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Regional total factor productivity and local employment growth: evidence from Korea

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Abstract This paper examines the effect of regional total factor productivity (TFP) on local employment growth using regional panel data from 2000 to 2014 in Korea. The employment equation derived from the constant elasticity of substitution production function is a function of wage rate, capital stock, and regional TFP. The demand for labor accounts for dynamics since there is a cost to adjusting demand for labor in the long-run. This paper introduces a dynamic panel regression model that considers the effect of lagged employment. TFP is a more appropriate measure of technology than Research and Development (R&D) expenditure or the number of patent applications. This paper measures regional TFP using a growth accounting method as a proxy variable of technology. This paper shows that an increase in regional TFP has a positive effect on local employment growth that is greater in the long-run than in the short-run. This suggests that employment policy such as vocational training adapting to the technological progress for product and process innovations increases labor force productivity in the long-run.

Keywords Regional total factor productivity · Local employment growth · Dynamic panel regression model

JEL Classification O33 · R58 · J23 · C33

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1 Introduction

Technological progress, which is considered as an increase in productivity, not only increases consumer surplus and firms' profits, but also improves quality of life in term of employment growth, accelerates the industrial structure, and promotes economic growth. Both the neoclassical growth theory since Solow (1956) and the endogenous growth theory proposed by Romer (1990) and Lucas (1988) emphasize the importance of technological progress in economic growth. Moreover, the relationship between technological progress and employment growth is also a key issue in the recent jobless growth. If technological progress improves productivity, a producer will have less demand for labor and workers will lose jobs and income, resulting in slower economic growth. On the other hand, technological progress lowers production costs and commodity prices can increase the demand for labor as the production factor.

Recently, job creation and economic growth are globally sensitive and serious issues. Specifically, Korea has experienced low economic growth and stagnant employment growth. Recent employment policies in Korea are based on short-term fiscal support focusing on job-support programs such as short-term or non-regular job creation. In the long-run, employment policy requires for qualitative job creation in private and public sectors. The purpose of this paper is to examine the effect of regional total factor productivity on local employment growth in Korea using dynamic panel regression model and regional panel data from 2000 to 2014 in Korea.

Previous studies account for variables such as Research and Development (R&D), agglomeration of industry or industrial complexes, and size of employment growth as a component of employment growth. For example, Van Reenen (1997) showed that the technological innovation has a positive effect on the demand for labor using panel data from 1976 to 1982 in 598 UK firms.[1] Similarly, Lachenmaier and Rottmann (2011) used data from German manufacturing firms from 1982 to 2002 to show that technological innovation has a positive impact on employment.[2] Bogliacino et al. (2012) also examined the effect of technological innovation with R&D expenditure using European data, finding that R&D expenditure has a positive effect on employment and service sector has a greater effect than the manufacturing sector. Furthermore, they demonstrated that the effect of high-tech manufacturing sector is greater than that of non-high-tech manufacturing sector.[3] Most previous studies confirm the job creation effect of technological innovations using R&D investment amount or the number of patents as a proxy variable of technological progress. In an agglomeration economy, Blien et al. (2006) investigated the effects of diversity and specialization for different industries at the local level. They set up

[1] Van Reenen (1997) matched innovations with the construction of a count of the number of innovations that a firm commercialized.

[2] Lachenmaier and Rottmann (2011) classified the innovation input and output, and measured them using innovation expenditure (R&D expenditure) and patents, respectively.

[3] High-tech manufacturing sectors include pharamceuticals, office, accounting and computing machinery, electrical machinery and apparatus, aircraft and spacecraft, measuring, analyzing, controlling, ... instruments. Non-high-tech manufacturing sectors include food and similar products, fabricated metal products, chemicals and allied products, and so on.

a dynamic panel model and defined explanatory variables such as sector specific effects, total regional size, specialization, and diversity.

This paper differs from the previous studies by introducing the regional total factor productivity (TFP) measured by growth accounting as a proxy variable of technology to investigate the effect of technological progress on local employment growth. This paper is organized as follows. Section 2 introduces the model and data. Section 3 estimates the model and describes the results. Finally, Sect. 4 provides the concluding remarks.

2 The model and data

This paper proposes employment equation model of Van Reenen (1997) derived from the constant elasticity of substitution (CES) production function to analyze the effect of technological progress on local employment growth. This analysis introduces the behavior of profit maximizing firms in a perfectly competitive market. The CES production function is specified as follows,

$$Y = T[(AL)^{-\rho} + (BK)^{-\rho}]^{-\frac{1}{\rho}}, \tag{1}$$

where Y is the output, and L and K are the employment and capital stock, respectively. Technological progress is divided into three types based on neutral technological progress, which regards the combination of production factors and output as constant. Hicks-neutral technological progress is factor-augmenting technological progress occurring when the ratio of marginal products remains unchanged at a constant capital–labor ratio. Harrod-neutral technological progress is labor-augmenting, evidenced by an increase in labor productivity with a constant capital–output ratio. Solow-neutral technological progress augments the capital stock and increases capital productivity. This means that even if labor input remains the same and capital input decreases, the firm can obtain the same amount of production as in the past.

The first-order condition for labor is equal to the real wage, and the first-order condition for capital is equal to the real interest rate. These can be written

$$\ln L = \ln Y + (\sigma - 1)\ln T + (\sigma - 1)\ln A - \sigma \ln(W/P) \tag{2}$$

$$\ln K = \ln Y + (\sigma - 1)\ln T + (\sigma - 1)\ln B - \sigma \ln(R/P), \tag{3}$$

where $\sigma = 1/(1+\rho)$ is the elasticity of substitution between labor and capital. Now, by combining Eqs. (2) and (3), the optimal demand for labor can be derived as follows,

$$\ln L = (\sigma - 1)\ln\left(\frac{A}{B}\right) - \sigma \ln\left(\frac{W}{P}\right) + \ln K + \sigma \ln(R/P). \tag{4}$$

For empirical analysis, Eq. (4) can be expressed in the following stochastic form:

$$\ln L_{i,t} = \beta_0 \ln(A_{i,t}/B_{i,t}) + \beta_1 \ln w_{i,t} + \beta_2 \ln K_{i,t} + v_t + u_i + \mu_{i,t}, \tag{5}$$

where $\ln L$ is employment (number of employees), w is the real wage (average monthly wage), and $\ln K$ is the capital stock. The cost of capital, (R/P) is the same for each panel entity but varies over time and can be expressed as time dummy v_t. u_i is the unobserved region-specific time-invariant effect that might be correlated with the explanatory variables but not with the usual error term $\mu_{i,t}$.

Previous studies interpreted (A/B) as an unobservable technological progress using R&D investments or patent applications that indirectly indicate technological progress as a proxy variable. However, it is not easy to assess or measure the economic value of technological progress. TFP is more appropriate than R&D stock or patent applications as a measure of technology.[4] This paper uses regional TFP measured using the growth accounting method for analysis as a proxy variable of technology. This paper defines (A/B) as the unobservable relative factor-augmenting technological progress.

To remove the unobserved regional specification u_i, Eq. (5) is changed to a first-difference. The demand for labor reflects dynamics because there is a cost for labor adjustment in the long-run. Thus, two lags of employment variables are added as the explanatory variable in employment Eq. (5). The panel analysis model, in which the lag values of the dependent variable are the explanatory variable as in Eq. (6), is called a dynamic panel regression model.

$$\Delta \ln L_{i,t} = \gamma_1 \Delta \ln L_{i,t-1} + \gamma_2 \Delta \ln L_{i,t-2} + \beta_0 \Delta \ln(A_{i,t}/B_{i,t}) + \beta_1 \Delta \ln w_{i,t} + \beta_2 \Delta \ln K_{i,t} + \Delta v_t + \Delta \mu_{i,t}. \tag{6}$$

The dynamic panel regression model can have endogeneity in the explanatory variables, that is, a correlation between $\Delta \ln L_{i,t-\tau}$ and $\Delta \mu_{i,t}$, $\tau = 1, 2$. This problem can be solved using Arellano and Bond (1991) method, which uses instrumental variables (IVs) of the endogenous explanatory variables in a first-difference model, where the IVs are set to the past values of the endogenous explanatory variables. If there is no autocorrelation in the error term, it is reasonable to use the values of the dependent variable as IVs since it satisfies the constraint of method of moments and the past employment variable is correlated with current employment. In other words, this methodology can obtain efficient estimators using a difference equation and solving the problem of endogeneity using generalized method of moments (GMM). In addition, the GMM estimator can be efficient when the IVs are over-identified. Dynamic panel GMM has two types of estimations; a one-step estimation and a two-step estimation. The latter is a method of substituting estimates obtained from the former into a new weighting matrix. The two-step estimator is asymptotically more efficient than the one-step estimator.

In this model, the estimators of $\Delta \ln L_{i,t-1}$ and $\Delta \ln L_{i,t-2}$ can be interpreted as the potential persistence toward equilibrium in the process of adjustment. Moreover,

[4] Keller (2010) identified many problems with R&D spending as a variable to estimate R&D stock and described the limitations of using patent applications as a measurement, in that firms file only a small part of all technological progresses; most filings are irrelevant to technological progress.

they show the speed of employment growth in that region.[5] If $0<\gamma<1$, local employment growth regresses to the mean in the long-run. If $\gamma > 1$, then it implies that employment increases explosively. We can use these parameters to examine the long-term effects of the explanatory variables on the dependent variables.

In this paper, we measure the TFP from the Cobb–Douglas production function by growth accounting, which is a good measure of technology, and derive labor demand function using CES production function to confirm the technological progress elasticity of demand for labor. Growth accounting is well known as a method which measures the TFP. This method is based on the Cobb–Douglas production function Solow residuals to measure TFP. To obtain the value of (A/B), which is a variable in Eq. (6), this paper assumes two cases of Cobb–Douglas production function where labor-augmented technological progress A, which is technological progress that make efficient use of labor inputs, and capital-augmented technological progress B, which is technological progress that make capital stock more efficient.[6] Although the model should consider the production factors that reflect the quality level of labor and capital, there is no statistical data on the average years of schooling, and there is a limit to the data to apply weights according to the types of capital in each region. Therefore, this paper does not consider the quality level of labor and capital. For growth accounting, the capital stock must be estimated first, which is estimated here using the perpetual inventory method. The permanent inventory method measures the initial capital stock by discounting the initial investment as the sum of the average investment growth rate and the depreciation rate, and then continuously accumulating capital stock according to the capital change formula.[7]

Common statistics of regional panel data are described in Table 1. Regional data in Korea are provided from the Korean Statistical Information Service (KOSIS). The panel data consist of 16 regions (7 metropolitan councils and 9 provinces) from 2000 to 2014 as annual data. The dependent variable is calculated by multiplying the monthly average hours worked by number of employees. These data are in the "Survey Report on the Labor Force at Establishments" of Korea. The explanatory variables are regional TFP, real wage (average monthly wage) and capital stock. Real wages are expressed as an hourly wage by converting the monthly average wages from the "Survey Report on the Labor Force at Establishments" into real variables using the Consumer Price Index (CPI). All data are collected at the local level and transformed into logarithm form.

[5] See Jiwattanakulpaisarn et al.'s (2009) explanation that the parameter γ reflects the potential persistence for equilibrium employment.

[6] The Cobb–Douglas production functions for measuring TFP are represented by $Y=(AL)^{1-\alpha}(K)^{\alpha}$ and $Y=(L)^{1-\alpha}(BK)^{\alpha}$, respectively. The former assumes the existence of labor-augmented technological progress, and the latter assumes the capital-augmented technological progress. Here, the capital income share, α is generally known to a value of 1/3.

[7] The initial capital stock of t is $K_{i,t}=I_{i,t}/(g_i+\delta)$ and the capital stock of $(t+1)$ is $K_{i,t+1}=I_{i,t}+(1-\delta)K_{i,t}$. In this paper, the average investment growth rate of the analysis period is the variable g_i and the depreciation rate δ is assumed to be 5%.

Table 1 Common statistics

Variables	Obs.	Mean	Std. dev.	Min.	Max.
L (one million hours)	240	1358.085	1447.846	166.240	6458.090
A/B	240	0.212	0.271	1.712E−09	1.121
w (KRW)	240	11,324.08	2002.239	7637	17,647
K (one million KRW)	240	319.969	315.281	26.773	1337.438

Table 2 Estimates of dynamic panel GMM

Variables	One-step GMM	Two-step GMM
$\ln L_{i,t-1}$	0.762*** [0.108]	0.743*** [0.125]
$\ln L_{i,t-2}$	− 0.230*** [0.042]	− 0.241*** [0.069]
$\ln(A_{i,t}/B_{i,t})$	0.007*** [0.002]	0.007*** [0.002]
$\ln w_{i,t}$	− 0.018 [0.060]	− 0.038 [0.070]
$\ln K_{i,t}$	0.507** [0.231]	0.550** [0.240]
AR(1) test: Z value	− 3.17	− 2.92
AR(2) test: Z value	− 1.60	− 1.56
Hansen test (df)	15.15 (10)	15.15 (10)
p value	0.127	0.127

[·] standard error

$^{**}p < 0.05$, $^{***}p < 0.01$

3 Analysis

In this section, we estimate Eq. (6) using a dynamic panel GMM. The effects of the regional TFP on local employment growth are reported in Table 2. For comparison, this analysis includes both a one-step and two-step estimation results, but there is no significant difference. The unobservable relative factor-augmenting technological progress has a positive effect on local employment growth; a one percent increase leads to an increase in local employment of 0.007%. The increase in the unobservable relative factor-augmenting technological progress $\ln(A_{i,t}/B_{i,t})$ means that productivity improved due to labor-augmenting technological progress. In other words, productivity improvement due to labor-augmenting technological progress increases employment (here, hours worked). In general, the labor productivity improvement due to technological progress can lead to a decrease in employment because of the increase in output per unit of input. On the other hand, creating new demand for a commodity may increase employment in the process of increasing production input.

In a dynamic panel model, the long-run effect can be confirmed by combining the past values of the explanatory variables with the dependent variables of the current period. The long-run effect of the unobservable relative factor-augmenting technological progress on employment is positive because $\frac{\beta_0}{(1-\gamma_1-\gamma_2)} = 0.014$. Since the short-run effect of the unobservable relative factor-augmenting technological progress is 0.007, the long-run effect of technological progress on employment is greater than the short-run effect.

From coefficients of $\ln L_{i,t-1}$ and $\ln L_{i,t-2}$, the coefficient of the two-lagged employment variable shows a negative sign reflecting substitutions between unskilled and skilled labor, while the coefficient of the one-lagged employment variable shows a positive sign representing adjustments of labor cost. The coefficients of lagged employment variables have between 0 and 1 in absolute value, which means that employment regresses to the mean value in the long-run.

The coefficient of real wage was negative, as expected, but not statistically significant. The capital stock elasticity of employment shows a statistically significant result of about 0.55. The autocorrelation of the error term in Table 2 appears in the results for AR(1) and AR(2) test. This result confirms that there is no autocorrelation in the error term of the regression model. To use GMM, the number of IVs should be greater than the number of endogenous explanatory variables. It is reasonable to use GMM because IVs are over-identified in this model.

4 Concluding remarks

This paper examines the effects of the regional TFP on local employment growth using regional panel data from the period 2000–2014 in the Korean economy and a dynamic panel GMM, which takes care of the endogeneity problem. This paper shows the improvement in regional TFP, implying that the unobservable relative factor-augmenting technological progress has a positive effect on local employment growth. In this sense, this shows that it is worth estimating regional TFP as an alternative to the method employed by previous studies that use proxy variables of technological progress such as R&D expenditure or number of patents applications. In addition, this paper reveals that two-lagged employment variable has a negative effect and the one-lagged employment variable has a positive effect on current employment and implies that the employment variables have the property of returning to the mean in the long-run, which comes from the fact that the coefficients of both lagged employment variables have between 0 and 1 in absolute value.

This paper also finds that the job creation effect of technological progress is more effective in the long-run than in the short-run. This suggests that employment policy such as vocational training adapting to the technological progress for product and process innovations increases labor force productivity in the long-run.

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References

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev Econ Stud 58(2):277–297

Blien U, Suedekum J, Wolf K (2006) Local employment growth in West Germany: a dynamic panel approach. Labour Econ 13(4):445–458

Bogliacino F, Piva M, Vivarelli M (2012) R&D and employment: an application of the LSDVC estimator using European microdata. Econ Lett 116(1):56–59

Jiwattanakulpaisarn P, Noland RB, Graham DJ, Polak JW (2009) Highway infrastructure investment and county employment growth: a dynamic panel regression analysis. J Reg Sci 49(2):263–286

Keller W (2010) International trade, foreign direct investment, and technology spillovers. In: Hall BH, Rosenberg N (eds) Handbook of the economics of innovation, vol 2. Elsevier, Amsterdam, pp 793–829

Lachenmaier S, Rottmann H (2011) Effects of innovation on employment: a dynamic panel analysis. Int J Ind Org 29(2):210–220

Lucas RE (1988) On the mechanics of economic development. J Monet Econ 22(1):3–42

Romer PM (1990) Endogenous technological change. J Polit Econ 98(5, Part 2):S71–S102

Solow RM (1956) A contribution to the theory of economic growth. Q J Econ 70(1):65–94

Van Reenen J (1997) Employment and technological innovation: evidence from UK manufacturing firms. J Labor Econ 15(2):255–284