Technological Progress and Youth Employment in South Korea*

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Abstract

This paper analyzes the extent to which technology progress and youth employment are related. In doing so, we divide workers into two groups - young workers and old (prime-aged) workers - and study how differently technology progress affects demand for different groups of workers. In particular, we estimate the elasticity of substitution between (physical) capital and workers à la Jaimovich et al. (2013) since the demand for different groups of labor crucially depends on the elasticity. By using the Korean labor market data between 2000 and 2014, we estimate key parameters of the production function by utilizing industry variations observed in the data. Our findings indicate that the elasticity of substitution is greater (or at least not smaller) for young workers than for old workers. This finding is robust to instrumental variable estimation and to different subgroups of workers, including educational attainment, different criteria for young/prime-aged workers, male workers, occupational groups, and size of firms.

Keywords: Labor demand, Technological progress, Youth employment

JEL Classification: J23, J13, O33

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1. Introduction

Youth labor market outcomes in South Korea have been persistently weak for the past decade. In particular, youth unemployment rates for those aged 15 to 29 years increased from 7.6% in the first quarter of 2007 to over 10% in the same quarter of 2018. Compared to a rather modest rise in the overall unemployment rate during the same period from 3.8% to 4.1%, the severity of the youth labor market in Korea posed pressing social problems. For instance, as Wee (2016) examined, those who enter a job market during a recession tend to suffer large initial wage losses, which may take up to 20 years to bridge the gap in earnings. The social costs of such high and persistent youth unemployment can be large and have long-term effects on economy, and thereby, it is imperative to examine potential causes, consequences, and solutions for the youth labor market problem.

Among various factors that affect the youth labor market outcomes, we study the impact of technology progress on the youth labor market in Korea. Theories may reach conflicting conclusions on the impact of technology progress on youth employment. For instance, if technology can substitute youth labor, technological advances may decrease the demand for young workers. On the contrary, if young workers tend to have skill sets that complement to new technology than their older peers do, technological progress can increase the demand for young workers. Therefore, the relationship between technology progress and youth employment needs to be examined empirically.

Technology progress increases the effectiveness of capital relative to labor, affecting demands for capital and labor. The magnitude and direction of the effect depend on whether labor and capital are complementary or substitutable. For example, there is voluminous literature that attributes rising skill premium or job polarization observed in the advanced

economies such as the U.S. and Europe to the complementary between capital and skilled labor.[5]

Exiting literature argues that the difference in the elasticity of substitution between capital and labor may depend on the educational level of workers (Krusell et al., 2000) or on routineness of tasks (Autor and Dorn, 2012). We depart from them by examining the elasticity of substitution that varies according to different age groups using the framework in Jaimovich et al. (2013). Using the U.S. data, they show that young workers between 15- and 29-years-old have larger elasticity of substitution than old workers between 30- and 64-years old.[6] Specifically, they focus on the large variations in working hours for young workers. The results of their study imply that technology progress that increases capital efficiency substitutes young workers more than old workers, and thus, in the long run, it is likely to hurt youth employment in the U.S. We examine whether these findings are present in South Korean labor market.

Following Jaimovich et al. (2013), we categorize workers into two groups – young and old (prime-aged) workers[7] – and then examine whether there are differences in the elasticity of substitution between capital and labor among these groups. Different from Jaimovich et al. (2013) that estimate elasticity parameters using time variations observed in the U.S. time series data, we use industry variations to estimate the key parameters. This is due to the lack of available time series data for South Korea and potential structural breaks as the country has experienced a rapid economic growth.

We use yearly data from the Mining and Manufacturing Survey and the Survey on Labor Conditions by Employment Type provided by Statistical Office of South Korea. The sample

[5] See Acemoglu (2002), Acemoglu and Autor (2011), Autor and Dorn (2013), and Shim and Yang (2018) among others.

[6] In Table 4 of Jaimovich et al. (2013), the estimated capital elasticity of young workers is 3.3 while that of older workers is 1.2.

[7] In this paper, we interchangeably use old and prime-aged workers since prime-aged workers are relatively old to young workers aged 15 to 29 years.

period is from 2000 to 2014.[8] Our analysis is limited to manufacturing sector due to the scope of the Mining and Manufacturing Survey. We identify our parameters of interest using industry-level heterogeneity. For the robustness check, we estimate the elasticity for different age groups using other cut-offs, male only, by education level, by occupation, and by firm size.

In the empirical analysis, we estimate the moment conditions derived from the production function that differentiates young and old workers by two-step generalized methods of moment (GMM, henceforth) as in Jaimovich et al. (2013). Our findings can be summarized as follows. First, the elasticity of substitution between capital and labor is greater (or at least not smaller) for young workers than for old workers. However, the difference in the estimated elasticity is not as large as that of the U.S. For instance, using the Ordinary Least Squares (OLS, henceforth) estimation, the elasticity for the young (15–29-year-old) age group is 1.77, while that for the prime (30–64-year-old) age group is 1.54. The difference in coefficients is statistically significant at the 10 percent level. Although the difference is smaller than the estimates in Jaimovich et al. (2013), we can conclude that, at the very least, technology progress does not have positive effects on young workers relative to old workers.

Moreover, our findings are robust to a different estimation methodology, instrumental variables approach, and to different subgroup analyses, including education attainment, male only, different age group cut-offs, occupations, and firm size. If we limit our sample to workers with some college and above, the estimated elasticity for young workers is 2.75 and the elasticity for old workers is 1.98, and the difference is significant at 1 percent level. Male-only sub-sample results also support our findings: the difference in the estimated elasticity between young (1.85) and old (1.60) workers is statistically significant. If the sample is

[8] Data for 2010 are unavailable since the Mining and Manufacturing Survey was not conducted for the year. Instead, the Economic Census, a quinquennial survey for all establishments with at least one employee that are doing business, was conducted.

divided into two based on the firm size, large (more than 300 employees) and small and medium sized (less than 300 employees) firms, the results are more pronounced for small and medium sized firms. The elasticity for young and old workers is 2.57 and 1.64, respectively, and the difference in the elasticity among two age groups is significant. However, the results for large firms do not exhibit statistically significant differences between two age groups.

Overall, our findings show that it is difficult to improve weakened youth employment conditions through technology progress and that the current high level of youth unemployment may persist due to this structural factor. The results of this paper suggest that technology advances can affect the labor market by demanding more prime-aged workers than young workers because old workers are relatively complementary for capital. Therefore, it is important to develop policies that can potentially lower the elasticity of substitution between capital and young workers.

The paper is organized as follows. Section 2 introduces the empirical framework and describes data. Section 3 presents our main empirical findings and Section 4 concludes.

2. Empirical Framework

2.1. Model and Estimation

To estimate the elasticity of substitution between labor and capital, we consider the following production function as in Jaimovich et al. (2013).

$$Y_t^i = \left[\mu\left(A_t H_{Yt}^i\right)^\sigma + (1-\mu)\left(\lambda\left(K_t^i\right)^\rho + (1-\lambda)\left(A_t H_{ot}^i\right)^\rho\right)^{\sigma/\rho}\right]^{\frac{1}{\sigma}}, \tag{1}$$

where $\mu > 0,\ \sigma, \rho < 1$.

H_{Yt}^i denotes total hours worked, i.e., labor input, for young workers of ith industry at time t and H_{ot}^i the same for old workers. K_t^i denotes (physical) capital (equipment), and A_t denotes the labor-augmenting technology change. The key parameters are the elasticity of substitution

between young workers and capital, $1/(1-\sigma)$, and the elasticity of substitution between old workers and capital, $1/(1-\rho)$. As σ increases, young workers are more likely to be substituted by capital when technology advances. If we consider age as labor market experience, as Krusell et al. (2000) and Jaimovich et al. (2013) do, the difference in σ and ρ can be explained by capital-experience complementarity. When $\sigma > \rho$, the elasticity of substitution between labor and capital is greater for young workers than prime age workers who have more experience.

Assuming perfectly competitive goods and factor markets, the first order conditions derived from the firm's profit maximization can be written as follows.

$$r_t^i = \left(Y_t^i\right)^{(1-\sigma)}(1-\mu)\Omega_t^i\lambda\left(K_t^i\right)^{(\rho-1)}, \tag{2}$$

$$W_{ot}^i = \left(Y_t^i\right)^{(1-\sigma)}(1-\mu)\Omega_t^i(1-\lambda)\left(H_{ot}^i\right)^{(\rho-1)}, \tag{3}$$

$$W_{Yt}^i = \left(Y_t^i\right)^{(1-\sigma)}\mu A_t^\sigma\left(H_{Yt}^i\right)^{(\sigma-1)}, \tag{4}$$

where $\Omega_t^i = \left[\lambda K_t^\rho + (1-\lambda)\left(A_t H_{ot}^i\right)^\rho\right]^{(\sigma-\rho)/\rho}$. r_t^i denotes the rate of return on capital and W_{ot}^i (resp. W_{Yt}^i) denotes the wage rate of old (resp. young) workers in industry *i* at time *t*.

To estimate the elasticity parameters, we consider the factor demand equations for each age group. First, we take logarithm of both sides of Equation (4) and first-difference them:

$$\Delta \ln W_{Yt}^i = \alpha_0 + (1-\sigma)\Delta ln\, Y_t^i + (\sigma-1)\Delta ln\, H_{Yt}^i + \sigma u_t, \tag{5}$$

where α_0 is a constant. $A_t = \exp(gt + z_t)$, where $z_t = \phi z_{t-1} + \epsilon_t$ and $\phi \in (0,1)$. Therefore, u_t is an error term that can be expressed as a function of current and lagged shocks.

$$u_t = \epsilon_t + (\phi - 1)(\epsilon_{t-1} + \phi\epsilon_{t-2} + \cdots). \tag{6}$$

Following Jaimovich et al. (2013), we derive the following equation from Equation (5) in order to estimate σ using the aggregate data.

$$\Delta\ln LI_{Yt}^{i} - \Delta\ln Y_{t}^{i} = \alpha_1 + \sigma\left(\Delta\ln H_{Yt}^{i} - \Delta\ln Y_{t}^{i}\right) + \sigma u_t, \tag{7}$$

where LI denotes labor income for workers. In order to estimate σ, we need data for labor income of young workers at the industry level, total hours worked, and industry-level GDP or value added.

Similarly, we can derive Equation (8) using Equations (2) and (3) to estimate ρ.

$$\Delta\ln W_{ot}^{i} - \Delta\ln r_{t}^{i} = \alpha_2 + (\rho - 1)\left(\Delta\ln \mathrm{H}_{\mathrm{ot}}^{\mathrm{i}} - \Delta\ln \mathrm{K}_{\mathrm{t}}^{\mathrm{i}}\right) + \rho u_t, \tag{8}$$

where α_2 is a constant. We transform Equation (8) similar to the case of young workers' labor demand equation.

$$\Delta\ln Q_{ot}^{i} - \Delta\ln Q_{Kt}^{i} = \alpha_2 + \rho\left(\Delta\ln H_{ot}^{i} - \Delta\ln K_{t}^{i}\right) + \rho u_t, \tag{9}$$

where Q_{ot}^{i} denotes the share of the prime-aged workers' labor income to national total income and Q_{Kt}^{i} the share of total income earned by capital by the industry level. In order to estimate ρ from Equation (9), we need data for the share of income earned by old workers, the share of income earned by capital, total hours worked by old workers, and total capital. The share of total income earned by capital is computed by 1 minus the labor share in national income.

To summarize, our aim is to estimate Equations (7) and (9). As Jaimovich et al. (2013) noted, the two equations share the same error term and joint estimation using two-step GMM is more efficient. The combined equation for joint estimation is

$$\Delta\ln LI_{y,t}^{i} - \Delta\ln Y_t^i - \alpha_1 + \sigma/\rho\alpha_2 - \sigma\left(\Delta\ln H_{y,t}^{i} - \Delta\ln Y_t^i\right)$$
$$-\sigma/\rho\left(\Delta\ln LI_{o,t}^{i} - \Delta\left(\ln \mathrm{Y}_\mathrm{t}^\mathrm{i} - \ln \mathrm{w}_\mathrm{t}^\mathrm{i}\right)\right) + \sigma\left(\Delta\ln H_{o,t}^{i} - \Delta\ln K_t^i\right) = 0. \qquad (10)$$

We estimate Equation (10) using the two-step GMM. However, as Jaimovich et al. (2013) pointed out, endogeneity issue may arise since we estimate factor demand equations. Hence, we employ an instrumental variable to address the endogeneity problem. We discuss the details of how we address the potential endogeneity using our instrumental variable in Section 3.

2.2. Data

Main variables for our empirical analyses are related to the data for physical assets and employment. Specifically, we construct a dataset of the industry-level labor income and total hours worked by age-group, GDP (or value added) by industry, and capital stocks. We use data from the Mining and Manufacturing Survey and the Survey of Labor Conditions by Employment Type produced by Statistics Korea.[9]

First, the Mining and Manufacturing Survey is conducted annually targeting establishments at least 10 employees that are located in South Korea and fall into the category of mining and manufacturing according to the Korean Standard Industrial Classification.[10] This survey is a census survey and carried out during the period between June 10th and July 14th. The survey reference period is between January 1st and December 31st. We use the data from 2000 to 2014, except 2010. The data for the year of 2010 is unavailable because the survey was not conducted. Instead of the Mining and Manufacturing Survey, the

[9] We refer to the official website of Statistics Korea for the detailed explanation of each statistics: Mining and Manufacturing Survey (https://meta.narastat.kr/metasvc/index.do?orgId=101&confmNo=101009&kosisYn=Y), Survey of Labor Conditions by Employment Type (https://meta.narastat.kr/metasvc/index.do?orgId=118&confmNo=118020&kosisYn=Y).
[10] The target population is approximately 70,000.

Economic Census, a quinquennial survey for all establishments with at least one employee that are doing business, was conducted in 2011. Due to the lack of data of 2010, we were not able to estimate the equations during the period of 2009-2010 and 2010-2011 as our empirical model is structured using the variables in annual growth rates. We also exclude data of the manufacture of tabaco products because the production of such products is limited to a specific region in Korea.[11] Altogether we use total value added, employee expenses, and equipment (physical assets) at the industry level from this data source.[12] To transform nominal variables into real terms, we use the industry-level investment deflators computed from Economic Statistics System (ECOS) of the Bank of Korea.

Second, the Survey on Labor Conditions by Employment Type is a sample survey of around 32,000 workplaces with at least one employee. To maintain consistency with the Mining and Manufacturing Survey, we restrict our sample to the enterprises with over 10 employees. This annual survey has been conducted since 1984 but we only consider the data from 2000 to ensure consistency in the industry classification with the Mining and Manufacturing Survey. The survey reference period is June. For our empirical analysis, we use total wage and hours worked at the industry level.

To aggregate the data into two age groups, we use the probability weights (pweight) provided in the Survey of Labor Condition by Employment Type. If necessary, we explain the variables in more detail in Section 3 as we present the empirical results.

3. Results

3.1. Baseline Results

[11] See Table A1 in Appendix A for the detailed industry classification used in our paper.

[12] Therefore, we limit our empirical analysis to the manufacturing sector. To expand our sample to service sector, we need to use data of total capital that include property. However, it is difficult to assume that the elasticity of substitution between property capital and labor differs across generations. Therefore, we only examine manufacturing sector of which the data for the capital (equipment) is available.

Table 1 presents the results from the OLS estimation of Equation (10). The main findings can be summarized into two. First, the elasticity of substitution between labor and capital is estimated to be greater than 1 for both age groups. The elasticity of substitution between young workers and capital is approximately 1.77 while that between old workers and capital is about 1.54. The result implies that the production of Korean economy tends to be more easily explained by the Constant Elasticity of Substitution (CES) function than Cobb-Douglass production function. Second, similar to the findings in Jaimovich et al. (2013), the difference in the parameters of young and old workers is statistically significant at 10 percent level albeit it is not as large as in the U.S. case.[13] This implies that technology advances that improve efficiency of physical capital may not actively increase the labor demand for young workers relative to prime age workers.

Table 1. Estimates of the elasticity parameters

	Point Estimate	Standard Error	p-value ($\sigma = \rho$)
σ	0.434***	0.116	< 0.10
ρ	0.350***	0.077	
Observations	228		

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

For instance, suppose young workers are perfectly substitutable for capital while old workers are perfect complement to composite of capital and young workers.[14] If the price of capital falls due to technological progress, the demand for young workers declines but the demand for old workers does not necessarily decline unless the composites of young workers and capital decrease. This example highlights the possibility that youth labor market conditions can suffer from structural problems even if there are substantial advances in technology in the fourth wave of the industrial revolution.

[13] In Jaimovich et al. (2013) using the U.S. data, the estimated σ is 0.662 and ρ 0.201.
[14] In mathematical terms, $Y = \min\{H^o, H^Y + K\}$.

Table 2 shows the results based on the estimation by various age cut-offs. The estimated parameters range from 0.2 to 0.5 and the differences between σ and ρ tend to be statistically significant in many specifications. If we conservatively interpret this result, the elasticity of substitution between young workers and capital is at least not as small as the elasticity between old workers and capital.

Table 2. Estimates of the elasticity parameters: various age cut-offs

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
25-35/ 50-60	σ	0.498***	0.140	< 0.05
	ρ	0.391***	0.100	
25-40/ 40-55	σ	0.348***	0.144	> 0.10
	ρ	0.298***	0.108	
15-34/ 35-64	σ	0.387***	0.148	> 0.10
	ρ	0.317***	0.100	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

As Jaimovich et al. (2013) discussed, there is potential endogeneity problem if the key elasticity parameters are estimated using the OLS regression of labor demand functions. For instance, other factors, such as major policy changes in the labor market, may affect hours worked and wage simultaneously. In order to identify exogenous changes that are uncorrelated with labor demand, Jaimovich et al. (2013) implement an instrumental variables approach using the 15-year lagged birth rate. It is a valid instrument because changes in the past fertility affect current labor supply but are exogenous to technology shock innovations.

Our empirical framework, however, does not allow us to adopt the lagged birth rate as an instrument. Our estimation scheme requires industry variations to identify labor demand but birth rate does not exhibit any industry variations.[15] We instead use occupational fatality rates

[15] It is possible to conduct additional robustness checks by constructing time series database as in Jaimovich et al. (2013). However, we have only 33 observations from 1983 to 2016 if we limit our sample to manufacturing sector. If we expand our sample to the entire sectors, data for equipment capital is not available. Therefore, we focus on the estimation scheme that uses industry variations.

– the number of work-related deaths per 10,000 workers – that potentially affect labor supply to the industry.[16] Occupational fatality rates are correlated with labor supply because workers are less willing to work for the industries with higher probability of occupational fatalities. Fatality rates are valid if they are uncorrelated with changes in the elasticity of substitution between labor and capital. Similar to the argument in Jaimovich et al. (2013), lagged occupational fatality rates can be more appropriate, but data are only available from 2000 where our sample starts. Therefore, we use industry-level occupational fatality rates from 2000 as our instrumental variable.

The results (see Table 3) by adopting the instrumental variables approach are consistent with the results from OLS regression, both qualitatively and quantitatively. Henceforth, we present the robustness results from instrumental variable estimations for simplicity.[17]

Table 3. Estimates of the elasticity parameters: Instrumental variable

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.387***	0.099	< 0.10
	ρ	0.324***	0.069	
25-35/ 50-60	σ	0.527***	0.122	< 0.01
	ρ	0.403***	0.097	
15-34/ 35-64	σ	0.327***	0.088	< 0.01
	ρ	0.281***	0.072	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

3.2. Robustness Check

3.2.1. Sample limited to male only

In general, the labor supply elasticity of female workers is likely to be more elastic than that of male workers (e.g. added worker effect). This can generate potential bias from changes in composition (Castro and Coen-Pirani, 2008). To address this issue, we restrict our

[16] Official data are available from Statistics Korea webpage: http://kosis.kr/statHtml/statHtml.do?orgId=118&tblId=DT_11806_N000&conn_path=I3.
[17] The OLS results are available upon request.

sample to male only and estimate the elasticity parameters to check if there are any differences in results.[18] The result in Table 4 shows that our findings in the baseline estimation remain unchanged: the elasticity of substitution is greater for young workers than old workers and the difference is statistically significant. The findings are also robust to changes in age cut-offs.

Table 4. Estimates of the elasticity parameters: male workers only

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.460***	0.112	< 0.05
	ρ	0.373***	0.076	
25-35/ 50-60	σ	0.576***	0.120	< 0.01
	ρ	0.444***	0.096	
15-34/ 35-64	σ	0.366***	0.105	< 0.05
	ρ	0.311***	0.083	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

3.2.2. The level of educational attainment

Existing literature has shown that the level of educational attainment, a proxy for workers' skill, may affect the elasticity of substitution between labor and capital (Krusell et al., 2000; Balleer and van Rens, 2013). Studies suggest that workers with higher levels of education, some college or above, tend to have higher values of the elasticity of substitution than those with low levels of education, secondary education or below (see, for example, Krusell et al., 2000). If the average levels of educational attainment are different between two age groups, the estimated parameters in our baseline model can be biased. To address this issue, we divide the sample into two based on the level of educational attainment: workers with at least some college and with below some college.

[18] The share of male employees in our sample is 75 percent.

Tables 5 and 6 show that the results are robust to the sub-sample estimations based on educational levels. This supports the baseline results of relatively higher elasticity of substitution for young workers than old workers. In addition, it suggests that the difference in the elasticity between the two age groups in the baseline is not due to the education level difference between generations.

Table 5. Estimates of the elasticity parameters: some college and above

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.637***	0.101	< 0.01
	ρ	0.494***	0.083	
25-35/ 50-60	σ	0.773***	0.104	< 0.01
	ρ	0.605***	0.085	
15-34/ 35-64	σ	0.538***	0.128	< 0.01
	ρ	0.444***	0.100	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

Table 6. Estimates of the elasticity parameters: high school graduate and below

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.414***	0.097	< 0.05
	ρ	0.352***	0.072	
25-35/ 50-60	σ	0.540***	0.141	< 0.01
	ρ	0.422***	0.111	
15-34/ 35-64	σ	0.323***	0.099	< 0.05
	ρ	0.283***	0.083	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

3.2.3. Occupation

To account for another potential bias, we consider different types of occupation in estimating the elasticity of substitution. As in Acemoglu and Autor (2011), Autor and Dorn (2013), and Shim and Yang (2018), workers dealing with routine tasks are more likely to be substituted with information and communication technology (ICT, henceforth) capital whereas cognitive, creative, jobs cannot be easily replaced by machines. Therefore, the type

of occupation is an important factor that can affect the elasticity of substitution between labor and capital. Following the job polarization literature, we classify occupations into three groups: non-routine cognitive, routine, and non-routine manual occupations. Non-routine cognitive occupations refer to occupations that require workers to conduct creative and cognitive tasks. Routine occupations, such as sales and administrative office occupation, are the jobs that can be easily replaced by machines. Non-routine manual occupations are services and jobs involving physical tasks.[19] Job polarization refers to the phenomenon where routine occupations have been replaced by machines, relative to other occupations, due to the increased automation since the mid-1980s. Biases can arise due to the heterogeneity in the elasticity of substitution across different types of occupations if not properly addressed. In order to address this issue, we divide our sample into three types of occupations and estimate the elasticity of substitution for two age groups.[20]

Tables 7-9 present the results that are consistent with our baseline findings: young workers are not as complementary to capital as old workers in general. The elasticity of substitution is greater for non-routine cognitive and non-routine manual jobs, which are in the extreme of the skill distribution, than for routine occupations. While this seems to be contrasting with the findings in job polarization literature, it is not: it is because we estimate the elasticity between total physical capital (equipment) and labor while the literature considers the elasticity between ICT capital and labor.[21]

Table 7. Estimates of the elasticity parameters: non-routine cognitive occupations

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.772***	0.089	< 0.01
	ρ	0.644***	0.069	

[19] See Table B1 in Appendix B for the details of how we classify occupations into three.
[20] The number of observations in each occupation group varies because routine and non-routine manual occupations are not observed in several industries.
[21] As discussed in Shim and Yang (2018), the effect of ICT capital on labor demand can be different from that of non-ICT capital on labor demand.

25-35/ 50-60	σ	1.034***	0.075	< 0.01
	ρ	0.839***	0.063	
15-34/ 35-64	σ	0.692***	0.114	< 0.01
	ρ	0.591***	0.081	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

Table 8. Estimates of the elasticity parameters: routine occupations

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.421***	0.087	< 0.05
	ρ	0.347***	0.061	
25-35/ 50-60	σ	0.566***	0.136	< 0.01
	ρ	0.430***	0.107	
15-34/ 35-64	σ	0.373***	0.086	< 0.01
	ρ	0.314***	0.070	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 153, 185, and 181, respectively.

Table 9. Estimates of the elasticity parameters: non-routine manual occupations

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.896***	0.027	> 0.10
	ρ	0.944***	0.061	
25-35/ 50-60	σ	0.942***	0.022	> 0.10
	ρ	0.812***	0.068	
15-34/ 35-64	σ	0.874***	0.025	> 0.10
	ρ	0.897***	0.047	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 153, 185, and 181, respectively.

3.2.4. Size of firms

Lastly, we consider potential biases due to the firm size. It is possible that the ability to develop high-level technology and ability to raise capital may differ across firms depending on their sizes. For instance, large firms may have enough funds to adopt new technology using ICT capital while small firms are financially constrained so that they are more labor-intensive. In order to confirm the robustness of our findings in this regard, we split our sample into large and small/medium sized firms with a cut-off of 300 employees.

Tables 10 and 11 present interesting findings. The results from small and medium sized firms show that the elasticity of young workers is significantly greater than that of old workers while the results from large firms do not exhibit significant differences in the elasticity between two age groups. In particular, if we classify age groups into 15–29-year-old and 30–64-year-old, following Jaimovich et al. (2013), the elasticity of substitution in small and medium sized firms is significantly greater for young workers than for old workers at 1 percent level. This implies that experienced (older) workers in small and medium firms have higher complementarity with capital than those in large firms.[22] This might also be because young workers in large firms are likely to be different from those in small and medium sized firms: the former are more selective and more likely to adjust themselves to the technological progress than the latter. As small and medium sized firms account for a large share of employment in Korea, the more elastic labor demand for young workers of small and medium sized firms can cause a structural problem that may worsen youth labor market conditions.[23]

Table 10. Estimates of the elasticity parameters: large firms (more than 300 employees)

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.167***	0.064	> 0.10
	ρ	0.173***	0.069	
25-35/ 50-60	σ	0.271***	0.056	> 0.10
	ρ	0.301***	0.067	
15-34/ 35-64	σ	0.123***	0.046	> 0.10
	ρ	0.137***	0.053	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 209.

[22] According to a survey by Incruit Corporation, a Korean internet company that provides a marketplace for job seekers and companies, 75 percent of recruiters working for small and medium sized firms prefer experienced workers to freshers when the economy suffers downturns. Source: https://news.v.daum.net/v/20081103085715784.

[23] As of 2017, the share of workers for the small and medium sized firms (less than 300 employees) amounts to 90 percent. Source: Statistics Korea, Employment by size of firms.

Table 11. Estimates of the elasticity parameters: small/medium size firms (less than 300 employees)

		Point Estimate	Standard Error	p-value ($\sigma = \rho$)
15-29/ 30-64	σ	0.611***	0.098	< 0.01
	ρ	0.391***	0.045	
25-35/ 50-60	σ	0.853***	0.132	< 0.01
	ρ	0.522***	0.060	
15-34/ 35-64	σ	0.598***	0.132	> 0.10
	ρ	0.439***	0.051	

Notes: Standard errors are robust standard errors. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is 228.

4. Conclusion

In this paper, we estimate the elasticity of substitution between capital and young (and old) workers à la Jaimovich et al. (2013). Our finding, which is robust to various empirical specifications and subgroup analyses, indicates that young workers are more substitutable for capital than old workers. A potential explanation for this result, which is in line with the previous findings, is that capital is more complementary to experienced (old) workers (Krusell et al., 2000). This finding implies that technology progress itself may not resolve the youth unemployment problem in South Korea as young workers are more vulnerable to the progress than older workers. One possible reason might be mismatch in the labor market: young workers tend to have less knowledge and information about their skills and potential employers, and hence they are likely to be employed in firms where the firm-specific capital is not complementary to their skills (Guvenen, 2007; Chang et al., 2018). On the other hand, old workers have relatively better knowledge about their skills and the mismatch problem is less severe comparing to young workers. Therefore, our finding has an important policy implication: the current youth unemployment problem could be partially resolved by providing young workers with specific information about skills required by potential

employers to lower the skill mismatch problem. We leave applying our finding in studying the property of business cycles with two age groups as a future work.

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Appendix A: Industrial Classification

Table A1. Korean Standard Industrial Classification Codes

Code	KSIC-9 Code	Industry	KSIC-8 Code	Industry
1	10	Manufacture of Food Products	15	Manufacture of Food Products and Beverages
	11	Manufacture of Beverages		
2	12	Manufacture of Tobacco Products	16	Manufacture of Tobacco Products
3	13	Manufacture of Textiles, Except Apparel	17	Manufacture of Textiles, Except Sewn Wearing Apparel
4	14	Manufacture of wearing apparel, Clothing Accessories and Fur Articles	18	Manufacture of Sewn Wearing Apparel and Fur Apparel
5	15	Tanning and Dressing of Leather, Manufacture of Luggage and Footwear	19	Tanning and Dressing of Leather, Manufacture of Luggage and Footwear
6	16	Manufacture of Wood Products of Wood and Cork; Except Furniture	20	Manufacture of Wood Products of Wood and Cork; Except Furniture
7	17	Manufacture of Pulp, Paper and Paper Products	21	Manufacture of Pulp, Paper and Paper Products
8	18	Printing and Reproduction of Recorded Media	22	Publishing, Printing and Reproduction of Recorded Media
9	19	Manufacture of Coke, hard-coal and lignite fuel briquettes and Refined Petroleum Products	23	Manufacture of Coke, Refined Petroleum Products and Nuclear Fuel
10	20	Manufacture of chemicals and chemical products except pharmaceuticals, medicinal chemicals	24	Manufacture of chemicals and chemical products
	21	Manufacture of Pharmaceuticals, Medicinal Chemicals and Botanical Products		
11	22	Manufacture of Rubber and Plastic Products	25	Manufacture of Rubber and Plastic Products
12	23	Manufacture of Other Non-metallic Mineral Products	26	Manufacture of Other Non-metallic Mineral Products
13	24	Manufacture of Basic Metal Products	27	Manufacture of Basic Metal Products
14	25	Manufacture of Fabricated Metal Products, Except Machinery and Furniture	28	Manufacture of Metal Components, Except Machinery and Furniture
15	26	Manufacture of Electronic Components, Computer, Radio, Television and Communication Equipment and Apparatuses	30	Manufacture of Computer, Office Equipment
			32	Manufacture of Electronic Components, Radio, Television and Communication Equipment and Apparatuses
16	27	Manufacture of Medical, Precision and Optical Instruments, Watches and Clocks	33	Manufacture of Medical, Precision and Optical Instruments, Watches and Clocks

17	28	Manufacture of electrical equipment	29	Manufacture of Other Machinery and Equipment
	29	Manufacture of Other Machinery and Equipment	31	Manufacture of Other Electrical Equipment and Transformers
18	30	Manufacture of Motor Vehicles, Trailers and Semitrailers	34	Manufacture of Motor Vehicles, Trailers and Semitrailers
19	31	Manufacture of Other Transport Equipment	35	Manufacture of Other Transport Equipment
20	32	Manufacture of Furniture	36	Manufacture of Furniture and Other manufacturing Products
	33	Other manufacturing		

Appendix B: Occupation Classification

Table B1. Korean Standard Classification of Occupations Codes

Code		Occupation	Type
1		Managers	Non-routine cognitive
2		Professionals and Related Workers	Non-routine cognitive
3		Clerks	Routine
4		Service Workers	Non-routine manual
5		Sales Workers	Routine
6		Skilled Agricultural, Forestry and Fishery Workers	-
7		Craft and Related Trades Workers	Routine
8		Equipment, Machine Operating and Assembling Workers	Routine
9		Elementary Workers	-
	91	Construction and Mining Related Elementary Occupations	Routine
	92	Transport Related Elementary Occupations	Routine
	93	Production Related Elementary Occupations	Routine
	94	Cleaning and Guard Related Elementary Occupations	Non-routine manual
	95	Household Helpers, Cooking Attendants and Sales Related Elementary Workers	Non-routine manual
	99	Agriculture, Forestry, Fishery and Other Service Elementary Occupations	Non-routine manual