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Empirical analysis on the effect of technology innovation on employment in Korean Inno-Biz SMEs

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Abstract

Using Korean panel data sets, this paper analyzes the employment effect of production process technology innovation and new product technology innovation in Korean Inno-Biz SMEs. In the presence of bi-directional causality between technology innovation and employment, the use of OLS can produce biased results when the technology innovation is treated as an exogenous variable. To address this endogeneity problem, this research uses the Two-Stage Residual Inclusion (2SRI) estimation method. It was found that the wage elasticity of employment is higher in the long run than in the short run and the effect of technology innovation on employment is larger in the long run than in the short run. The estimated coefficients for product innovation variable are not statistically significant, while the estimates for process innovation were found to be positive and statistically significant in all models.

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1. Introduction

Suffering from low growth coupled with low employment, the relationship between technology innovation and employment in Korean economy has received much attention among academic circles and policy makers. The interwoven relationship of technology and employment is mostly seen as a positive synergy alleviating unemployment by creating jobs of good quality or decent jobs. Generally, technology innovation is regarded as an important factor that induces employment expansion although the effect of technology innovation on employment is not clear. This is because both positive and negative effects on employment dependent on the types of technological innovation were separately observed. Thus, the effect of technology innovation on employment in firm levels depends largely on the product innovation and process innovation.

Product innovation is known to increase the labor demand by raising the product demand. While it is true that the labor demand rises with an increase in product demand as a result of product innovation, the impact of product innovation on employment may vary depending on different factors. If the process innovation is implemented for the purpose of improving productivity or reducing production cost, the effect on employment will be negative as the same level of output would be produced with fewer factors of production input. However, if the firms pass the cost-reduction effect on the product price, the lower product price will induce the product demand to rise and employment to expand.

Against the backdrop of these uncertainties for the effect of technology innovation on employment, this research aims to empirically analyze the employment effects of types of technology innovation by using the dynamic employment model. This research categorizes the SMEs into Inno-Biz SMEs (Technology innovation type SMEs) and non Inno-Biz SMEs to compare the effects of technology innovation on employment.

In Korea, the Inno-Biz SMEs are the SMEs that are certified based on the competitiveness of technology and substantiality through research and development. This is certified the Small and Medium Business Administration, a government agency in Korea to promote the Inno-Biz as "growth engine" of its economy.

To apply for Inno-Biz designation, SMEs should meet the following criteria: 1) minimum 3 years of business operation history; 2) minimum 650 out of 1000 points from the on-line self-diagnostic test. The test consist of approximately 60 evaluation criteria items for 4 categories such as technology innovation capability, technology commercialization capability, management capability of technology innovation, and technology innovation performance; 3) minimum 700 out of 1000 points from the on-site evaluation by the Korea Technology Finance Corporation (KOTEC), which was founded by the Korean government to provide financial assistance to SMEs under "Financial Assistance to New Technology Business Act."

An evaluation of individual firm's technology is also performed on 4 categories (technology capability, nature of technology, marketability, and profitability) and approximately 34 evaluation items. The evaluation result of individual applicant will be given in 10 ratings: AAA, AA, A, BBB, BB, B, CCC, CC, C and D. At least a B rating is requited to be nominated as Inno-Biz. When the applicant firm meets these criteria, the Korea Small and Medium Business Administration (SMBA) issues an Inno-Biz certificate with an identification number to the SME. The Korea SMBA also notifies this award information to the Small and Medium Business Corporation (SMC) and designated banks for financial assistance. The certificate will be valid for three years and can be renewed upon re-application and re-evaluation.[1]

Accordingly, this paper analyzes if the Inno-Biz SMEs, characterized by the growth potential in the future rather than the historical record, fare better than non Inno-Biz SMEs in expanding employment. Due to the lack of detailed data in SMEs level on Korean firms' technology innovation efforts, research conducted on the effect of technology innovation on employment within the Korean context are lacking, thus incomplete.

Presently, the assistance policies toward the SMEs are being actively discussed as scholarly interests rise on the SMEs' employment creation potential. Thus, an analysis on the employment effects of technological innovation of SMEs with a focus on the Inno-Biz SMEs has important policy implications. In order to analyze the employment effect of technology innovation, this paper uses a dynamic adjustment model for employment based on the CES (constant elasticity of substitution) production function that considers not only labor adjustment cost but also the process during which expectation-formation occurs about the future product price, and the employment decision process which derives from the labor-management wage negotiations.

To address this endogeneity problem rising from the types of technology innovation, this research uses the Two-Stage Residual Inclusion (2SRI) estimation method. To analyze the employment effect of technology innovation, this research uses a panel data set constructed from the technology innovation survey data collected two times in 2008 and 2010 by the Science and Technology Policy Institute (STEPI) in Korea. The remainder of this paper proceeds as follows. Section 2 provides a review of previous research. Section 3 introduces an empirical framework, conducts an empirical analysis and reports findings. Section 4 summarizes findings and concludes.

2. Literature Survey

Currently, studies on the employment effects of technology innovation show contradictory results depending on the type of technology innovation. Several studies have found positive employment effect of technology innovation (Van Reenen, 1997; Smolny, 1998; Blanchflower and Burgess, 1998; Garcia *et al*., 2004; Lachenmaier and Rottmann, 2011). After considering the fixed effect, endogeneity problem and dynamic pattern, Van Reenen (1997) found positive impact of technology change on employment in U.K. firm-level panel data.

Smolny (1998), using the German survey data for manufacturing firms, also found that technology innovation has a positive effect on employment. He found that both product innovation and process innovation had positive effects on job creation. Furthermore, firms practicing technology innovation were found to contribute more to production and job creation than firms without technology innovation.

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[1] http://www.innobiz.net/authen/authen2_1.asp

These studies all tested firm-level displacement and compensation effects using a model where knowledge as capital increased firms' efficiency through process innovation, thus raising the product demand through product innovation. Their empirical findings evidenced that the potential employment compensation effect of process innovations is greater than that of the displacement effect both in the short run and long run. In fact, the studies found that the effect of product innovation is more than two times in terms of unit expenditure.

Then Lachenmaier and Rottmann (2011) furthered the empirical analysis to gauge the firm-level effects of technology innovation on employment. Using a dynamic panel model and a data set for German manufacturing firms from 1982 to 2002, they found positive effects of technology innovation on employment. On the other hand, Zimmermann (1991) and Klette and Forre (1998) reported that technology innovation either reduces employment or does not have a statistically significant effect. Zimmermann (1991), using a cross-section data for German firms, found negative effect of technology innovation on employment.

This paper's focus is different from the existing research that concentrates on the effect of technology innovation on employment in Korean context. Representative studies in Korean context that consider product innovation and process innovation separately are Mun and Chun (2008) and Cin, Song, and Choi (2012). Mun and Chun (2008) make a distinction between ICT (Information & Communication Technology) firms and non-ICT firms, and compare the effect of technology innovation on employment in each of these firms. They found that the effect of technology innovation on employment for product innovation is positive regardless of the types of firms, but the employment effect in process innovation was not found.

To assess the effect of technology innovation on employment, Cin *et al*. (2012) used the financial statement data from 2000 to 2007 published by the Korea Credit Rating & Information and the panel data constructed from the technology innovation survey in 2008 prepared by the Science and Technology Policy Institute (STEPI) in Korea. They found that the effect of product innovation on employment is statistically insignificant while the estimates of the process innovation variable are statistically significant at 1 percent level in all models, implying the positive effect on employment.

3. Empirical Analysis

3.1. Empirical Model and Estimation Method

This research utilizes the following dynamic adjustment model for employment derived by Cin *et al*. (2012).

$$\ln L_{i,t} = \delta_0 + \varphi \ln L_{i,t-1} + \delta_1 \ln(w/p)_{i,t} + \delta_2 \ln Q_{i,t} + \delta_3 I^N_{i,t} + \delta_4 I^P_{i,t} + \beta Z_{i,t} + \sum_k \gamma_k dInd_{i,k} + \tau d10_t + \varepsilon_{i,t} \quad (1)$$

In equation (1), L_{it} is the labor demand for firm i in time t. w/p is real wage, Q is the total product, I indicates a dummy variable which is equal to 1 if there was either product innovation ($I^N_{i,t}$) or process innovation ($I^P_{i,t}$) in the SME for the last three years, 0 otherwise, and Z is a vector of control variables that could affect employment. $dInd_{i,k}$ indicates industry dummies, $d10_t$ represents time dummy for the 2010 survey data, and $\varepsilon_{i,t}$ is the stochastic error term. Equation (1) shows that firm's employment level depends on the employment level of the previous period. The value of the adjustment speed variable φ ranges between 0 and 1. If the value does not fall in this range, the labor demand will be unstable as the firm's employment fails to return to the equilibrium when the employment level departs from the equilibrium.

The short-run wage elasticity of employment δ_1 expects to have a positive value because the labor demand declines when the wage rises. The short-run production elasticity of employment δ_2 also expects to be positive since the labor demand rises when the production expands. In other words, when the product demand rises, so does the level of production, and as a result, employment also expands. The product innovation raises labor demand through the channel in which product demand rises. In this case, it is expected that $\delta_3 > 0$. However, the effect of new product on demand expansion may differ depending on the degree of market competition and the extent of substitutability of product demand.

If the demand for a new product completely substitutes the demand for existing products, δ_3 may not be statistically significant. Also, if a firm has a monopoly in the product market, it can maximize profit without expanding employment. The effect of process innovation on employment, in the form of production method change and improvement, is also uncertain. In general, the process innovation is implemented to raise productivity and reduce cost, using fewer factor inputs to produce the same amount. If substitution effect or displacement effect among production inputs occurs during the process innovation, it is expected that $\delta_4 < 0$. However, if the firms pass the effect of cost reduction to the price, the lower product price can induce the compensation effect by expanding product demand and employment. In this case, it is expected that $\delta_4 > 0$.

Despite these variances, its intensity or degree of fluctuations all seems to point to the magnitude of compensation effect which may differ depending on the price elasticity of demand. For example, if the monopolist maximizes profit in the monopoly market, the cost reduction from the process innovation may not raise production and may reduce employment. After all, theoretically the employment effect can be expected from the product innovation and process innovation. However, the net employment effect may differ depending on several factors discussed above. The empirical model considers a control variable *Z* that includes dummy variables controlling for government assistance and tax subsidy. To control for production heterogeneity across firms, the model also considers a dummy variable for industry. All these variables may affect employment.

The problems arising from applying the conventional OLS on the dynamic model mentioned above to analyze the employment effect of technology innovation are twofold; first, it may produce biased results due to the endogeneity problem and secondly, that little attention is paid to firms' heterogeneity. If equation (1) is estimated by the OLS, the result would also be biased due to the unobservable fixed effect of firms, η_i.

To address this problem, a fixed effect model (i.e., within estimator) can be used. In the fixed effect model, each variable is demeaned to construct transformed variables which are used in OLS estimation. These transformed variables will be estimated by the OLS. However, since the correlation between the transformed variable and the stochastic error term $\varepsilon_{i,t}$ is negative, the estimated coefficients for the lagged dependent variable would be underestimated even if the stochastic error term is not auto-correlated (Arellano and Bover, 1995). Adding more explanatory variables will not completely remove this bias. This within estimator becomes consistent in a dynamic model when the sample observation increases infinitely.

The data set used for this research is a panel data that covers a relatively short period of 6 years. Therefore, to identify firms' heterogeneous characteristics, this paper will use industry dummy variables, instead of fixed effect model or random effect model. The endogeneity problem is not only limited to the lagged variables for employment. The wage variable and technology variable also encounter a potential endogeneity problem.

Since the firm-level wage and the employment are simultaneously determined, if the wage is simply treated as an exogenous variable, the empirical results would be biased (Wooldridge, 2002). As shown in the model, the technology innovation affects employment. Conversely, it is also possible that firms' stable employment and improvement of work environment may affect the productivity and technology innovation. Therefore, the bilateral relationship is expected between employment and technology innovation. The presence of bilateral causal relationship implies that applying the OLS will produce biased results when the technology innovation is simply treated as an exogenous variable without examining its interdependent relationship with other relevant variables. In order to alleviate the endogeneity problem, the two-stage estimation method is generally used. There are two forms of two-stage estimation method: traditional Two-Stage Predictor Substitution (2SPS) method and Two-Stage Residual Inclusion (2SRI) method. Two methods are similar in that the first stage involves a regression of a potentially endogenous variable against the instrumental variables.

However, the two methods differ in that while the traditional 2SPS includes the predicted value obtained from the first stage as an independent variable in the second stage, the 2SRI includes the residuals from the first stage as an independent variable in the second stage to address the endogeneity problem. In the linear model, the estimation methods for 2SPS and 2SRI are identical. But in the non-linear model, the 2SRI estimators are inconsistent while the 2SPS estimators are not. Terza *et al.* (2008) show that the use of 2SPS in non-linear model when the endogeneity problem is ignored can produce biased results. In particular, while the 2SPS estimators from the simultaneous probit models and count data model where the data are non-negative integers are biased, the 2SRI estimators are not biased. The variables used in the employment model in this research such as lagged variables for employment, wage and technology innovation are subject to potential endogeneity. While the model used in this paper is not necessarily a true non-linear model as shown in Terza *et al.* (2008), the model is still subject to potential non-linearity since both the use of probit model or logit model is needed to remove the endogeneity from the technology innovation. For this reason, this paper chooses the 2SRI estimation method.

3.2. Data

To analyze the employment effect of technology innovation in SMEs, this research uses a panel data set constructed from the technology innovation activity survey data collected two times, in 2008 and 2010 by the STEPI in Korea. The merged data set includes the standard industry classification and basic financial statement. If this data for technology innovation and other data from different sources are combined, many companies would be excluded from the sample, resulting in a loss of information. Accordingly, this research uses the financial statement provided by the survey data.

The variables used to estimate the Equation (1) are as follows. The labor demand and employment is represented by the log of the number of employees, *ln(worker)*. Due to the lack of information on the total amount of wage in the STEPI data, the real wage is measured by dividing the cost of goods sold (COGS) by the number of employees.[2] The log of the real variable, *ln(w)*, is used in the model. The log of sales, *ln(sales)* is used for the total production.

The dummy variable for production technology innovation I^N, constructed from the survey data, takes the value of 1 if a new product was released in the past 3 years before 2008 in 2008 data or before 2010 in 2010 data, and 0 otherwise. The dummy variable for production process innovation takes the value of 1 if new or greatly improved production process, logistics system, and other support systems were introduced in the past 3 years, and 0 otherwise. For other variables that affect the employment, this research also considers dummy variables for government assistance and tax subsidy. The dummy variable for government assistance *dGovSub* takes the value of 1 if the firms received government assistance for product development and product commercialization support, and 0 otherwise.

Table 1 Sample Statistics

	SMEs			Inno-Biz Firms			Non Inno-Biz Firrms		
	No. of Observation	Mean	Standard Deviation	No. of Observation	Mean	Standard Deviation	No. of Observation	Mean	Standard Deviation
ln(worker)	6,220	3.706	1.039	1,219	4.014	0.981	5,001	3.631	1.039
ln(w)	5,648	18.645	0.994	1,178	18.764	0.822	4,470	18.613	1.033
ln(sales)	5,911	22.666	1.549	1,203	23.084	1.354	4,708	22.559	1.578
I^N	6,222	0.471	0.499	1,219	0.878	0.328	5,003	0.371	0.483
I^P	6,222	0.354	0.478	1,219	0.683	0.465	5,003	0.273	0.446
dGovSub	6,222	0.167	0.373	1,219	0.484	0.500	5,003	0.090	0.286
dTaxcredit	6,222	0.100	0.300	1,219	0.263	0.441	5,003	0.060	0.237

The dummy variable for tax subsidy *dTaxcredit* takes the value of 1 if firms received tax subsidy from technology development in the past 3 years before 2008 in 2008 data or

[2] The STEPI data unfortunately did not provide wage information. Given this constraint, we had no other options but to impute the wage variable by dividing COGS by employment. In this way, we may also reduce omitted variable bias by using the COGS per employee as a proxy for wage rather than dropping these two relevant variables (COGS and the number of employees). Nonetheless, we acknowledge that COGS also includes the cost of other inputs, and as such the way how the wage variable was created may be less than satisfactory.

before 2010 in 2010 data, and 0 otherwise. In the technology innovation data collected in 2008 and 2010 respectively, 6,222 SMEs are eligible for sample to be used for this research. The sample includes 1,219 Inno-Biz firms (19.6%) and 5,003 Non Inno-Biz firms (80.4%). Firms in the sample are distributed across 23 industries, in which the machinery and equipment industry is most prominent. Then, follow electrical equipment, automobile industry, and chemical industry in order. Table 1 lists the descriptive statistics of the sample.[3]

As can be seen in Table 1, the proportion of firms that implemented product innovation is 87.8% in Inno-Biz category, but the percentage is decreased to 37.1% from the non Inno-Biz firms. The proportion of the firms that introduced production process innovation is 68.3% in Inno-Biz category while firms in non Inno-Biz category is also lower at 27.3%. The proportion of firms that received government assistance is 48.4% in Inno-Biz category, but that of the firms in non Inno-Biz category is much lower at 9.0%. Similar pattern was found for tax subsidy. The proportion of Inno-Biz firms that received tax subsidy is higher at 26.3% in comparison with 6% for non Inno-Biz firms.

3.3. Empirical Results

To analyze the employment effect of the types of technology innovation, this paper compares the empirical results from the OLS and those of the 2SRI method that address the potential endogeneity problems caused by the lagged variables of technology innovation. Table 2 shows the OLS estimation results of the dynamic employment model.[4] In all models, the estimates of the first-order lagged variable of employment (number of employees in the previous period) were found to be statistically significant at 1 percent level and to be positive and less than 1 in magnitude. This implies the stability of the dynamic employment model. The implication of those estimates being close to 1 is that the employment level in the current period is quite similar to that of the previous period and a large difference can be observed between the short-run and the long-run elasticities.

The estimated coefficients of the real wage variable are negative and statistically significant. This implies that the wage increase can reduce employment. Also, the estimated coefficients of the sales variable, a proxy for production, were found to be positive and statistically significant in all models. This implies that the sales increase will expand employment.

The estimated coefficients for the variable controlling for production process innovation ($I_{i,t}^{P}$) are statistically significant at 1% level in all models. These results imply that production cost effects of the production process innovation on labor demand are dominated by market demand effects. Theoretically, the production process innovation can lead to a decrease in production cost, thus in labor demand. On the other hand, the decrease in production cost can also lower the commodity price, which in turn can increase market demand for the product, thus the labor demand also. When the latter effects dominate the former, the production process innovation may positively affect employment. This usually

3 Since we used unbalanced data across the variables, the numbers of observations for variables used here are different depending on the number of missing observations.

4 Basically, the estimated results using the balanced data across variables are not much different from those presented in the paper. The empirical results using the balanced data are available upon request.

happens in SMEs, especially Inno-Biz firms, which actively strive to maximize the revenue and market share to survive in the market.

Table 2. Employment Effect of Technology Innovation

	SMEs		**Inno-Biz firms**		**Non Inno-Biz firms**	
	OLS①	**OLS②**	**OLS①**	**OLS②**	**OLS①**	**OLS②**
$\ln L_{i,t-1}$	0.874***	0.871***	0.912***	0.911***	0.862***	0.858***
	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(0.006)
$\ln(w/p)_{i,t}$	-0.073***	-0.073***	-0.063***	-0.061***	-0.079***	-0.079***
	(0.004)	(0.004)	(0.008)	(0.008)	(0.004)	(0.004)
$\ln(sale)_{i,t}$	0.092***	0.093***	0.066***	0.065***	0.101***	0.102***
	(0.004)	(0.004)	(0.007)	(0.008)	(0.004)	(0.004)
I^N	-0.004	-0.002	-0.026	-0.023	-0.005	-0.003
	(0.007)	(0.007)	(0.017)	(0.017)	(0.008)	(0.008)
I^P	0.034***	0.033***	0.042***	0.042***	0.027***	0.025***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.008)	(0.008)
dGovSub	0.005	0.003	-0.001	-0.000	-0.002	-0.005
	(0.007)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
dTaxcredit	0.015*	0.016*	-0.006	-0.006	0.030**	0.032***
	(0.009)	(0.009)	(0.012)	(0.013)	(0.012)	(0.012)
d10	-0.005	-0.006	0.008	0.009	-0.006	-0.007
	(0.005)	(0.005)	(0.011)	(0.011)	(0.005)	(0.006)
Industry Dummy	No	Yes	No	Yes	No	Yes
$\overline{R}^2$	0.971	0.971	0.968	0.968	0.971	0.971
No. of observations	5,644	5,644	1,177	1,177	4,467	4,467

Note 1) *** , **, * represent 1%, 5%, and 10% significance level, respectively
2) Values in the parentheses are standard errors.

However, the estimated coefficients for the variable controlling for new product innovation ($I^N_{i,t}$) are not statistically significant. These results can be interpreted as the new products supplied from the production innovation would not expand the employment because they substituted the existing products in a large scale. The estimates for dummy variables controlling for government assistance are not statistically significant in all models. Lastly, the estimates for dummy variables controlling for tax subsidy are statistically significant for all SMEs and non Inno-Biz firms. Such findings, however, should be qualified in that these estimation results may have been overestimated since the endogeneity problem of technology innovation was not adequately addressed.

Table 3 Employment Effect of Technology Innovation

	SMEs		**Inno-Biz firms**		**Non Inno-Biz firms**	
	2SRI①	**2SRI②**	**2SRI①**	**2SRI②**	**2SRI①**	**2SRI②**
$\ln L_{i,t-1}$	0.903***	0.903***	0.909***	0.909***	0.896***	0.897***
	(0.013)	(0.013)	(0.022)	(0.022)	(0.014)	(0.014)
$\ln(w/p)_{i,t}$	-0.038***	-0.037***	-0.053***	-0.053***	-0.041***	-0.041***
	(0.010)	(0.010)	(0.019)	(0.019)	(0.011)	(0.011)
$\ln(sale)_{i,t}$	0.058***	0.058***	0.056***	0.056***	0.064***	0.064***
	(0.011)	(0.011)	(0.021)	(0.021)	(0.012)	(0.012)
$I_{i,t}^{N}$	-0.001	-0.004	-0.019	-0.019	-0.002	-0.005
	(0.007)	(0.007)	(0.020)	(0.021)	(0.007)	(0.007)
$I_{i,t}^{P}$	0.035***	0.032***	0.038***	0.038***	0.021***	0.019**
	(0.007)	(0.007)	(0.012)	(0.012)	(0.007)	(0.008)
I_{r}^{N}	0.124	0.124	0.369***	0.371***	0.155	0.151
	(0.078)	(0.078)	(0.108)	(0.108)	(0.110)	(0.109)
I_{r}^{P}	-0.185**	-0.176**	-0.372***	-0.374***	-0.221*	-0.206*
	(0.086)	(0.086)	(0.094)	(0.094)	(0.122)	(0.121)
dGovSub		0.011		0.004		0.003
		(0.008)		(0.011)		(0.011)
dTaxcredit		0.014*		-0.007		0.029***
		(0.008)		(0.012)		(0.010)
d10	-0.014**	-0.012**	0.000	0.000	-0.012*	-0.011*
	(0.006)	(0.006)	(0.017)	(0.016)	(0.007)	(0.006)
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
$\overline{R}^2$	0.971	0.971	0.968	0.968	0.971	0.971
No. of observation	5,547	5,547	1,150	1,150	4,381	4,381

Note 1) *** , **, * represent 1%, 5%, and 10% significance level, respectively
2) Values in the parentheses are standard errors.

Table 3 shows the empirical results estimated by the 2SRI method. In the first stage, we used the "product innovation" and "process innovation" as the dependent variable. Each dependent variable was regressed on such instrumental variables as the volume of sales, wage, the number of employees in the previous year, the earnings before interest and tax (EBIT) in the previous year, and the volume of exports in the previous year. From the first stage, we obtained residuals for each regression (one for product innovation and the other for process innovation). Those residuals were included in equation (1), and the equation was estimated in line with Terza *et al.* (2008). The results from the first stage were not reported to save space.

The results in table 3 are quite similar to those in table 2. The estimated coefficients for residuals of new product innovation (I_r^N) and production process innovation (I_r^P) are statistically significant for eight out of twelve cases. In particular, all six cases for those of the production process innovations are statistically significant, which confirms the presence of potential endogeneity. For the insignificant coefficients for the residuals, we may have little efficient gains from the two-step procedure, implying that we rather look at the OLS estimation results for them. The estimates of the lagged variable of employment take on values between 0 and 1 in all models. Also, the estimates for real wage variable are negative and statistically significant in all models, meaning that wage increase can reduce employment.

The estimated coefficients for sales variable, a proxy controlling for production, are also positive and statistically significant in all models, implying that the production expansion would raise employment. Considering both the OLS and the two-stage estimation results, the estimated coefficients of technology innovation for new product are not statistically significant. On the other hand, the estimates of technology innovation for production process are statistically significant in all models.

This result implies that first, the newly-developed products substituting the existing product does not create an employment effect; second, the production process innovation expands employment as a result of the larger compensation effect since the cost reduction increases product market demand which in turn expands employment. Lastly, the estimates for dummy variable controlling for government assistance are not statistically significant, while the estimates for dummy variable controlling for tax subsidy are statistically significant in all SMEs and non Inno-Biz firms.

4. Summary and Conclusions

This research, using a dynamic adjustment model for employment, empirically analyzes the employment effect of types of technology innovation. Specifically, this paper aims to analyze the employment effect of production process technology innovation and new product technology innovation. In all models, the estimates of the first-order lagged variable of employment were found to be statistically significant at less than 1 in magnitude and positive. This implies the stability of the dynamic employment model. The implication of those estimates being close to 1 is that the long-run employment elasticity is high. Therefore, the wage elasticity of employment is higher in the long run than in the short run and the effect of technology innovation on employment is larger in the long run than in the short run. The estimated coefficients of the real wage variable are negative and statistically significant. This result, as expected, shows that the wage increase reduces employment.

The estimated coefficients for product innovation variable are not statistically significant, while the estimates for process innovation were found to be positive and statistically significant in all models.

This result can be interpreted as follows. When the product innovation occurs, the effect of new product development to substitute existing products is large so as not to expand employment. The production process innovation, on the other hand, is found to expand employment. To the extent that product innovation introduced new products that replace old (or existing) ones, product innovation may not expand employment. On the other hand, the small-and-medium sized firms that are usually in a weaker position in terms of competition with larger firms, the SMEs may strategically focus on the less-costly process innovation. If the process innovation is labor-intensive or requires more human touch (finishing and packaging products, for example), the level of labor demand and employment will rise. Unfortunately, the data used in this study is less than satisfactory to empirically substantiate this interpretation. When a more complete data set is available, we will be better able to address this issue.

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