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# Employment Effects of Technological Innovation in Korean Manufacturing Firms

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### I. Introduction

According to the theory of economic growth, growth that depends only on the additional input of production factors such as labor and capital has reached its limit. This is the reason why technological innovation is essential for sustainable growth. Many countries are continuously making efforts to improve their productivity. In other words, the governments in each country are actively promoting investment in R&D for technological innovation of the importance of productivity improvement for sustainable growth and the improvement of people's standard of living.

On the other hand, the debate over the impact of technological innovation on employment has been going on for quite some time. This is because technological innovation can have double-edged effect on employment, both increasing and reducing employment. In Korea and other countries, the economy has grown rapidly due to technological innovation, but the problem of "jobless growth" has arisen as the employment creation effect was limited. In addition, employment is becoming one of the most important policy tasks of the government as companies go abroad, resulting in job cuts.

In academia, the relationship between technological innovation and employment has been actively researched to reflect the trends of the time. The relationship between technological innovation and employment, however, cannot be easily concluded. There are conflicting views on the impact of technological innovation on employment: some people claim that it reduces employment(Zimmerman, 1991; Aghion and Howitt, 1994; Michelacci and Lopez-Salido, 2007), while others claim that it increases employment (Vivarelli et al., 1996; Evangelista and Savona, 2003; Pissarides, 2000; Verspagen, 2004; Harrison et al., 2005; Lachenmaier and Rottmann, 2011).<sup>1</sup>

Technological innovation can be generally divided into two categories: one is related to improvement and development of products and process innovation, and the other is associated with improvement and changes in production methods according to their characteristics(Utterback and Abernathy, 1975). Many previous studies have shown that product innovation positively affects employment, which is due to "demand enlargement," in which new products increase demand(Moon and Jeon, 2008). The effect of process innovation on employment is less clear than in product innovation. This is

The arguments are divided into two groups: those who think that technological innovation reduces employment by the emergence of new products, capital substituting for labor, price rigidity, and lack of aggregate demand, etc., and those who claim that technological innovation increases employment by increasing income and demand.

due to the "labor displacement effect" causing a negative effect or a less positive effect on employment than product innovation(Vivarelli, 1996). For example, if a company's cost savings leads to a price drop, then demand may increase as prices fall, positively affecting employment. On the other hand, depending on the structure of the market, process innovation can have a negative effect on employment(Moon and Jeon, 2008). Thus, from a theoretical point of view, each case of innovation is assumed to have some effects (positive (+) or negative (-) on employment, but it is hard to accurately determine the net effect. In other words, the effect of technological innovation on employment is "uncertain," which leads to the topic of empirical analysis.

It is not easy to estimate the net effect of technological innovation on employment. This is because bias can be caused by the characteristics of individual companies and various factors. For example, individual companies may have different employment effects depending on their features, other than technological innovation, such as size, assets, and government subsidies. In many previous studies, the effects of technological innovation and employment are focused only on labor productivity, and the problems of bias that can be generated by individual companies are overlooked. To solve this problem, this study used PSM(Propensity Score Matching), which controls the endogeneity that can occur within the two groups (treatment group and control group), focusing on the heterogeneity of observable individual companies. This is a way to efficiently solve the problem of selection bias when measuring the treatment effect(Blundell & Costa Dias, 2009). Therefore, this study analyzed the effect of technological innovation of Korean manufacturing companies on the number of employees by using PSM, a nonparametric estimation method.

In the rest of this study, we will examine previous studies in Chapter II, and examine the causes and matching theories of selection bias in Chapter III. Chapter IV explains the variables used in the study and the characteristics of the variables. Chapter V describes the results of the empirical analysis, and Chapter VI proposes conclusions and implications based on the results of the study, and then suggests future research directions.

### II. Previous Studies

Previous studies analyzing the impact of technological innovation on employment have different views that are largely divided into two major camps: one asserts that technological innovation reduces employment and research, and the other claims that technological innovation increases employment. According to the research suggesting that technological innovation increases employment, unemployment occurs(creative destruction effect) as capital productivity substitutes for labor productivity when the innovation is embodied in capital. In the long run, however, thanks to increased production, incomes rise and savings and investment increase, recovering employment rate to the previous level or even increasing it(Caballero and Hammour, 1997). Mortensen and Pissarides (1998) argued that technological innovation promotes the entry of new operators and facilities, thus creating the so-called capitalization effect of reducing unemployment. Pissarides(2000) argued that innovation increases productivity and, as a result, firms increase employment by offering higher wages. Jaumandreu(2003) and Peters(2004) have used OLS to show that product innovation has a positive (+) effect, while process innovation has no significant impact, based on the European Community Innovation Survey(CIS III) data. Lachenmaier and Rottmann(2011) reported the positive (+) effects of both product innovation and process innovation using Fixed Effect, using the data from Germany's corporate unit panel(1981-1991). Evangelista and Vezzani (2011) analyzed the data from the European Community Innovation Survey(CIS IV) using 3 Stage Least Squares(3SLS) regression and argued that innovation has a positive (+) effect on employment. Several previous studies in Korea have also suggested that technological innovation has a positive (+) effect on employment.

Bae et al.(2006) analyzed the employment inducement effect of technological innovation divided by industry. As a result, the high technology industry showed a continuous increase in employment, and the low technology industry showed a decrease in employment. By industry size, employment growth continued in small firms, while employment declined in large firms. However, it was argued that among the large enterprises, companies belonging to the high-technology industry showed an increase in employment. Ha(2005) argues that technological innovation increases employment by reducing structural unemployment. Kang(2006) reported that technological innovation increases employment and output as well as labor productivity. Shin et al.(2012) used the dynamic employment model to argue that product innovation did not have a statistically

significant effect on employment, and that process innovation positively affects corporate employment.

In contrast to the above logic, there are arguments that technological innovation reduces employment. The traditional hypothesis on the claim that technological innovation reduces employment is based on the creative destruction process theory proposed by Schumpeter, which causes the emergence of new products and labor displacement by capital. When new technology emerges, new products are invented to replace existing ones. Then, the demand for labor in the sectors that produced the existing commodities decreases, and the volume of employment decreases. Zimmerman(1991) conducted an empirical analysis based on the probit model using 16 industrial data from Germany, and explained that innovation results in a negative (-) effect on employment. Aghion and Howitt(1994) argue that technological innovation creates and cuts employment at the same time because workers no longer need the skills they possess when the pace of technological innovation is the result of creative destruction, resulting in the elimination of companies that are not competitive and that these factors result in a decline in employment.

The impact of technological innovation on employment, as in many of the preceding studies, may have different consequences depending on the methods of empirical analysis. In other words, the outcome may vary, depending on how much of the heterogeneity in individual companies has been controlled. Many prior studies have largely controlled the size, market, and industry characteristics of firms, but did not control the bias of individual companies. Therefore, unlike the previous studies, this research differs from the previous research in that it has tried the matching method—a nonparametric method—to control the bias from individual companies.

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### III. Study Method

#### 1. Problem of selection bias

When  $Y_1$  and  $Y_0$  are the probabilities that affect the enforcement of company's technological innovation, the variables for each of these companies can be expressed as  $Y_{1i}$  and  $Y_{oi}$ .  $D_i$  can be expressed as a dummy variable indicating whether technological innovation is active or not (Companies engaged in innovation activities: 1, Companies not engaged in innovation activities: 0). The following Equations (1), (2), and (3) show the effects of companies on innovation activities.

- (1)  $Y_i = \beta X_i + \alpha D_i + \epsilon_i$
- (2)  $Y_{0i} = \beta X_i + \epsilon_i$ ,  $D_i = 0$
- (3)  $Y_{1i} = \beta X_i + \alpha + \epsilon_i$ ,  $D_i = 1$

In general, the treatment effect is defined as the difference between the "performance( $Y_{1i}$ ) obtained by participation in observations" and the "performance( $Y_{0i}$ ) not participating in the same observations" (Heckman et al., 1997). Therefore, the effect of a firm's technological innovation on employment can be defined as the difference between "a company that innovates technology" and "a company that does not innovate technology," which can be expressed as Equation (2). However, the individual companies used in this study are not all the same ones. In other words, what you can actually observe is  $Y_{0i} \cup Y_{1i}$ , not  $Y_{0i} \cap Y_{1i}$ . Therefore, the calculation of treatment effect has a problem of difference caused by whether the companies perform technological innovation activities or not. Heckman(1997) pointed out the problem of these observations and suggested the ATT (Average Treatment Effect on the Treated), which is a means to solve this problem. The ATT in Equation (5) implies the employment effect indicated by the company's technological innovation activities, and Equation (6) is the subdivision of the expected value according to the Equation (5), depending on whether the companies perform technological innovation activities or not.

### (4) Treatment Effect $= \alpha_i = Y_{1i} - Y_{0i}$

(5) ATT = 
$$E(Y_1 - Y_0|D=1) = E(Y_1|D=1) - E(Y_0|D=1)$$
  
(6)  $E(Y_1|D=1) - E(Y_0|D=1) = \text{ATT} + E(Y_0|D=1) - E(Y_0|D=0)$ 

However, an important problem may arise in Equation (6). This is because the treatment effect does not have the same probability distribution, so the sign may be different. In other words, of  $E(Y_0|D=1) - E(Y_0|D=0)$  may not show the situation of  $E(Y_0|D=1) - E(Y_0|D=0) = 0$  due to unexpected factors (e.g., corporate financial status, government intervention, company experience, etc.) other than the innovation activities by the company, and this leads to a problem of bias. Of course, you may get a pure ATT value from technological innovation activities. However, since the data used in this paper is obtained by a questionnaire rather than probabilistic data, the employment effect of firms' technological innovation can suffer from the problem of selection bias.

Estimation methods widely used to solve the bias problem include tool parameter estimation, Heckman's 2SLS, fixed effect etc. Each of these methods is excellent for bias control, but they also have their own shortcomings. When using cross-sectional data as in this study, it is difficult to find proper tool parameters. The fixed effect model should use lagged variables as independent variables. Using Heckman's 2SLS, it is difficult to find appropriate explanatory variables to distinguish the selection formula from the calculation formula.

Another way to control the selection bias of cross-sectional data is by using analysis based on matching. The basic framework of this method is to extract the covariates by finding common support between the companies that do or do not engage in technological innovation activities. Using this covariate extraction, you can estimate the employment effect by several matching methods with similar characteristics. Common support can be estimated through propensity scores. In this process, you can control and solve the problems of bias as well as dimension that can be caused by many common variables.<sup>2)</sup>

#### 2. PSM(Propensity Score Matching)

The estimation of PSM is made in two stages. The first step is to define the propensity scores. This implies the conditional probability of economic activities when

<sup>2)</sup> Theoretically, the covariates used in the study can be matched to any number of cases it can have. However, if the number of covariates is large, this is not possible. For example, if there are 10 covariates and all of them are variable numbers with two values, then the number of possible cases is 210—1,024 kinds. This is a dimensional problem, and PSM is used in order to solve it. PSM is a method to apply propensity scores as a basis of matching (Dehejia and Wahba, 1999).

a vector is given to observe the characteristics of firms engaged in innovation activities.

### (7) Propensity Score = $P(X) = \Pr(D_i = 1 | X) = E(D_i | X)$

In Equation (7), X is the individual feature vector of the treatment group that does innovation activities and the control group that does not perform innovation activities. P (X) is the probability of doing the innovation activities based on these characteristics. This propensity scores can be defined as the assumption5) of strong indifference between the two groups. The following Equations (8) and (9) summarize the hypotheses for defining the propensity scores.

(8) Conditional Independent Assumption  $=(Y_{0i}, Y_{1i}) \perp D_i | X$ 

### (9) Common Support Assumption $= 0 < \Pr(D_i = 1 | X) < 1$

Equation (8) is Conditional Independent Assumption(CIA). It is assumed that when the covariate X is given, the response variable is independent of , depending on the presence or absence of technological innovation activities. This means that any different factors that affect technological innovation activities can be controlled by individual variables, and that any unobserved characteristics do not affect employment effects.

Equation (9) indicates the Common Support Assumption(CSA). This assumes that the probability distributions used by the treatment group and the control group have the same common support (Rosenbaum and Rubin, 1983). Therefore, Propensity Score satisfies the above two assumptions, and if there are many variables that can measure the characteristics, then it is possible to calculate the bias-controlled employment effect by controlling them.

The second stage of PSM is to analyze the employment effects of firms through differences between groups that have similar propensity scores to the treatment group and are not engaged in technological innovation activities. In other words, when matching with the variables themselves, the magnitude of the effect can be examined by comparing the differences of the dimensional problems that occur using propensity scores that summarize the characteristics of the variables as one number. Equation (10) shows ATT, which is the effect of economic activities on employment through this estimation.

### (10) The effect of technological innovation on employment

$$\begin{split} &= \alpha = E(Y_{1i} - Y_{0i} | D_i = 1) \\ &= E\{E\{Y_{1i} - Y_{0i} | D_i = 1, P(X)\}\} \\ &= E\{E\{Y_{1i} | D_i = 1, P(X)\} - E\{Y_{0i} | D_i = 0, P(X) | D = 1\}\} \end{split}$$

PSM can be classified into Nearest Neighbor (NN), Radius, Stratification, Kernel, and Matching, depending on the method they use (Heckman et al, 1997). First, to do the NN matching, randomly arrange two groups: technologically innovative companies and non-innovative companies. Then, select non-innovative companies that have the closest propensity scores with the innovative companies. If we express this as a formula, let T be the group of companies that performs technological innovation activities, and C be the companies that do not perform innovation activities. Their employment effects can be expressed as  $Y_i^T$  and  $Y_j^C$ , respectively. In addition, if C(i) is the X-th firm that does not carry out technological innovation, and has a propensity score of P, NN matching can extract it as a sample as shown in Equation (11).

(11) 
$$C(i) = \min_{j} || p_i - p_j ||$$

Radius matching extracts the comparative group in a manner similar to NN matching. However, there is a difference in that the group of firms that are not engaged in the innovation activities with a propensity score within a certain radius (r) is regarded as a comparative group. Equation (12) represents the extraction of the comparative group in the Radius matching.

(12) 
$$C(i) = \{p_j | \| p_i - p_j \| < r\}$$

The employment effect of the NN and Radius matching is calculated as the mean value of the difference in the number of employees between the innovative group and the non-innovative group, which can be used to estimate ATT in the same way as Equation (13).

(13) 
$$\alpha = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \sum_{j \in C(i)} w_{ij} Y_j^C \right\} = \frac{1}{N^T} \left\{ \sum_{i \in T} Y_i^T - \sum_{i \in T} \sum_{j \in C(i)} w_{ij} Y_j^C \right\}$$

In Equation (13),  $N^T$  is the number of firms in a group of technologically innovative firms, and  $N_i^C$  is the number of non-innovative firms in pairs with  $i \in T$ . Also,  $w_{ij}$  is a weighting value, and if it is  $j \in C(i)$ , it has a value of  $w_{ij} = \frac{1}{N_i^C}$ ; otherwise it is  $w_{ij} = 0$ . The dispersion of the employment effect of the NN and Radius matching can be expressed by the following Equation (14). In the case of the NN matching, there is a disadvantage in that the number of samples is reduced when estimating the employment effect because the closest object is selected as the comparative group.

Kernel and Stratification matching is a way to overcome the disadvantages of the NN matching. Kernel matching is characterized by focusing on the comparative group as a whole to comprehend the effect. In other words, each firm that performs the innovation activities compares with the weighted average value of all firms in the non-innovative enterprise group, and a high weight is applied to good matching. The employment effect by Kernel matching is estimated by Equation (15).

(15) 
$$\alpha = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{j \in C} Y_j^C G\left(\frac{P_j - P_i}{b_n}\right)}{\sum_{k \in C} G\left(\frac{P_k - P_i}{b_n}\right)} \right\}$$

In Equation (15), G (•) is the Kernel function, and  $b_n$  in the function is the bandwidth. The standard deviation of the employment effect through the Kernel matching can be calculated through bootstrapping.

Stratification matching is a method of estimating the characteristics of business groups according to the presence or absence of technological innovation activities identified by the propensity scores by grouping them into several blocks within a common support between the two groups. Each of these blocks can show the employment effects of innovation activities by firms through averaged work. The estimation of the employment effect through Stratification matching is shown in Equation (16).

(16) 
$$\alpha_k = \frac{\sum_{i \in I(k)} Y_i^T}{N_k^T} - \frac{\sum_{j \in I(k)} Y_j^C}{N_k^C}$$

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In Equation (16), I(k) refers to the companies belonging to the k-th group,  $N_k^T$  and  $N_k^C$  are the number of firms in the treatment group that perform technological innovation activities and the number of firms in the control group that do not perform such activities. In addition, we can summarize Equation (16) based on Equation (10). The employment effect of Stratification matching by technological innovation of the company can be expressed by Equations (17) and (18). In the equation, K denotes the number of blocks, and denotes a dummy variable having a weight value of 0 and 1.

(17) 
$$\alpha = \sum_{b=1}^{K} \alpha_k \frac{\sum_{i \in I(k)} D_i}{\sum_{\forall i} D_i}$$

(18) 
$$Var(\alpha) = \frac{1}{N^T} \left\{ Var(Y_i^T) + \sum_{j \in I(k)} \frac{N_k^T N_k^T}{N^T N_k^C} Var(Y_j^C) \right\}$$

Each matching method shows that there is a trade-off between bias and dispersion when evaluated based on the two factors, and there is no superior matching method in all cases. So we compare the estimation results from various matching methods(Becker, Sascha O., 2002; Calendo and Kopeining, 2008).

### IV. Description of materials and variables

### 1. Materials

This study analyzed the financial statements of NICE Information Service and Science and Technology Policy Institute (STEPI)'s Korean Innovation Survey 2014 (manufacturing sector) to examine the employment effects of technological innovation activities on manufacturing companies. The Korean Innovation Survey is the national statistics approved by the Korean government, which is surveyed every two or three years, based on the OECD Oslo Manual, and it is internationally comparable. The data makes it easy to analyze the performance of the innovation activities because it has systematized the current status and characteristics of the innovation activities by domestic companies. In addition, there is an advantage in examining the characteristics of a company because it is organized and divided into types of companies (large, medium, and small enterprises) and industries.

On the other hand, there is a limit in accurately understanding the financial characteristics and employment status of the company. We used the financial variables in the financial statements of the NICE Information Service. In other words, the construction of the data was made in the form of cross-sectional data in accordance with the financial statements in 2014, which corresponds to the Korean Innovation Survey. In the process of building the data, a large number of specimens were missing. Therefore, in this paper, we use the enterprise data of 1,358 cases (378 large enterprises, 980 medium and small enterprises) excluding the missing data among the 4,075 companies sampled in the Korean Innovation Survey 2014.

#### 2. Description of variables and basic statistics

The propensity scores can be extrapolated from Probit or Logit analysis. These two methods can be used to obtain an estimate of the probability of a process assignment of observed variables in a given condition. In Probit analysis, the variables are assumed to be multivariate normal distributions. Logit analysis offers advantages in that it is more flexible in this assumption and more effective in bias control than Probit analysis(Rubin, 1979). Therefore, this study used logit analysis which is widely used.

In order to effectively estimate the propensity score matching, it is important to adjust

the balance within the common support through the propensity score.<sup>3)</sup> However, it is difficult to find mutually balanced variables in a limited area. In particular, there was a limit in finding balanced variables for the data used in the research because a large number of data was missing due to the special nature of corporate data, and the number of samples was reduced in the process of integrating the two different collections of data. However, this study could find variables that can meet a causal relation between the innovation activities, and it can also satisfy the conditional independence and the assumption of the common support in estimating the propensity scores by referring to the previous research(Oh and Kim, 2017). Table 1 shows the basic statistics of these explanatory variables.

Variable name	Description of variables	classification	Average	Std.
	Propensity Score dependent	All companies	0.375	0.484
Status of technological	variable,	Major companies	0.444	0.497
Innovation	Non-innovative: 0	Small companies	0.349	0.477
	Matching	All companies	0.320	1.025
Employment growth rate	Dependent variable,	Major companies	0.371	1.135
	previous vear	Small companies	0.230	0.956
Sales		All companies	10.846	1.223
	Unit: (USD1,000, In value)	Major companies	12.183	1.171
		Small companies	10.279	0.872
		All companies	22.322	13.162
Years of operation	Unit: Year	Major companies	28.293	16.040
		Small companies	20.019	11.044
		All companies	0.475	0.500
Main market	Domestic: 1	Major companies	0.405	0.491
	Overseas: 0	Small companies	0.503	0.500

TABLE1.	Basic	statistics	of	manut	facturir	Ŋ	companies
						<u> </u>	

Variable name	Description of variables	classification	Average	Std.
Machinery, equipment,		All companies	0.547	0.498
software, and building acquisition	Acquired: 1 Not acquired: 0	Major companies	0.679	0.467
activities		Small companies	0.485	0.500
External knowledge purchase		All companies	0.151	0.358
	Purchased: 1	Major companies	0.177	0.382
2011/1005		Small companies	0.138	0.345
<b>.</b>		All companies	0.225	0.417
Participation in government B&D projects	Participated: 1 Not participated: 0	Major companies	0.270	0.444
		Small companies	0.208	0.406
-	-	All companies	0.219	0.414
lax reduction	Tax reduction: 1	Major companies	0.222	0.416
		Small companies	0.218	0.413

<sup>3)</sup> Balancing means to block the similar segments of propensity scores between 0 and 100% to satisfy the common support between the companies that are engaged in innovation activities and those that are not engaged. If the balance between the blocks is not satisfied, then the common support cannot be calculated.

It is a variable<sup>4)</sup> that combines the results of whether product and process innovation have been conducted by companies during the past three years (2011 to 2013). To represent the carrying out of technological innovation activities, a value of 1 is given; for no innovation activities, 0 is given. As shown in the first row of Table 1, technological innovation activities accounted for 37.5% of all companies, 44.4% of major companies, and 34.9% of small companies. We investigated major factors that can affect technological innovation activities. When we compared the total sales of selected groups, we found that major companies were higher in those factors than small companies. The average years of operation was 28 years for major companies and 20 years for small companies. In general, major companies have been in operation longer. Participation rate in the domestic main market was 40.5% for major companies and 50.3% for small companies. It was observed that small companies participate in domestic market more than major companies. The proportion of major companies was higher than that of small companies in the following categories: purchase of external knowledge (small companie s: 14.1%, major companies: 16.7%), participation in government research and development projects (small companies: 8.5%, major companies: 24.7%), and tax reduction for technological development (small companies: 20.2%, major companies: 26.3%).

<sup>4)</sup> Technological innovation refers to the technological development of new products and processes, as well as the technological improvement of products and processes. It only applies when the results are introduced into the market or used in the production process (Um, 2004).

### V. Analytical results

#### 1. Propensity score and common support

The logit model was used to calculate the propensity scores according to the technological innovation of the manufacturing companies. The parameters estimated by the logit analysis are used in the computation of the propensity scores to find the common support of the sample used in the matching analysis. Table 2 shows the results of the logit analysis by company size for the propensity score estimation.

TABLE2. The results of the logit analysis by company size for the propensity score estimation

Verieble	All	companies	Major o	companies	Small c	ompanies
variable –	Coef.	Std. Err.	Coef.	Std. Err.	Small         companies           r.         Coef.         Std.         Err.           0.131         0.258           0.151***         0.277           0.357**         0.289           0.002         0.010           -0.117**         0.152           0.292**         0.245           2.216***         0.733           1.327**         1.933           -221.150         0.073           31.01         0.073	
Main market	0.301	0.256	0.126*	0.382	0.131	0.258
Participation in government research and development projects	0.227	0.219	0.201	0.415	0.151***	0.277
Tax reduction for technological development	0.405***	0.325	0.415**	0.431	0.357**	0.289
Years of operation	0.012*	0.037	-0.005	0.010	0.002	0.010
Sales	-0.102*	0.135	-0.193	0.313	-0.117**	0.152
Machinery, equipment, software, and building acquisition activities	0.375*	0.264	0.851*	0.375	0.292**	0.245
External knowledge purchase activities	1.382***	0.400	0.164***	0.543	2.216***	0.733
Constant	0.851***	2.515	0.912***	1.251	1.327**	1.933
Log likelihood		-315.533	-93	.113	-221	.150
Pseudo		0.085	0.0	086	0.0	73
Prob >		33.19	16	.52	31.	01

Note: \*, \*\* and \*\*\* mean that there is significance at the 1%, 5%, and 10% levels, respectively.

According to the estimated coefficients, in case of the overall companies, those participating in the technological innovation activities showed that they're more likely to focus on the domestic main market, actively participate in government research and development projects, have more total assets, and acquire more machinery, equipment, software, and external knowledge. On the other hand, the lower the sales, the higher the participation rate in technological innovation activities.

Among the variables by company size, the variables showing the difference in the signs of the coefficients are the total assets and the years of operation. In the case of major companies, start-up firms with less assets participate more in technological innovation. Whereas, in the case of small companies, older firms with more assets are more likely to participate in technological innovation.

Among the significant variables, those of high significance with large coefficients were

indicated by external knowledge purchase activities and tax reduction for technological development. The government's investment and corporate profits seem to have played a major role in the participation of technological innovation activities.

	Before	After	1	Common	Support
	Propensi	ty Score	- LOSUIT %	6 Min 0.612 0.332	Max
All companies	1358	538	60.38	0.612	0.951
Major companies	378	106	71.96	0.332	0.975
Small companies	980	432	55.92	0.503	0.981

TABLE3. Common support calculated from the propensity scores

Table 3 shows the result of the common support calculated by using the parameter estimates of the logit analysis derived from the propensity scores. As shown in the table, the sample size is reduced by the covariate characteristics in calculating the propensity scores, and the common support is larger than 0 and smaller than 1, thus satisfying the common support assumption. The common support of each of these was calculated as 0.612 to 0.951 for all companies, 0.332 to 0.975 for major companies, and 0.503 to 0.981 for small companies.

Figure 1 shows the propensity scores of this common support in a graph. The upper part shows the treatment group that does technological innovation activities and the lower part shows the control group that does not do such activities. It can be concluded that the more similar the height of the two bars, the more similar the propensity scores of the two groups. As shown in Figure 1, it can be seen that the density functions of the propensity scores of the two groups overlap each other in the common support.



FIGURE 1. Propensity score graph of technological innovation by company

To confirm whether the assumptions of conditional independence were met, the samples in the common support were divided into several blocks under the propensity score range. The blocks are divided into 7 overall companies and 5 major and small companies. The average value of the propensity scores of the companies shows the

difference between the two groups. As a result of the analysis, the average value of propensity scores did not differ between the two groups and satisfied the assumption of conditional independence.<sup>5)</sup>

### 2. Employment effects of technological innovation in manufacturing firms

I use the four PSMs mentioned above for the employment effects of technological innovation in manufacturing firms. Radius matching was performed with Caliper values of 0.1, 0.05, and 0.01.<sup>6</sup>) In the Kernel matching, the Epanechnikov kernel function is used, and the value of each bandwidth is 0.05. NN matching was performed using one-to-one matching, which is generally used. Matching of Stratification and NN were analyzed by dividing into 7 blocks of overall companies, and 5 blocks of major and small companies, equal to the number of blocks obtained in the common support. The analysis of all matches performed 100 bootstrapping for t-test.

The PSM can check how much bias has been reduced since each matching. Table 4 shows the percentage of bias reduction after the matching.

	Matching	Bias reduction after matching (%)	
	Stratification	-70.0(%)	
	Nearest Neighbor (NN)	-79.5(%)	
All companies	Radius (caliper 0.1)	-71.2(%)	
	Radius (caliper 0.05)	-75.3(%)	
	Radius (caliper 0.01)	-78.1(%)	
	Kernel	-73.3(%)	
	Stratification	-60.1(%)	
	Nearest Neighbor (NN)	-70.7(%)	
	Radius (caliper 0.1)	-64.5(%)	
Major companies	Radius (caliper 0.05)	-66.9(%)	
	Radius (caliper 0.01)	-69.1(%)	
	Kernel	-67.9(%)	
	Stratification	-75.5(%)	
	Nearest Neighbor (NN)	-80.5(%)	
Small companies	Radius (caliper 0.1)	-72.8(%)	
onan oompanioo	Radius (caliper 0.05)	-75.3(%)	
	Radius (caliper 0.01)	-78.1(%)	
	Kernel	-76.0(%)	

TABLE4. The percentage of bias reduction by PSM

<sup>5)</sup> The test for conditional independence is basically performed in the statistical package that provides PSM analysis. Therefore, the results of this study are omitted in this paper.

<sup>6)</sup> A caliper is used to measure the degree of innovation activities of companies (Rubin, 1979).

As shown in Table 4, the bias of all matching is reduced.10) In particular, small companies generally had a greater reduction width of bias than major companies. The reason why small companies have a higher proportion of bias reduction compared to major companies is due to the difference in sample decrease ratios when the common support is calculated. The proportion of reduction of each bias varied according to the type of matching. In this case, the NN matching made the most of the bias reduction, followed by radius, kernel, and Stratification. In the case of Radius matching, the lower the caliper was set, the higher the rate of bias reduction was measured.

Table 5 shows the ATT, which is the employment effect according to the technological innovation activities by the manufacturing companies. This shows the average difference between the treatment group and the control group belonging to the common support for each matching. The sample used for the matching showed a slight difference, depending on each method. Overall companies are divided into 473 to 509 treatment groups and 82 to 140 control groups for each analysis. Major companies are divided into 134 to 167 treatment groups and 37 to 40 control groups. Small companies are divided into 310 to 342 treatment groups and 84 to 99 control groups.

For the qualitative evaluation of the matching, an imbalance test was performed for each analysis. The imbalance test confirms the similarity of the variables between the treatment group and the control group. As a result, the NN and Radius matching showed relatively low imbalance, and Stratification and Kernel matching showed high values. Therefore, when these two analyses match, it can be interpreted that the similarity of individual characteristics between the two groups is lower than other matching.

Matching		Imbalance	Technological	Non-technical	ATT	Ord Err
	Matching	test	innovation	innovation	AII	Sta. Err.
	Stratification	0.093	389	139	0.370*	1.051
	Nearest Neighbor (NN)	0.070	389	135	0.381**	1.048
	Radius (caliper 0.1)	0.081	389	71	0.295*	1.020
All companies	Radius (caliper 0.05)	0.075	370	65	0.310*	1.036
	Radius (caliper 0.01)	0.071	365	52	0.321**	1.051
	Kernel	0.082	389	139	0.376*	1.137
	Stratification	0.115	65	41	0.373*	1.315
	Nearest Neighbor (NN)	0.093	65	35	0.392***	1.528
Maior componies	Radius (caliper 0.1)	0.100	65	41	0.306*	1.121
Major companies	Radius (caliper 0.05)	0.092	60	37	0.312**	1.155
	Radius (caliper 0.01)	0.089	57	33	0.327**	1.176
	Kernel	0.095	65	41	0.315*	1.150
	Stratification	0.120	331	101	0.105*	0.677
	Nearest Neighbor (NN)	0.078	331	95	0.127**	0.289
Small componies	Radius (caliper 0.1)	0.095	331	101	-0.005	0.302
Smail companies	Radius (caliper 0.05)	0.080	337	92	0.025*	0.315
	Radius (caliper 0.01)	0.079	310	83	0.097**	0.322
	Kernel	0.113	331	101	0.052*	0.330

TABLE5. Employment effects of technological innovation in manufacturing firms: PSM

Note: \*, \*\* and \*\*\* mean that there is significance at the 1%, 5%, and 10% levels, respectively

The employment effects of the firms' innovation activities based on the results of the ATT can be interpreted as a positive (+) sign in most ATT values, indicating that technological innovation produces an increase in employment. Comparing the ATT by company size, the overall group showed an increase in the number of employees as follows: 0.370 in Stratification, 0.381 in NN, 0.295 to 0.321 in Radius, and 0.376 in Kernel. In addition, major companies showed employment increase by 0.373 in Stratification, 0.392 in NN, 0.306 to 0.327 in Radius, and 0.315 in Kernel, and the figures in the case of small companies were 0.105 in Stratification, 0.127 in NN, -0.005 to 0.097 in Radius, and 0.052 in Kernel. We can see the severe difference in the employment effects between small companies and major companies. This is interpreted as the difference in the number of the employees according to the size of the enterprises. The ATT of the radius (caliper 0.1) of small companies was estimated to be negative, but not statistically significant. Also, the more unique part in the matching method was that the lower the caliper value in Radius, the more the ATT value increases. This suggests that as the caliper decreases, the similarity in the characteristics between the treatment group and the control group becomes closer, increasing the ATT levels. For this reason, the imbalance of the two groups decreases.

In summary, the effect of participation in the innovation activities by manufacturing companies on the employment (ATT) was positive (+), which increased the employment effect. The major companies experienced a larger employment effect than the small companies. In addition, this study further compares the employment effects of product and process innovation on manufacturing firms. The table of results is included in Appendix 1 and Appendix 2. The table shows that product innovation and process innovation has less employment effect than product innovation. In addition, in an analysis by the size of the enterprises, process innovation of major and small companies has a negative (-) effect on employment.

### VI. Conclusion and Implications

In this study, we analyzed the size of firms to measure the employment effects of technological innovation. The analysis used PSM as a measure to control the problem of bias that could arise from the characteristics of the cross-sectional data. According to the results of the analysis, the participation of manufacturing firms in technological innovation activities produced a positive (+) effect on employment, and major companies showed a stronger (+) effect than those of small companies.

The implications of employment effects created by technological innovation are as follows:

First, manufacturing firms that showed higher participation in technological innovation activities indicated higher total assets, lower sales, as well as higher government subsidies. This shows that the total amount of assets means the capacity to make technological innovation activities, the small amount of sales shows the motivation for participation in technological innovation activities, and the government subsidies act as the catalysts for such activities.

Second, it is confirmed that major companies showed greater effects of technological innovation activities on employment than small companies. It is interpreted that the company's competitiveness is largely involved. Therefore, measures should be taken to enhance the competitiveness of small companies in order to enhance the employment effect.

Third, the effect of process innovation on employment was positive (+) in major companies, but negative (-) in small companies. This is seen as a phenomenon in which the labor displacement effect of small companies is larger than that of major companies. Therefore, it is necessary for the government to take measures to increase the labor stability in small companies.

Finally, one the limitations of this study that should be complemented is the incompleteness of the sample data. The Korean Innovation Survey used in this study is meaningful in that it systematically summarizes all the information related to the innovation of the company. However, a great deal of data was missing due to the special nature of corporate data, and the number of samples was significantly reduced. In addition, since the data is panel data, not cross-sectional data, there are limitations in estimating dynamic employment effects because companies subject to the survey are different every year.

This study is meaningful in that it examines the effects of technological innovation activities by Korean manufacturing companies on employment, and used more rigorous analysis methods than previous studies to control endogeneity and bias. However, there is a limit in that the propensity score equation of the innovation activities does not consider various factors that affect the innovation of the companies. This is left as a future research project.

## **APPENDIX**

	Matching		Technological	Non-technical	ATT	Ctd Err
	Matching	test	innovation	innovation	ALL	Stu. En.
	Stratification	0.072	310	115	0.359	1.101
	Nearest Neighbor (NN)	0.055	310	115	0.372**	1.085
All componies	Radius (caliper 0.1)	0.071	310	115	0.285*	1.210
All companies	Radius (caliper 0.05)	0.076	281	108	0.291*	1.231
	Radius (caliper 0.01)	0.085	377	101	0.303**	1.252
	Kernel	0.113	310	115	0.311**	1.116
	Stratification	0.110	50	51	0.335*	1.215
	Nearest Neighbor (NN)	0.098	50	38	0.342	1.290
	Radius (caliper 0.1)	0.105	50	51	0.301*	1.131
Major companies	Radius (caliper 0.05)	0.112	48	45	0.309*	1.139
	Radius (caliper 0.01)	0.128	43	41	0.315*	1.145
	Kernel	0.131	50	52	0.327	1.203
	Stratification	0.125	206	109	0.120*	0.487
	Nearest Neighbor (NN)	0.073	206	98	0.138**	0.325
	Radius (caliper 0.1)	0.082	210	109	0.115*	0.359
Small companies	Radius (caliper 0.05)	0.089	201	98	0.129*	0.372
	Radius (caliper 0.01)	0.091	195	90	0.133*	0.391
	Kernel	0.103	206	109	0.131*	0.380

TABLE A1. Employment effects of product innovation in manufacturing firms: PSM

Note: \*, \*\* and \*\*\* mean that there is significance at the 1%, 5%, and 10% levels, respectively

TABLE A2, Employment	t effects	of process	innovation	in manufacturing	firms: PSM

	Matching	Imbalanc e test	Technological innovation	Non-technical innovation	ATT	Std. Err.
	Stratification	0.098	115	105	-0.021*	0.041
	Nearest Neighbor (NN)	0.095	115	105	-0.012**	0.057
	Radius (caliper 0.1)	0.100	115	102	0.011	0.028
All companies	Radius (caliper 0.05)	0.102	105	98	0.008*	0.022
	Radius (caliper 0.01)	0.105	100	90	0.003*	0.020
	Kernel	0.115	211	105	-0.018	0.031
	Stratification	0.115	42	49	-0.026*	0.013
	Nearest Neighbor (NN)	0.083	42	49	-0.028	0.289
Maina	Radius (caliper 0.1)	0.107	40	43	0.016	0.031
iviajor	Radius (caliper 0.05)	0.121	38	40	0.015	0.025
companies	Radius (caliper 0.01)	0.130	32	38	-0.002*	0.009
	Kernel	0.135	35	49	0.025	0.331
	Stratification	0.150	210	138	-0.113*	0.015
	Nearest Neighbor (NN)	0.130	210	138	-0.159**	0.019
Small	Radius (caliper 0.1)	0.115	210	135	-0.109**	0.025
Small	Radius (caliper 0.05)	0.127	195	125	-0115**	0.035
companies	Radius (caliper 0.01)	0.131	181	116	-0.121***	0.042
	Kernel	0.136	210	151	-0.098**	0.051

Note: \*, \*\* and \*\*\* mean that there is significance at the 1%, 5%, and 10% levels, respectively

### References

- Aghion P. and Howitt, P. (1994), Growth and Unemployment, Review of Economic Studies, 61(3), pp. 477-494.
- Becker, Sascha O. (2002), Estimation of Average Treatment Effects Based on Propensity Scores, The STATA Journal, 3(3)
- Blundell, R. and Costa-Dias, M. (2009), Alternative Approaches to Evaluation in Empirical Microeconomics, Journal of Human Resources, 44(3), pp. 565-640.
- Bae, Yongho, Ha, Taejeong, Kim, Byungwoo and Chang Byungyeol (2006), Direction of Innovation Policy for Growth and Employment Promotion, STEPI Policy Research, No. 05.
- Caballero, R. J. and Hammour M. L., Jobless Growth (1997), Appropriability, Factor Substitution, and Unemployment, NBER Working Paper No. 6221.
- Caliendo M, and S. Kopeining (2008), Some Practical Guidance for the Implementation of
- Propensity Score Matching", Journal of Economics Surveys, 22(1), pp 31-72.
- Dehejia, Rajeev H. and Sadek Wahba (1999), Causal Effects in Nonexperimental Stuies: Reevaluating the Evaluation of Training programs, Journal of Economic Review, 85(4), pp.923-937.
- Evangelista, R. and Savona, M. (2003), Innovation, employment and skills in services. Firm and sectoral evidence, Structural Change and Economic Dynamics, 14(4), pp. 449-474.
- Evangelista, R., and Vezzani, A. (2011), The impact of technological and organizational innovations on employment in European firms, Industrial and Corporate Change, 21(4), pp. 871–899.
- Harrison, R. aumandreu, Mairesse and Peters, B. (2005), Does innovation stimulate employment? A firm-level analysis using comparable micro data on four European countries, MPRA Paper 1245, University Library of Munich, Germany.
- Heckman, J.J.and Ichmura H., Todd P. E. (1997), Matching as a Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme, Review of Metric Study, pp.605-654
- Ha, Taejeong (2005), An Empirical Study on Technological Innovation and Structural Unemployment, STEPI Policy Research, No. 03.
- Iacus, S., King G., and Porro, G. (2012), Multivariate Matching Methods That Are Monotonic Imblance Bounding", Journal of the American Statistical Association, 106(493), pp. 345-346.
- Jaumandreu, J. (2003), Does innovation spur employment? A Firm-level analysis using Spanish CIS data, paper prepared for discussion as part of the European project innovation and Employment in European Firms: Microeconometric Evidence.
- Kang, Gyuho (2006), Technological Innovation and Job Creation, Economic Analysis, 12(1), pp. 53-75.
- Lachenmaier, S. and Rottmann, H. (2011), Employment Effects of Innovation at the Firm Level, International Journal of Industrial Organization, 29(2), pp. 210-220.

- Lachenmaier, S. and Rottmann, H., (2007), Employment effects of innovation at the firm level, Journal of Economics and Statistics, 227(3), pp. 254-272.
- Lachenmaier, S. and Rottmann, H. (2015), Effects Of Innovation on Employment: A Dynamic Panel Analysis, CESifo Working Paper No. 2015.
- Mun, Sungbae and Chun, Hyunbae (2008), The Effects of Innovation Activities on Employment: Evidence from Korean ICT Firms, Korean Journal of Industrial Organization, 16(1), pp.1-24.
- Michelacci, C. and Lopez-Salido, D. (2007), Technology Shocks and Job Flows, Review of Economic Studies, 74(4), pp. 1195-1227.
- Mortensen, D. and Pissarides, C. (1998), Technological Progress, Job Creation and Job Destruction, Review of Economic Dynamics, 1(4), pp. 733-753
- Oh, Seunghwan and Kim, Sunwoo (2017), Status and Performance Analysis of R&D Support for Small Companies, STEPI Insight. Vol. 211.
- Pissarides, C.(2000), Equilibrium Unemployment Theory, 2nd Edition, MIT Press.
- Peters, B. (2004), employment effects of different innovation activities: microeconomic evidence, ZEW Discussion Paper, pp. 04–73
- Rosenbaum, P.R. and Rubin (1983), The central role of the propensity score in observational studies for causal effects, Biometrika, 70(1), pp. 41-55.
- Rubin D. B. (1979), Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational studies", Journal of the American Statistical Association
- Shin, Bumcheol, Song, Chiwoong and Choi, Kukhyeon (2012), Comparative Analysis of Employment Effects according to Types of Technological Innovation, Korean Corporation Management Association (KOCOMO), 19(6), pp. 75-91.
- Utterback, J.M. and Abernathy, W.J. (1975). A Dynamic Model of Process and Product Innovation, Omega, The Int. Jl of Mgmt Sci., 3(6), pp. 639–656.
- Um Mijung (2004), Analysis of Actual Condition of Technological Innovation Activities by Company Size: Focusing on Small Companies, STEPI Survey Research, No. 02.
- Verspagen, B. (2004), Innovation and jobs: A micro-and-macro perspective, ECIS Working Papers, 04(15), Eindhoven Center for Innovation Studies.
- Vivarelli, M., Evangelista, R., and Pianta, M., (1996), Innovation and employment in Italian manufacturing industry, Research Policy, 25(7), pp. 1013-1026.
- Zimmerman, V. (2008), The impact of innovation on employment in small and medium enterprises with different growth rates, ZEW Discussion Paper pp. 08–134.
- Zimmerman, K. (1991), The Employment Consequences of Technological Advance: Demand and Labor Costs in 16 German Industries, Empirical Economics, 16(2), pp. 253-266.