs. Japanese (Respondence) Firms (Sakakibara, 1997 and this study)

Cooperation	Goals		
KIS 2018 (This Study)	new product (PRODUCT)	price competitiveness (PRICE)	(1) new customers (CUSTOMER) (2) solutions for customers (SOLUTION) (3) improvement (NEW)
Coefficient in Probit	0.028	0.10	(1) –0.110 (2) 0.089 (3) 0.270
Sakakibara (1997)	skill-sharing (1) to gain complementary knowledge	cost-sharing (1) to share fixed costs (2) to avoid duplication	Others: (1) to catch advanced tech

Table 12 shows that the incentive for Improvement is strongest for joining cooperative R&D. Table 12 also emphasizes that cost-sharing motivation decreases R&D spending, so we can conclude that firms have a strong incentive to upgrade quality efficiently by cooperation.

Table 13 shows that the cooperation for new product innovation (PRODUCTCO) incentive is larger in location of industry complex (See footnote 36). Using ordered logit or probit model does not make significant difference. In this case, logit model has higher Pseudo *R*-squared, and we accept result of logit model rather than that of probit. Logit model has the following probability.

$$\Pr\left(y=1\middle|x,\beta\right)=\frac{\exp\left(x^{'}\beta\right)}{1+\exp\left(x^{'}\beta\right)}. \tag{4}$$

In addition, the incentive to cooperate increases in both types of innovation by the increase in spending cooperation R&D spending. Using panel data from 2018 to 2020 and probit model, we can see the magnitude of total revenue reduces the incentive of co-operative activities. This supports the view of cost-sharing incentive of cooperation. Table 13 also shows the results of pairwise Granger causality between product innovation cooperation and firm characteristics. Location of firms (COMPLEX) and R&D spending (TOTALRD) may cause to adopt R&D cooperation strategy in product innovation. While Lee, Kim and Zo (2017) emphasized that participation of large and small firms in public domain consortia affect ICT convergence differently, causality of SIZE is not significant.

Table 13 Determination of Joint R&D in Product Innovation[34)]

Dependent Variable: PRODUCTCO2
Sample: 2018-2020

Method: ML - Ordered Logit				Method: ML - Ordered Probit			
Variable	Coefficient Prob.			Variable	Coefficient Prob.		
LOG(SIZE)	1.479489 0**			LOG(SIZE)	0.191469 0**		
COMPLEX2	–0.458133 0**			COMPLEX2	–0.266415 0**		
LOG(SALE1)	0.235842 0**			LOG(SALE1)	0.130771 0**		
LOG(TOTALRD)	–0.06775 0**			LOG(TOTALRD)	–0.050072 0**		
	Limit Points				Limit Points		
LIMIT_1:	0.626347 0.0041**			LIMIT_1:	–0.22964 0.0303**		
LIMIT_2:	2.422432 0**			LIMIT_2:	0.665623 0**		
LIMIT_3:	3.670453 0**			LIMIT_3:	1.347052 0**		
LIMIT_4:	4.665697 0**			LIMIT_4:	1.871569 0**		
LIMIT_5:	6.585604 0**			LIMIT_5:	2.905683 0**		
Pseudo R-squared	0.088358	Akaike info criterion	3.110928	Pseudo R-squared	0.059643	Akaike info criterion	3.208741
Prob (LR statistic)	0**			Prob (LR statistic)	0**		

Table 13-1 Granger Causality Tests

Pairwise Granger Causality Tests
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
PRODUCTCO2 does not Granger Cause SIZE	2472	1.48055	0.2238
SIZE does not Granger Cause PRODUCTCO2		0.65269	0.4192
PRODUCTCO2 does not Granger Cause COMPLEX2	3500	40.1579	3.E-10**
COMPLEX2 does not Granger Cause PRODUCTCO2		116.751	9.E-27**
PRODUCTCO2 does not Granger Cause SALE1	3500	0.13602	0.7123
SALE1 does not Granger Cause PRODUCTCO2		0.28858	0.5912
PRODUCTCO2 does not Granger Cause TOTALRD	1086	3.46844	0.0628**
TOTALRD does not Granger Cause PRODUCTCO2		4.24321	0.0396**

34) PRODUCTCO2 denotes ordered data for the sentiment of importance arranged by descending order. So we have to interpret the sign inversely. But PRODUCTCO denotes binary variable in standard format.

Dependent Variable: PRODUCTCO				Dependent Variable: PROCESSCO			
Method: ML-Binary Probit Sample: 2018 - 2020							
Variable		Coefficient Prob.		Variable		Coefficient Prob.	
C		2.54127 0.0027**		C		4.041194 0**	
LOG(OUTRD)		0.468008 0.0061**		LOG(OUTRD)		0.5859 0**	
LOG(SALE)		–0.158459 0.0025**		LOG(SALE)		–0.369427 0**	
McFadden R-squared	0.140994	Mean dependent var	0.983368	McFadden R-squared	0.330974	Mean dependent var	0.934511
Prob (LR statistic)	0.00001**			Prob (LR statistic)	0**		
Obs with Dep=0	16	Total obs	962	Obs with dep=0	63	Total obs	962
Obs with Dep=1	946			Obs with dep=1	899		

We estimated a standard binary logit model with both cross section data of 2018 and panel data from 2018-2020 for the joint (PRODUCTCO, PROCESSCO) type of innovation. Table 13 shows panel data estimation results. We used Probit estimation under the normal distribution and Logit under logistic one assumption. We can find the following implications for the drastic case:

(1) The effects of size of firms are mixed for the probability of nondrastic product innovation.[35)]

(2) A 1% increase in R&D expenditures leads to the increase of the probability of innovation by the function of estimates (= 0.068*φ[$X'\beta$]). The marginal effect in probit model is: $dp/dx_{mi} = \varphi(\beta' x_{mi})\beta$, m=RD. P-value for the LR statistic shows that the overall significance for the regression approach of binary model.[36)]

In the Probit case, marginal effect is not the coefficient, but the multiplication with pdf of standard normal. Considering estimate for coefficient, $X'\beta$ is 0.0635. This means that 1 unit (person) increase in the number of household members cause the probability of innovation to increase by 0.068*φ (0.0635).

In the case of nondrastic innovation (COMMODITY), we applied random effects in panel data estimation after we do not reject the null hypothesis of random model.[37)] We also applied quantile regression which adjusts the outliers in survey data. In this case, whether a firm employ women workers affects the probability of success in nondrastic product innovation. (coefficient estimate

35) Variable SIZE is coded as 1 (large), 2 (medium) and 3 (small).

36) The ratio of having success for drastic innovation is (586/1213=48%). We have tried to estimate the marginal effect of the amount of R&D expenditure (RD) on the probability of nondrastic product innovation. Table 13 McFadden (1974) R-squared is likelihood ratio index.

37) Panel EGLS estimation result shows that interaction term is significant. This means that the marginal effect of R&D organization on innovation depends on the magnitude of female employees. Panel binary probit result shows that whether the firm employing female labor affects the probability of nondrastic technical change.

= 0.099145, omitted).

The dependent variable in this regression is whether to occur in nondrastic innovation in the firm or not. Table 14 shows that SIZE (firm size) and GOVERN (firm governance or organization) are significantly positive in explaining success of nondrastic innovation. Table 14 shows that the effect of GOVERN is positive significantly and decreasing in regime of high level of R&D cost (206≤RD<1284) in explaining the innovation.[38] We have to notice that the estimation of binary or discrete choice models is based not on fitting rule. It sometimes depends on numerical, not analytic solutions.

Tab 14 Discrete Threshold Regression

Dependent Variable: COMMODITY
Discrete Threshold Regression

Variable	Coefficient Prob.	Variable	Coefficient Prob.	Variable	Coefficient Prob.
RD < 206 - 463 obs		206 ≤ RD < 1284 - 492 obs		1284 ≤ RD - 258obs	
C	0.201566 0.3834	C	0.264142 0.2929	C	0.785456 0.0353**
GOVERN	0.179724 0.0685*	GOVERN	–0.137572 0.0447**	GOVERN	0.010392 0.8776
LOG(SALE)	–0.004447 0.7740	LOG(SALE)	–0.001834 0.9119	LOG(SALE)	-0.004848 0.8360
SIZE	0.095012 0.0547*	SIZE	–0.083564 0.3437	SIZE	–0.038328 0.6039
(INTERNALRD)/100	–0.262260 0.0009**	(INTERNALRD)/100	–0.083564 0.3437	(INTERNALRD)/100	–0.265599 0.0274**
WOMAN	1.58E-05 0.9877	WOMAN	–0.000315 0.7757	WOMAN	0.002852 0.0783*
Prob(F-statistic)	0.000000**				

We can also try panel Granger causality tests reject the null of non-causality between R&D spending and the success of innovation. So that our study can considers the simultaneous determination of research input and the product innovation.

Hausman Test result shows that *t* (3500–1) = 3.97 with [Significance Level] 0.0001 implies endogeneity problem for the variable EXTERNAL in the equation for whether cooperative R&D is performed or not. We applied 2SLS as an instrumental variable estimation into sample selection model. We focus on the endogeneity problem of method of R&D variable of EXTERNAL. Due to correlation with error for explaining cooperative R&D, OLS may give inconsistent estimate for parameter.

Considering endogeneity of explanatory variable, 2SLS produces positive and significant estimate for coefficient parameter, 0.4238. That implies that outsourcing R&D to external source increases the probability of cooperation.

38) In the case of Smooth Threshold Model, the output displays the dependent variable, method, date, sample, thresh old specification, and procedure.

In this section, we examined the effects of R&D spending and the performance of innovative firms. In the next one, we examine subjective importance of R&D strategies and the magnitude of R&D input.

4.3. Other Empirical Results

We estimated ordered probit model since simple LS (or LPM) could give misleading interpretation for the nominal dependent variable. We also tried ordered logit and found the robustness of the assumption of distribution for errors.

Table 15 shows that, for example, the magnitude of increase in R&D input increases the subjective importance of innovation strategy (price competitiveness). The additional calculation of marginal effect needs other formula and is omitted. The importance of strategy may be affected by the existence of joint R&D such as consortia. We estimated the determinants for (new) product improvement, new customer, and solutions for customers, respectively. Table 15 summarizes the results of empirical analysis for the choice of R&D organization types with firm characteristics. Importance of Strategies for Innovative Firms and Probability of Innovation and Average Probability of Product Innovation. In table 6, we saw the meaning of variables that denote the importance of R&D strategies for innovative firms. We performed causality test for the cae of new product creation (PRODUCT). R&D expenditures (RD) and firm size (SIZE) cause firms to put priority on new product creation.

Table 15 Ordered Probit Estimation

Dependent Variable: PRODUCT		Dependent Variable: NEW		Dependent Variable: CUSTOMER		Dependent Variable: SOLUTION	
Method: ML - Ordered Probit							
Variable	Coefficient Prob.	Variable	Coefficient Prob.	Variable	Coefficiet Prob.	Variable	Coefficient Prob.
COOPERATE	0.339373 0.0398**	COOPERATE	–0.361333 0.0079**	COOPERATE	0. 352437 0.0119**	COOPERATE	–0.214915 0.1339
COOPERATE* LOG(RD)	–0.022504 0.2455	COOPERATE* LOG(RD)	0.024369 0.1173	COOPERATE* LOG(RD)	–0.00649 0.6848	COOPERAT* LOG(RD)	0.003385 0.8376
LOG(RD)	0.037164 0.2916	LOG(RD)	–0.054477 0.0526*	LOG(RD)	0.026773 0.3553	LOG(RD)	–0.005735 0.8477
GOVERN	–0.301518 0.0048**	GOVERN	0.124258 0.1807	GOVERN	–0.160106 0.0957*	GOVERN	0.008462 0.9302
SIZE	–0.292889 0.0000**	SIZE	0.033302 0.5492	SIZE	–0.120402 0.0351**	SIZE	0.049088 0.4035
EXTERNAL	–0.040346 0.6731	EXTERNAL	0.174607 0.0244**	EXTERNAL	–0.359563 0.0000**	EXTERNAL	0.137922 0.0910*
Limit Points		Limit Points		Limit Points		Limit Points	
LIMIT_2:C(7)	–1.157173 0.0024**	LIMIT_1:C(7)	–2.10053 0.0000**	LIMIT_2:C(7)	–0.393496 0.2239	LIMIT_1:C(7)	–2.236584 0.0000**
		LIMIT_2:C(8)	–1.261826 0.0001**	LIMIT_3:C(8)	0.916078 0.0047**	LIMIT_2:C(8)	–1.351077 0.0001**
		LIMIT_3:C(9)	–0.027545	LIMIT_4:C(9)	1.847213	LIMIT_3:C(9)	–0.227717

			0.9302		0.0000**		0.4937
LR statistic	29.55822	LR statistic	14.97785	LR statistic	37.04658	LR statistic	7.361989
Prob (LR statistic)	0.000048**	Prob (LR statistic)	0.020430**	Prob (LR statistic)	0.000002**	Prob (LR statistic)	0.288664

Table 15-1 Granger Causality Tests

Pairwise Granger Causality Tests Null Hypothesis:	Obs	F-Statistic	Prob.
PRODUCT does not Granger Cause RD	726	1.19443	0.2748
RD does not Granger Cause PRODUCT		3.36611	0.0670*
PRODUCT does not Granger Cause COOPERATE	726	2.86470	0.0910*
COOPERATE does not Granger Cause PRODUCT		0.66632	0.4146
PRODUCT does not Granger Cause GOVERN	3499	3.10281	0.0782*
GOVERN does not Granger Cause PRODUCT		0.00405	0.9493
PRODUCT does not Granger Cause SIZE	3499	16.0754	6.E-05**
SIZE does not Granger Cause PRODUCT		5.65806	0.0174**
PRODUCT does not Granger Cause EXTERNAL	726	0.17241	0.6781
EXTERNAL does not Granger Cause PRODUCT		0.14296	0.7055

4.4. Results for Protecting and Enhancing Research

The decision for choosing a specific method of intellectual property is related with forms of R&D organization. We can see the adoption of patenting is potitively related with R&D spending, but using petty patent is negatively related. Kremer (1996) examined patent buyouts (policy) by government to increase incentives for original research. Table 16 shows the estimated effects on probability in choosing IPR protection strategies of firm characteristics. In the case of petty patents (PETTY), we used extreme value (EV) distribution for error term. Finally, we selected specific binary models by the criterion of McFadden R-squared. In addition, through causality tests, we can see almost all the variables in binary estimation cause to adopt a specific type of IPR protection such as holding patents.

Table 16 Probit Estimation for IPR Protection

Dependent Variable: PATENT ML – Binary Probit		Dependent Variable: PETTY ML – Binary Extreme Value	
Variable	Coefficient Prob.	Variable	Coefficient Prob.
C	0.163194 0.2617	C	–4.090943 0**
LOG(SIZE)	–0.277296 0**	LOG(SIZE)	1.619547 0**

COMPLEX		0.4989 0**		COMPLEX		−0.736025 0**	
LOG(SALE)		−0.081011 0**		LOG(SALE)		0.280537 0**	
LOG (TOTALRD)		0.05661 0**		LOG (TOTALRD)		−0.025725 0.0008**	
Prob	0**	Mean dependent var	0.221391	Prob(LR tatistic)	0**	Mean dependent var	0.434664
McFadden R-squared		0.193263		McFadden R-squared		0.421429	
(LR tatistic)							
Obs with Dep=0	2497	Total obs	3207	Obs with Dep=0	1246	Total obs	2204
Obs with Dep=1	710			Obs with Dep=1	958		

Table 16-1 Granger Causality Tests

Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
PATENT does not Granger Cause SIZE	2472	0.29581	0.5866
SIZE does not Granger Cause PATENT		0.85075	0.3564
PATENT does not Granger Cause COMPLEX	3500	46.1912	1.E-11**
COMPLEX does not Granger Cause PATENT		239.758	2.E-52**
PATENT does not Granger Cause SALE	3500	9.92192	0.0016**
SALE does not Granger Cause PATENT		6.45587	0.0111**
PATENT does not Granger Cause TOTALRD	1086	7.76862	0.0054**
TOTALRD does not Granger Cause PATENT		7.31722	0.0069**

5. SUMMARY AND LIMITATIONS

We developed and estimated the model of multiple choices that find the characteristics of innovative firms employing a specific R&D activity(strategy) affect the choice for R&D organization. We also examine how the factors affect the choice probabilities of activities.

Our results show that main determinants for deciding to employ R&D strategy and IPR protection instrument. And they show that the estimated coefficients in the characteristics change from those of not considering structural change in the estimation equation across the magnitude of R&D spending.[39)]

Estimation of binary probit results shows that the coefficients for product or process innovation, or drastic or nondrastic innovation are significant, which coincide with economic theory.

In summary, empirical results implicate that there may be causality from R&D-related firm characteristics to the amount of R&D spending. And it may be possible that R&D input affect the probability of product innovation of Korean manufacturing firms.[40)] Main shortcoming of

39) This estimate implies that small firms employ higher rate of female worker.
40) Female labor demand (share) is affected by R&D organization and wage level mainly.

this study may be not considering service industry. If we can construct panel data across industries, we can control individual heterogeneity of industries using conditional logit or heteroskedastic extreme value (HEV) model.

Our empirical research may be extended in the future research. This job can give high incentive for implementing labor policies for women and give implications for STI policy. Second, we can also use Multinomial Probit Model (MNP).[41] If we accept Normal distribution assumption, we can use multinomial probit model for choice among several alternatives of R&D performance methods.[42]

Finally, in this study, we used data of only 2016-2020 KIS survey. In future research we can extend this analysis to panel data from 2012-2018. This can control individual heterogeneity of innovating firms in estimation.

We postpone the analysis of multinomial probit model (MPL), which relaxes the assumption of (IIA). Recent development for simulation of multi-normal integrals made this estimation for multivariate normal distributions for higher dimension available.

If we also use full set of panel survey data (2012-2020), we can try the estimation of the mixed logit or stated choice experiment.[43] This analysis can be postponed to future research. We hope that this study may be a help for government seeking promotion of innovative activities choosing optimal type of innovation activity.

Greene and Hensher (2010) considered functional forms that incorporate (individual firm) heterogeneity in both marginal utilities (profits and scaling of technology).[44] Research has been continuing to produce realistic forms of heterogeneity.

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41) Recently, the simulation based methods are popular.

42) Main problem in MNP is that accurate computation of multivariate normal is difficult.

43) Disadvantage of mixed model is that the estimates are obtained by simulating the log-likelihood function.

44) $\beta_i = \sigma_i \beta + [\gamma + \sigma_i (1-\gamma)] v_i \beta_i$.

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