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The Impact of COVID-19 on Jobs in Korea: Does Contact-intensiveness Matter?†

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This paper studies how COVID-19 has affected the labor market in Korea through a general equilibrium model with multiple industries and occupations. In the model, workers are allocated to one of many occupations in an industry, and industrial or occupational shocks alter the employment structure. I calibrate the model with Korean data and identify industrial and occupational shocks, referred to here as COVID-19 shocks, behind the employment dynamics in 2020 and 2021. I find that COVID-19 shocks are more severe for those with jobs with a higher risk of infection and in those that are more difficult to do from home. Interestingly, the relationship between COVID-19 shocks and infection risk weakened as the pandemic progressed, whereas the relationship between COVID-19 shocks and easiness of work-from-home strengthened. I interpret the results as meaning that the pandemic may direct future technological changes to replace tasks that require contact-intensive steps, and I simulate the impact of such technological changes through the lens of the model. The results show that such technological changes will lower the demand for manual workers compared to the demands for other occupations. This contrasts with the earlier trend of job polarization, where manual workers continued to increase their employment share, with the share of routine workers secularly declining at the same time.

Key Word: COVID-19, Contact Intensiveness, Job Polarization, Directed Technological Change
JEL Code: E24, I14, J23, O33

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I. Introduction

COVID-19 has led the world economy to the worst economic crisis since the Great Depression. The IMF's World Economic Outlook estimates a -3.1% drop in global GDP in 2020, a much more severe recession than the -0.1% drop in global GDP during the Global Financial Crisis. The labor market was hit especially hard by the spread of the virus. COVID-19 dampened labor demand and reduced the labor supply due to quarantine policies and fear of infection. In Korea, the number of employed persons decreased by 1.8% (473 thousands persons) from February of 2020 to February of 2021.

The economic impact of the pandemic may not be confined to a short-term recession. Structural changes in the labor market were underway even before the pandemic, and these changes continued intensively during the economic recession. Many studies have documented a declining trend of middle-skill routine worker employment (as opposed to high-skill cognitive workers and low-skill manual workers) over several decades, a phenomenon referred to as job polarization. This disappearance of middle-skill jobs has also been more prominent during economic recessions as compared to normal times (Jaimovich and Siu, 2020). The recent recession with the COVID-19 pandemic, not an exception, could also accelerate structural changes in the labor market.

The pandemic appears to affect not only the speed but also the direction of structural changes in the labor market. The COVID-19 recession has had significantly heterogeneous impacts across industries and occupations compared to previous recessions (Aum, Lee, and Shin, 2021a). The heterogeneous nature of the COVID-19 shock implies that relative productivity levels between occupations and industries must have diverged to a substantial extent during the pandemic, likely affecting the direction of technological change. Therefore, as researchers grope for the direction of change in the labor market structure after the COVID-19 pandemic, analyses of the nature of shocks that stand out during the pandemic are necessary.

This paper aims to identify COVID-19 shocks that differ across industries and occupations during the pandemic, thereby deriving implications pertaining to the post-COVID-19 labor market structure. To this end, I introduce a general equilibrium model with multiple industries and occupations in which agents are allocated to one of many occupations in one of many industries. Each industry employs all occupations but with different intensities, and hence both industry- and occupation-specific shocks alter the industrial and occupational employment structures simultaneously. For example, when an occupational shock hits service jobs, it affects the industrial structure as well because the fraction of service jobs differs across industries. The model suitably captures structural changes in the labor market before the pandemic and hence enables us to compare past trends and future changes within a single framework.

I calibrate the model based on Korean data in 2019, just prior to the pandemic, after which I estimate the industrial and occupational productivity shocks that generate Korea's employment dynamics in 2020 and 2021. To examine the characteristics of the identified shocks, I check whether and how the shocks correlate with the infection risk or the easiness of work from home by industry and occupation.

The results are mainly twofold.

First, during the pandemic, employment was hit harder in industries and occupations with higher infection risks and/or difficulties in work from home. In particular, the easiness of work from home was more closely linked to occupational shocks than industrial shocks, implying that it is crucial to pay particular attention to occupational heterogeneity to understand employment dynamics in Korea.

Second, the relationship between employment shocks and the infection risk or easiness of work from home varies over time. In 2020, when employment fell rapidly due to the spread of COVID-19, only the risk of infection showed a significant correlation with COVID-19 shocks. However, in 2021, when employment began gradually to recover, the correlation with easiness of work from home became more significant, whereas the correlation with the risk of infection weakened. This result seems to indicate that the risk of infection was important in the earlier stage of the pandemic, whereas easiness of work-from-home gradually came to eclipse the risk of infection as the pandemic progressed. In this regard, I consider that the effect of infection risk is transitory, while the effect of easiness of work-from-home is more structural and of the type of effect to which technology responds. That is, the cost of contact-intensive tasks rose sharply during the pandemic, especially in its later stage, inducing technological progress to replace such tasks. Recent technological changes have already made the replacement of contact-intensive tasks feasible, as seen in telemedicine, smart finance, and online education platforms. The rapid growth of the online-to-offline (O2O) market before and during the pandemic also suggests that replacing contact-intensive tasks is feasible to some extent. These incentives and the feasibility issue indicate the possibility that technological changes will accelerate the replacement of contact-intensive tasks in the future.

Against this backdrop, I utilize the model to quantify the impacts of the Contact-intensive task Biased Technological Changes (henceforth CBTC) on employment structures in the future, though accurately predicting the future direction of technological change is not possible. Specifically, I compare the employment structure over the next five years with and without CBTC as measured based on each occupation's easiness of work from home. Note that CBTC in this paper would have distinct implications on the labor market structure from Routine Biased Technological Change (henceforth RBTC), a widely accepted view in the recent literature before the pandemic. Jobs have been polarized at least since 1980, and the polarization of the labor market has been often linked to the effect of RBTC (Autor, Levy, and Murnane, 2003, Autor and Dorn, 2013, among others). Specifically, the RBTC hypothesis argued that the rapid evolution of IT technology has displaced jobs that mainly involve routine tasks, which are mostly middle-wage jobs. At the same time, RBTC raised the demand for both low-wage manual workers and high-wage cognitive workers, leading to the disappearance of middle-skill routine jobs

The simulation results in this paper confirm that CBTC has a different impact on the labor market structure from RBTC. Specifically, CBTC reduces the demand for manual workers compared to the pre-COVID-19 trend. Accordingly, due to CBTC, the decline of routine workers is eased and the demand for cognitive workers becomes stronger compared to the earlier trend. This result contrasts with the significant increase in manual employment, accompanied by the decline in routine employment before the pandemic, i.e., job polarization driven by RBTC. An example

that can illustrate the different impacts of CBTC from RBTC is the widespread use of kiosks in restaurants during the pandemic. Kiosks not only automate the routine receipt of food orders but also reduce face-to-face contact between customers and workers. In the view of my analysis, this type of automation differs from the automation of an assembly process in a manufacturing plant, which only replaces routine tasks.

The remainder of the paper is as follows. Section 2 introduces the model. In Section 3, I set the parameter values of the model based on Korean data. Section 4 identifies and examines the characteristics of structural shocks by industry and occupation ultimately to explain the labor market in 2020 and 2021. Section 5 discusses implications related to structural changes in the post-COVID-19 labor market if technological changes continue to replace contact-intensive tasks in the coming years. Section 6 concludes the paper.

II. Model

The model here is a multi-sector macroeconomic model similar to that of Aum, Lee, and Shin (2018). Different from Aum, Lee, and Shin (2018), I do not distinguish between different types of capital goods, instead stressing the endogenous allocation of labor into both industry and occupation. The endogenous determination of the industrial and occupational structure enables an analysis of structural changes both in an occupational dimension and an industrial dimension. There are at least two reasons why I focus on both industrial and occupational dimensions simultaneously.

First, because the labor market has undergone structural changes before the pandemic, it is necessary to take past trends into account for a clear understanding of how the post-pandemic labor market structure would be different with and without the pandemic. It is well known that previous structural changes appeared in both industrial and occupational dimensions. For example, there has been a continuous decline in the employment share of routine jobs, a phenomenon referred to as job polarization. Also, the employment shares of manufacturing industries shrink during the process of structural transformation. I examine whether this trend will continue to prevail for the post-pandemic labor market structure.

Second, the COVID-19 shock has a heterogeneous nature in terms of both industry and occupation. The two main channels by which COVID-19 deters economic activities are fear of infection and restrictions on face-to-face contact due to quarantine policies, which vary across industries and occupations (Aum, Lee, and Shin, 2021b). For example, Aum, Lee, and Shin (2021a) showed that the labor market impact of COVID-19 has been very heterogeneous across occupations, even after controlling for industrial effects.

A. *Environment*

The representative household maximizes utility under the given budget constraints as follows:

$$\max \sum_{t=0}^{\infty} \beta^t u(C_t) \quad s.t.\ C_t + I_t \le Y_t,$$

where C_t denotes consumption, I_t is investment, and Y_t is total output.

The law of motion for capital is expressed as

$$K_{t+1} = I_t + (1-\delta)K_t,$$

where K_t is capital stock and δ represents the rate of depreciation.

Final goods are produced by combining industry output using the CES aggregator, as follows:

(1) $$Y_t = \left(\sum_i \gamma_i^{\frac{1}{\varepsilon}} Y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}.$$

An industry i produces industrial output using capital and labor, where labor is a composite of J occupations. Specifically, an industry i's output is given by

(2) $$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha_i} Z_{i,t}^{1-\alpha_i},$$

(3) $$Z_{i,t} = \left[\sum_{j=1}^{J} \nu_{ij}^{\frac{1}{\sigma}} (M_{j,t} L_{i,j,t})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where $A_{i,t}$ is industry i's productivity, $K_{i,t}$ is industry i's capital stock, $Z_{i,t}$ is industry i's labor composite, $L_{i,j,t}$ is the labor supplied to industry i and occupation j, and $M_{j,t}$ is occupation j's productivity. The parameter σ captures the elasticity of substitution across occupations (or tasks), and ν_{ij} is a weight parameter of occupation j used in industry i.

Note that ν_{ij} in equation (3) differs both by industry i and occupation j such that any change in occupation-specific productivity M_j has heterogeneous effects across industries as well. Similarly, a change in industry-specific productivity A_i also alters occupational employment because each industry employs labor at different levels of intensity.

B. *Equilibrium*

The final goods producer solves the following profit maximization problem:

$$\max\left\{Y-\sum_{i=1}^{I}p_iY_i\right\},$$

where p_i is the price of industry i normalized by the price of the final goods; here I normalize the price of final goods to one.

Solving the final goods producer's problem, we obtain

(4) $$\left(\frac{\gamma_i Y}{Y_i}\right)^{\frac{1}{\varepsilon}}=p_i,\ \text{for}\ i\in\{1,\cdots,I\}.$$

Each industry i 's producer solves

$$\max\left\{p_iY_i-RK-w\sum_{j=1}^{J}L_{ij}\right\},$$

where R is the rate of return on capital and w is the effective wage rate per unit of labor.

From equation (2), a solution to the industry-level producer's problem can be expressed as

(5) $$R=\frac{\alpha_i p_i Y_i}{K_i},$$

(6) $$w=(1-\alpha_i)\left(\frac{p_iY_i}{Z_i}\right)\left(\frac{v_{ij}\tilde{M}_jZ_i}{L_{ij}}\right)^{\frac{1}{\sigma}},\ \text{for}\ j\in\{1,\cdots,J\},$$

where $\tilde{M}_j=M_j^{\sigma-1}$.

The market clearing conditions are

(7) $$K=\sum_i K_i,\ \text{and}\ L=\sum_i L_i=\sum_i\sum_j L_{ij}.$$

Finally, the representative household's problem is expressed as

(8) $$\frac{u'(C)}{\beta u'(C')}=1+r=R+(1-\delta),\ \text{and}\ \lim_{t\to\infty}\beta^t u'(C_t)K_t=0.$$

C. *Model Solution*

Given labor endowment L and capital endowment K, I compute the equilibrium allocation as shown below. For notational convenience, I denote industrial capital stock per capita as $k_i (= K_i / L_i)$, industrial output per capita as $y_i (= Y_i / L_i)$, and industrial labor composite per capita as $z_i (= Z_i / L_i)$.

From equation (6), I have $L_{ij} / L_{i1} = \nu_{ij} \tilde{M}_j / (\nu_{i1} \tilde{M}_1)$ for all j. Therefore, we can express the occupational share in industry i's employment and industrial labor composite per capita as

$$L_{ij} / L_i = \nu_{ij} \tilde{M}_j \tilde{V}_i^{1-\sigma}, \tag{9}$$

$$z_i = \tilde{V}_i := \left(\sum_j \nu_{ij} \tilde{M}_j \right)^{\frac{1}{\sigma-1}}. \tag{10}$$

From equations (5), (6), and (9), we have $R / w = \alpha_i / [(1-\alpha_i) k_i]$. Accordingly, the ratio of capital stock per capita between two industries (i and I) satisfies

$$\frac{k_i}{k_I} = \frac{(1-\alpha_I)\alpha_i}{(1-\alpha_i)\alpha_I}. \tag{11}$$

Also, from equations (4) and (5),

$$\frac{k_i}{k_I} = \left(\frac{\alpha_i}{\alpha_I} \right) \left(\frac{\gamma_i}{\gamma_I} \right)^{\frac{1}{\varepsilon}} \left(\frac{y_i}{y_I} \right)^{\frac{\varepsilon-1}{\varepsilon}} \left(\frac{L_i}{L_I} \right)^{-\frac{1}{\varepsilon}}.$$

Combining this with equation (2), we have the following expression for the ratio of industrial employment.

$$\frac{L_i}{L_I} = \left(\frac{A_i}{A_I} \right)^{\varepsilon-1} \left(\frac{\tilde{V}_i^{(1-\alpha_i)(\varepsilon-1)}}{\tilde{V}_I^{(1-\alpha_I)(\varepsilon-1)}} \right) \left(\frac{\alpha_i}{\alpha_I} \right)^{\varepsilon} \left(\frac{k_i^{\alpha_i(\varepsilon-1)-\varepsilon}}{k_I^{\alpha_I(\varepsilon-1)-\varepsilon}} \right) \left(\frac{\gamma_i}{\gamma_I} \right). \tag{12}$$

At this point, I can compute the ratio of industrial employment and industrial capital per capita from equations (11) and (12) and hence industrial employment and capital stock. Substituting industrial employment and capital stock into equation (2), we can compute industrial output (Y_i). Subsequently, we can compute the final output (Y) from equation (1) and the industrial price (p_i) from equation (4). The equilibrium level of rate of return (R) and the wage rate (w) are obtained

correspondingly from equations (5) and (6). Lastly, substituting industrial employment into equation (9), we find the occupational employment in each industry (L_{ij}), from which occupational employment is determined, as follows:

$$L_j = \sum_i L_{ij} = \sum_i (v_{ij} \tilde{M}_j \tilde{V}_i^{1-\sigma}) L_i. \tag{13}$$

Equations (9), (12), and (13) show how changes in exogenous productivity A_i and M_j affect industrial and/or occupational employment. For example, a rise in A_i would reduce the price of industry i, p_i. When the elasticity of substitution across industries is less than one ($\varepsilon < 1$), the amount of input in industry i would become smaller. The first bracket in equation (12) shows this substitution effect.

Each industry employs all occupations with different levels of intensity, meaning that changes in occupational productivity (M_j) also affect the industrial total factor productivity and hence industrial employment. For example, a rise in M_j would increase $\tilde{V}_i$ more in an industry that employs occupation j more intensively than others (i.e., an industry with a higher v_{ij}). This would affect industrial employment through the second bracket on the right-hand side of equation (12). More formally, industry i 's production is $Y_i = A_i Z_i^{1-\alpha_i} K_i^{\alpha_i} L_i^{1-\alpha_i}$ from equations (2) and (10), indicating that industry i 's measured total factor productivity is $A_i Z_i^{1-\alpha_i}$, a combination of these values of A_i and M_j.

Similar to industrial employment, changes in both A_i and M_j affect occupational employment. Changes in M_j would alter occupational employment directly in equation (13) and indirectly through changes in industrial employment L_i. Because changes in A_i alter industrial employment, they also affect occupational employment, as shown in equation (13).

Note that an increase in $\tilde{M}_j$ would raise demand for occupation j (equation 13). Given that $\tilde{M}_j := M_j^{\sigma-1}$, an increase in $\tilde{M}_j$ is associated with an increase in M_j if $\sigma > 1$ and a decrease in M_j if $\sigma < 1$. Empirically, the literature finds elasticity of substitution across different occupations to be less than one, implying that an increase in occupation-specific productivity can be interpreted as technological progress substituting for labor in occupation j.

III. Parameterization

First, I define industry and occupation to connect the model with the data. The model's industry and occupation are classified into thirteen industries and eight occupations referring to the Korean Standard Industry Classification (KSIC), Economic Activities in the National Account, and the Korean Standard Occupational Classification (KSOC) (see Table A1 for details). This classification yields 104 (= 13 industries × 8 occupations) industry-occupation pairs, but I report parameter values for three broad industries and three broad occupations in the main text for an intuitive explanation, while reporting detailed results in Appendix A. The three broad occupational groups are set as cognitive, routine, and manual occupations, following

TABLE 1—CATEGORIES OF INDUSTRY AND OCCUPATION

	Broad categories	Detailed categories
Industry (*i*)	Manufacturing	Manufacturing (1), Construction (3)
	Contact-intensive services	Electricity, gas, water supply (2), Wholesale and retail, accommodation, and food (4), Transportation and storage (5), Business support (9), Human health and social work (11)
	Other services	Finance and insurance (6), Real estate (7), Information and communication (8), Education (10), Cultural and other (12), Professional, scientific, and technical (13)
Occupation (*j*)	Cognitive	Management (1), Professional (2)
	Routine	Clerks (3), Sales workers (5), Craft and trades workers (6), and Equipment, machine operating and assembling workers (7)
	Manual	Service workers (4), Elementary workers (8)

Acemoglu and Autor (2010), and the three broad industry categories are manufacturing, contact-intensive services, and other services. Classification of service industries is based on the industry's employment-weighted average of work-from-home index, which I describe in detail later. Table 1 summarizes the industrial and occupational classifications.

A. *Estimation of production function parameters*

The parameters of the final goods production function in equation (1) are the elasticity of substitution between industries (ε) and the weight parameters (γ_i). From the equilibrium condition in equation (4), I formulate the following relationship:

$$\log\frac{p_i Y_i}{p_I Y_I} = \frac{1}{\varepsilon}\log\frac{\gamma_i}{\gamma_I} + \frac{\varepsilon - 1}{\varepsilon}\log\frac{Y_i}{Y_I}.$$

I estimate the equation above by the iterated feasible generalized non-linear least squares (IFGNLS) method following Herrendorf, Rogers, and Valentinyi (2013). Because the substitution elasticity is greater than 0 and the weight parameters are located between 0 and 1, the estimation equation becomes

$$\log\frac{p_i Y_i}{p_I Y_I} = (1+e^b)c_i + e^b \log\frac{Y_i}{Y_I} + u_i,$$

where the elasticity of substitution ($\varepsilon = 1/(1+e^b)$) and the weight parameters ($\gamma_i = e^{c_i} / (1+\sum e^{c_i})$ are inferred from estimates of b and c_i. The sample period is from 2005 to 2019, and the nominal and the real value added by economic activity from the National Accounts correspond to $p_i Y_i$ and Y_i, respectively.

The estimation results are shown in Table 2. The estimated value of the elasticity of substitution between industries is 0.503 within the range of the values in previous studies that report complementarities ($\varepsilon < 1$) in one-digit industry classification schemes.

TABLE 2—ESTIMATION RESULTS: FINAL PRODUCTION

Parameter	Estimates
ε	0.503
γ_{manu}	0.156
$\gamma_{contact\ serv.}$	0.380
$\gamma_{other\ serv.}$	0.464
AIC	-980.79

Source: Author's calculations.

B. *Calibration*

The elasticity of substitution between occupations (σ) governs how employment responds to a change in occupation-specific productivity (M_j). Unfortunately, occupation-specific productivity (M_j) and the elasticity of substitution between occupations (σ) are not separately identified in our model. Therefore, I set the elasticity of substitution between occupations to 0.65, an average value of estimates in previous studies.[1]

Other parameters have been identified through the method of moments such that the data and endogenous variables of the model become similar in 2019. I calibrate the parameters to target the year 2019, not the average of 2010 to 2019, because one of the paper's goals is to derive implications pertaining to structural changes over the medium run in the labor market after the pandemic. To do this, I assume that the year just before the pandemic represents the steady state and view the labor market after the pandemic as a transitional path from one steady state to another steady state. Note that this is somewhat different from the analysis of the business cycle, where average values over total sample periods are usually set as the steady state and where the analysis focuses on the short-run deviation from the steady state.

To be specific, I calibrate the values of ν_{ij} such that they match the employment share by occupation and by industry, the value of α_i to match the labor income share by industry, and the values of $A_{i,2019}$ to match the capital stock by industry as well as the level of aggregate output per total employment. Note that the model does not allow aggregate shocks to employment and the levels of total employment are given exogenously. That is, the model takes aggregate fluctuations as given and instead focuses on structural changes in the allocation of employment across industries and occupations. I therefore normalize the total number of workers in 2019 and the values of $M_{j,2019}$ to one. I then infer changes in the values of A_i, and M_j for the last decade (i.e., between 2010 and 2019) from the changes in employment by occupation and by industry. More specifically, I set the $A_{i,2010}$ to match industrial employment and the aggregate level of output in 2010 and the $M_{j,2010}$ to match occupational employment in 2010. I include detailed procedures for the calibration and data sources in Appendix A.

[1]The elasticity of substitution between occupations ranges from 0.56 to 0.81 in previous studies. Specifically, Aum, Lee, and Shin (2018) find a value of 0.81, Aum (2020) finds 0.58, Lee and Shin (2017) show a value of 0.70, and Duernecker and Herrendorf (2020) report 0.56.

TABLE 3—CALIBRATED PARAMETERS

Occupation intensity within industry (ν_{ij})			
Industry	Occupation		
	Cognitive	Routine	Manual
Manufacturing	0.128	0.735	0.138
Contact services	0.167	0.515	0.318
Other services	0.452	0.399	0.148
Industrial capital income share and growth of industry-specific productivity			
Industry	α_i	$\log A_{i,2019} - \log A_{i,2010}$	
Manufacturing	0.459	+0.061	
Contact services	0.236	-0.106	
Other services	0.408	+0.172	
Growth of occupation-specific productivity			
	Occupation		
	Cognitive	Routine	Manual
$\log M_{j,2019} - \log M_{j,2010}$	+0.119	+0.212	+0.140

Source: Author's calculations.

Table 3 summarizes the calibrated parameter values. The parameters for the occupational intensity levels (ν_{ij}) reflect each industry's employment structure by occupation. For example, the manufacturing industry features the highest fraction of routine workers compared to the services industries. Similarly, I can also confirm that the share of manual occupations is largest in the contact-intensive services industry, implying that a shock to routine occupations would disproportionately affect the manufacturing industry more, and a shock to manual occupations would have a more severe effect on contact-intensive industries.

Not surprisingly, manufacturing is the most capital-intensive sector (the highest α_i). Among the service industries, the contact-intensive services sector is more labor-intensive than other services ($\alpha_{contact} < \alpha_{other}$).

Between 2010 and 2019, the sector-specific productivity of the contact-intensive services sector declined most rapidly among the three broad sectors, but this should not be interpreted as a decline in total factor productivity, a combination of the sector-specific productivity and occupation-specific productivity rates. The manufacturing sector experienced slower growth in sector-specific productivity than other services, possibly indicating that the rate of the decline of manufacturing employment slowed after the Great Recession. In addition, I could confirm that routine occupations experienced the fastest growth in their occupation-specific productivity rates in an occupational dimension.

C. *Model Fit*

The employment structure in the model is set to be equal to the data in 2019 in terms of construction. On the other hand, the model and the data do not match

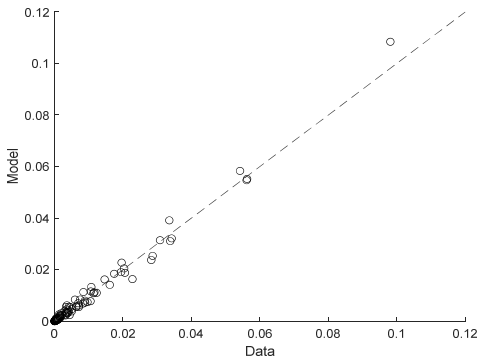

FIGURE 1. COMPARISON OF THE 2010 EMPLOYMENT SHARES BETWEEN THE MODELS AND THE DATA

Note: The x-axis is the share of employment by industry and occupation in the data, and the y-axis is the share of employment by industry and occupation in the model. The dotted line is the 45-degree line.

Source: Author's calculations.

precisely in 2010 because only industrial shocks (A_i) and occupational shocks (M_j) are allowed to change between 2010 and 2019. Therefore, by examining how similar the employment structures in the model and data are in 2010, I check how well the model explains the employment structure in Korea before the pandemic.

Figure 1 compares the employment share of the model with data by industry and occupation in 2010. The x-axis is the share of employment by industry and occupation in the data, and the y-axis is the share of employment by industry and occupation in the model. The dotted line is the 45-degree line. As shown in the figure, the employment shares in the model are very similar to the employment shares by industry and occupation observed in the data with an R-square value of.987, indicating that the model is suitable for an analysis of the employment structure in Korea. Again, aggregate variables should precisely match the data through the calibration procedure by construction.

IV. COVID-19 Shocks and their Characteristics

In this section, I estimate industry- and occupation-specific shocks (A_i and M_j) from the employment dynamics during the COVID-19 periods, i.e., 2020 and 2021. Note that I refer to the industry- and occupation-specific shocks governing the employment dynamics during the COVID-19 periods as COVID-19 shocks. I then analyze the characteristics of COVID-19 shocks to understand the factors behind the employment dynamics during the pandemic.

A. *Identification of shocks*

The employment shocks during the COVID-19 period have a form that shows changes in A_i and M_j. I identify A_i and M_j that match employment in 2020 and 2021 as follows:

1) Set the total number of employed persons in 2020 and 2021 to the data.

2) Set arbitrary values for $M_{j,t}$.

3) Set arbitrary values for $A_{I,t}$ and $k_{I,t}$.

4) Find $k_{i,t}$ based on $k_{I,t}$ and equation (11).

5) Find $A_{i,t}$ for 2020 and 2021 from the following equation:

$$A_{i,t} = \left[\left(\frac{L_{I,t}^{data}}{L_{i,t}^{data}} \right) \left(\frac{\tilde{V}_{i,t}^{(1-\alpha_i)(\varepsilon-1)}}{\tilde{V}_{I,t}^{(1-\alpha_I)(\varepsilon-1)}} \right) \left(\frac{\alpha_i}{\alpha_I} \right)^{\varepsilon} \left(\frac{k_{i,t}^{\alpha_i(\varepsilon-1)-\varepsilon}}{k_{I,t}^{\alpha_I(\varepsilon-1)-\varepsilon}} \right) \left(\frac{\gamma_i}{\gamma_I} \right) \right]^{\frac{1}{1-\varepsilon}} \times A_{I,t},$$

where $L_{i,t}^{data}$ represents employment in industry i at time t in the data.

6) Iterate 3) to 5) over $A_{I,t}$ and $k_{I,t}$ until K_t is equal to the capital stock in 2019 and Y_{2020} / Y_{2019} (or Y_{2021} / Y_{2019}) is equal to economic growth in the data.

7) Iterate 2) to 6) over M_j until $L_{j,t} / L_t$ in the model is equal to the data in 2020 and 2021.[2]

The procedure above produces A_i and M_j that match the thirteen industrial employment and eight occupational employment categories in 2020 and 2021 precisely. However, even if the thirteen employment by industry and eight employment by occupation categories coincide with the data, the detailed 104 (=13×8) employment cells by industry and occupation may not exactly coincide with the data. To check the accuracy, I compare the model with the data for the detailed 104 employment cells in Figure 2, finding that the model suitably explains the employment structure by industry

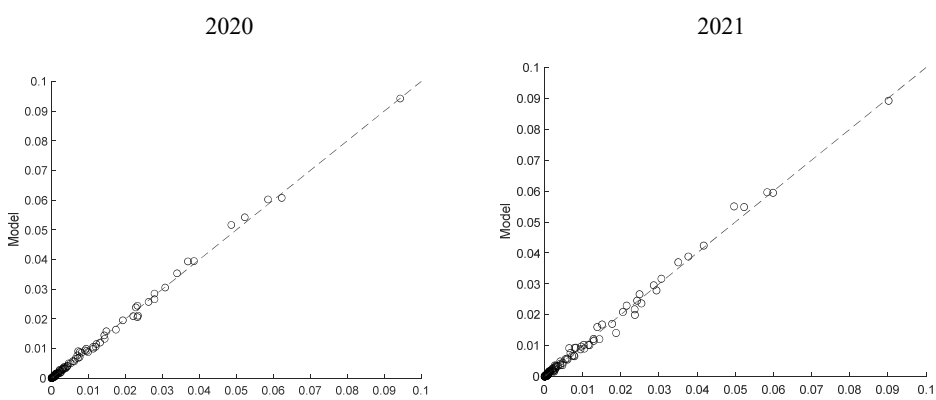

FIGURE 2. COMPARISON OF THE 2010 EMPLOYMENT SHARES BETWEEN THE MODELS AND THE DATA

Note: The x-axis is the share of employment by industry and occupation in the data, and the y-axis is the share of employment by industry and occupation in the model. The dotted line is the 45-degree line.

Source: Author's calculations.

[2]To be specific, I use the Fsolve function in MATLAB for the iterations over $A_{I,t}$, $k_{I,t}$, and M_j.

and occupation during the pandemic. For example, the corresponding R-square outcomes between the occupational and industrial employment shares in the model and the data are 0.9975 and 0.9946 in 2020 and 2021, respectively.

B. *Characteristics of COVID-19 shocks*

Although I identify the shocks that generate the employment dynamics during the pandemic, the economic meaning of these shocks is not straightforward. In the model, the only sources of exogenous variations are changes in A_i and M_j, which represent the productivity rates in each industry and each occupation. It would be natural to interpret these shocks as technological changes biased toward a certain industry or occupation when we focus on the long-run changes in the employment structure. However, there must be a much greater variety of shocks ongoing with regard to short-run fluctuations, such as markup, preference, and labor supply shocks, among others. Therefore, I would like to emphasize that the identified shocks herein should not be interpreted as structural sources of the variations in employment during the pandemic. Instead, the COVID-19 shocks identified herein should be understood as a combination of many structural shocks not explicitly reflected in the model.

However, the primary purpose of the identification of shocks is to gain an idea of which characteristics of an occupation or industry would be related to the observed changes in employment, rather than to delineate the contributions of various structural shocks on employment dynamics. For example, an occupation with higher infection risk would show lower employment caused by factors on both the demand and supply sides, and our exercise does not provide a clue as to exactly how much of the decrease in employment stems from a specific reason. Our exercise is still useful in that it defines the general nature of heterogeneity involved in the overall shocks to a certain occupation or industry, despite the fact that we do not know the contribution of each.

To provide economic implications with regard to COVID-19 shocks, I examine whether and how COVID-19 shocks are correlated with two variables that are suggested to be closely related to the pandemic in the literature: (1) the risk of infection and (2) easiness of remote work.

Recent studies utilize O*NET data to calculate the risk of infection index, and O*NET or the American Time Use Survey (ATUS) data to measure the ease of remote work (Adams-Prassl *et al*., 2020; Aum, *et al*., 2021c; Dingel and Neiman, 2020; Hicks *et al*., 2020; Mongey *et al*., 2021). O*NET asks experts and workers to give numerical answers to questions that capture detailed characteristics of an occupation, as defined by the Standard Occupation Classification (SOC) code. The ATUS data measure the amount of time people spend on various activities. In particular, it asks about "time worked from home," which varies across industries as well as occupations.

I adopt the infection risk index and index for ease of remote work from Aum, Lee, and Shin (2021b) (henceforth work-from-home or wfh index) by industry and by occupation. The infection risk index is obtained using O*NET data examining the characteristics of each occupation in the US. Specifically, in O*NET, the degree of physical contact and exposure to diseases and infections are investigated and scored for each job. The infection risk index is the average value of two – the degree of physical contact and exposure to diseases and infections – after the standardization of

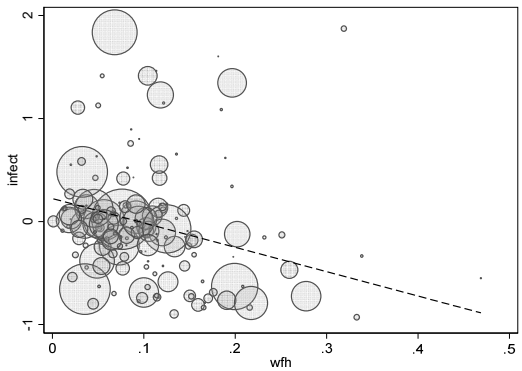

FIGURE 3. INFECTION RISK AND WORK-FROM-HOME INDEX BY INDUSTRY AND OCCUPATION

Note: The x-axis is work-from-home index (wfh), and the y-axis is the infection risk index (infect). The size of the circle represents the share of employment by industry and occupation in 2019.

Source: Author's calculations based on O*NET, ATUS, and EAPS.

each score. The work-from-home index is calculated using the weighted average of actual working at home in ATUS by industry and occupation. Finally, to match the indexes with our COVID-19 shocks, I assign US Census occupation codes and NAICS (North American Industry Classification System) to one-digit KSOC and KSIC.

Figure 3 shows the infection risk index against the work-from-home index by industry and occupation in Korea. Specifically, the x-axis is the work-from-home index (wfh) and the y-axis is the infection risk index (infect). The size of the circle represents the share of employment by industry and occupation in 2019. There is a negative (-) correlation between the two indexes, meaning that jobs with a lower risk of infection are generally more easily done at home. However, there is also considerable deviation from the regression line, implying that one index cannot completely represent the other and that the two indexes need to be examined separately. Aum, Lee, and Shin (2021b) also emphasized that the relationship between two indexes is far from tight, with an R-squared value only 0.034.

I estimate the following regression to examine the relationship between COVID-19 shocks and the two indexes using employment by industry and occupation as a weight.

$$\Delta \ln(M_{j,t} / M_{j,t-1})^{\sigma-1} = c + \beta_1 wfh_{ij} + \beta_2 infect_j + \varepsilon_{i,j,t},$$
$$\Delta \ln(A_{i,t} / A_{i,t-1})^{\varepsilon-1} = c + \beta_1 wfh_{ij} + \beta_2 infect_j + \varepsilon_{i,j,t},$$

where wfh is the work-from-home index (by industry and by occupation), $infect$ is the risk of infection index (by occupation), $M_{j,t}$ is an occupation-specific shock, and $A_{i,t}$ is an industry-specific shock. Note that $\beta_1 > 0$ if jobs with lower wfh outcomes (i.e., more difficult to do remote work) were hit harder by adverse employment shocks, and $\beta_2 < 0$ if jobs with higher infection risk were hit harder by adverse employment shocks. The regression analysis would guide us to a better understanding of the underlying sources of the variation in employment shocks by industry and occupation during the pandemic.

TABLE 4—RELATIONSHIP BETWEEN COVID-19 SHOCKS AND THE WFH OR INFECTION RISK INDEXES

	Occupational shocks			Industrial shocks		
	All periods	2020	2021	All periods	2020	2021
Work-from-home	1.105*** (0.152)	0.284 (0.185)	1.900*** (0.198)	0.165* (0.098)	0.004 (0.139)	0.322** (0.138)
Infection risk	-0.111*** (0.017)	-0.113*** (0.020)	-0.109*** (0.022)	-0.040*** (0.011)	-0.044*** (0.015)	-0.036** (0.015)
R^2	0.300	0.238	0.517	0.070	0.077	0.090

Note: Standard error in parenthesis. *, **, and ** indicate significance at the 90%, 95%, and 99% percentiles, respectively.

Source: Author's calculations.

Table 4 shows the estimation results, which deliver three main results. First, in both 2020 and 2021, we have $\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$, confirming the intuition that jobs that are more difficult to do remotely and with a higher risk of infection were hit harder both by occupation shocks and industry shocks, although these relationships were not always significant.

Second, the relationships vary over time. In 2020, when employment rapidly declined, COVID-19 shocks show a significant correlation only with infection risk. However, the work-from-home index began to show a significant correlation with COVID-19 shocks in 2021, as employment began gradually to recover. On the other hand, the coefficient of infection risk (β_2) becomes smaller in 2021 compared to this value in 2020.

Third, both indexes, risk of infection and work-from-home, have tighter relationships with COVID-19 shocks in an occupational dimension than in an industrial dimension. For example, the R-squared outcome in the regression with occupational shocks is 0.300, whereas that with industrial shocks is only 0.070. In addition, the t-value corresponding to the relationship between the work-from-home index and industrial shocks was 1.69, significantly smaller than with occupational shocks, at 7.28. This is not surprising given that the easiness of remote work is mainly related to the tasks a worker performs as opposed to the industry in which she/he works. I interpret this as meaning that occupational heterogeneity plays a more critical role in deriving the employment structure during the pandemic.

V. Post COVID-19 Employment Structure

As of January of 2022, the COVID-19 virus continues to spread with multiple variants, and it remains uncertain as to when the pandemic will end and how COVID-19 will affect the employment structure in the future. Nevertheless, I attempt to derive implications related to the post-pandemic employment structure in view of our model.

A. *Future Technological Changes*

The results in Section 4 suggest that COVID-19 raised the cost of employing contact-intensive tasks (specifically jobs for which the work-from-home is more

difficult). According to the literature on directed technological change (e.g., Acemoglu and Restrepo, 2018, among others), an increase in the cost of employing contact-intensive tasks provides incentives to implement technological changes to replace these tasks. A natural question is whether such technological changes are feasible.

Although the literature has actively investigated the impact of technological changes on the labor market structure, it did not pay much attention to how contact-intensive each job is and whether new technology can replace contact-intensive tasks. However, even before the pandemic, recent technological changes enabled the replacement of contact-intensive tasks to some extent. For example, the widespread use of food-delivery applications through various platforms has replaced food-serving services in the restaurants with fewer workers. Many other examples indicate similar possibilities, such as the expansion of telemedicine due to the CPRSA Act in the US, the provision of online education services through the development of MOOC, or the development of smart-finance applications. Reflecting such trends, the Ministry of Science and ICT (2020; 2021) reports that the amount of O2O (online-to-offline) transactions in Korea grew by 22.3% in 2019, even before the pandemic, and its growth rate accelerated to 29.6% in 2020 through the pandemic. Therefore, I consider the acceleration of technological changes to replace contact-intensive tasks as a scenario that merits investigation.

B. *Scenarios*

The baseline scenario is that only past trends continue for five years, with no additional effects from COVID-19 appearing. I label this scenario as the baseline scenario, or Scenario 1.

Scenario 1. *(past trends) For* $2022 \le t \le 2026$, *occupation- and industry-specific productivity evolve as follows:*

$$M_{j,t} = M_{j,2021} \times (M_{j,2019} / M_{j,2010})^{\frac{t-2021}{2019-2010}}, \text{ and}$$

$$A_{i,t} = A_{i,2021} \times (A_{i,2019} / A_{i,2010})^{\frac{t-2021}{2019-2010}}.$$

The expression above may seem complicated, but it merely says that the sector-specific and occupation-specific productivity rates grow at the average rate of growth between 2010 and 2019.

Compared to this scenario, I consider an alternative scenario in which the replacement of contact-intensive tasks will accelerate due to technological change biased toward contact-intensive task (CBTC) in the coming years. To reflect such technological changes, I assume that occupations with a lower work-from-home share will experience a more rapid increase in occupation-specific productivity compared to earlier trends. Hence, when new technologies replace contact-intensive tasks, occupations having more contact-intensive tasks will become relatively more productive. As shown in equation (13) in Section 2, a faster increase in an

occupation's productivity reduces its demand when occupations are complementary to each other ($\sigma < 1$). Intuitively, firms allocate fewer resources to more productive tasks when tasks are complementary to each other.

To be specific, the alternative scenario (scenario 2) is expressed as follows:

Scenario 2. *(past trends + COVID-19) For* $2022 \le t \le 2026$, *occupation- and industry-specific productivity evolve as follows:*

$$M_{j,t} = \underbrace{M_{j,2021} \times (M_{j,2019} / M_{j,2010})^{\frac{t-2021}{2019-2010}}}_{past\ trends} \times \underbrace{m_j^{t-2021}}_{CBTC}, \ and$$

$$A_{i,t} = A_{i,2021} \times (A_{i,2019} / A_{i,2010})^{\frac{t-2021}{2019-2010}}.$$

$$where \ \ m_j \ \ is\ defined\ as \ \ m_j := wfh_j + (1 - wfh_j) \times e^{\tau}, \tau > 0.$$

Note that Scenario 2 is identical to Scenario 1 except for the m_j in the first equation. The additional term m_j captures CBTC, implying that the productivity rates of occupations that are difficult to do from home increase more rapidly. In other words, owing to CBTC (m_j), $M_j > M_l$ when $1 - wfh_j > 1 - wfh_l$. Note again that the demand for occupation j falls when M_j becomes higher when $\sigma < 1$ (equation 13).

The parameter τ governs the speed of CBTC and determines the distance between the productivity of the highest wfh_j and the productivity of the lowest wfh_j. I set $\tau = 0.14$, referring to the average speed of divergence between the highest M_j and the lowest M_j between 2010 and 2019, the pre-pandemic period.

Contrary to the previous section, the simulation exercise in this section is structural because I simulate a situation in which technological change is biased toward contact-intensive tasks. In other words, the simulation seeks to determine the structural effect of contact-intensive-task-biased technological changes on occupational and industrial employment rather than accurately to predict the employment dynamics after the pandemic. In this sense, I would like to clarify that the previous exercise does not provide evidence but suggests the possibility of CBTC. This is certainly a limitation of this analysis. Finding evidence of CBTC would require more data and analyses after the pandemic. This can be examined in future research.

C. *Simulation Results*

I simulate the model and the obtained equilibrium employment structures ($L_{i,j,t} / L_t$) under Scenario 1 and Scenario 2. Figure 5 depicts the occupational structures under the two scenarios. The line demarcated by the circle shows the observed employment share between 2005 and 2020. Not surprisingly, there was a declining trend in the routine employment share (-2.5%p between 2010 and 2021). Accompanying this trend, the cognitive employment share and manual employment share rose by +0.3%p and +2.3%p, respectively.

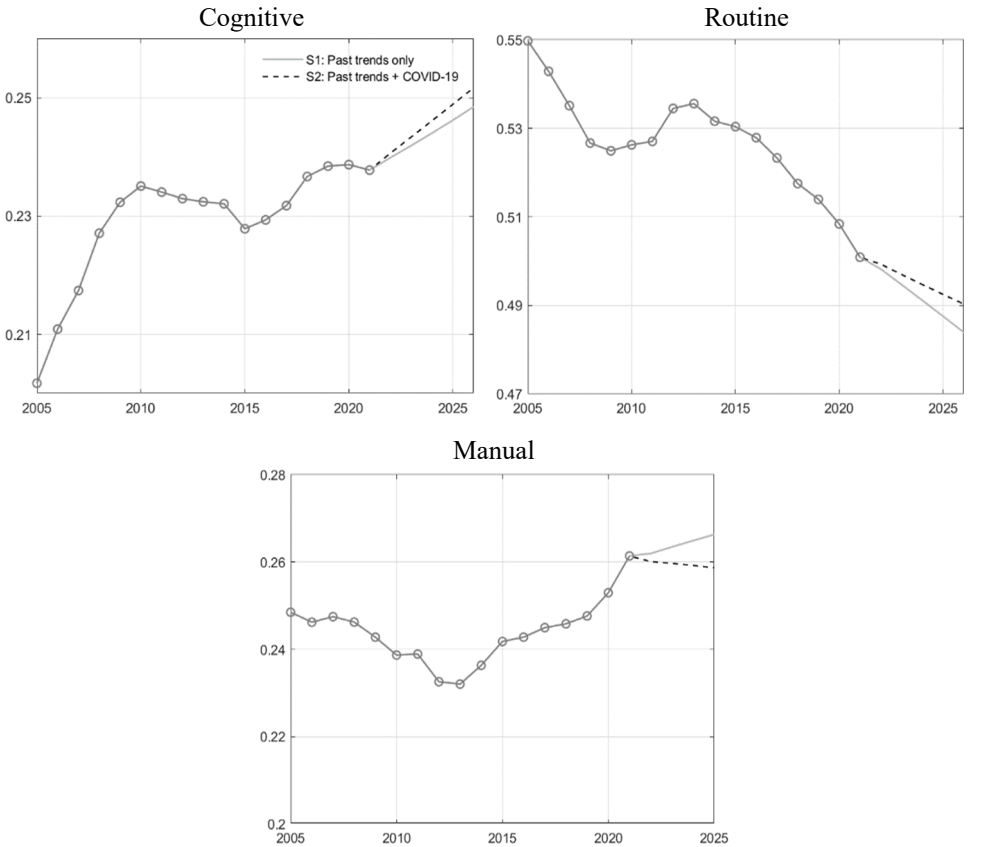

FIGURE 5. OCCUPATIONAL STRUCTURE UNDER THE TWO SCENARIOS

Note: The line marked with circles is the observed employment share in the data; the black dotted line is Scenario 1, and the gray solid line is Scenario 2.

Source: Author's calculations.

Similar to the continuous decline of routine employment before the pandemic, the routine employment share continues to fall by as much as -1.7%p for the next five years under the baseline scenario (solid gray line). At the same time, the cognitive employment share rises by +1.1%p, and the manual employment share rises by +0.6%p, a continuation of job polarization (or the declining trend of routine employment).

When the replacement of contact-intensive task accelerates (black dotted line, Scenario 2), however, the manual employment share changes, turning negative (+0.6%p → -0.3%p). A reduction in the demand for manual employment translates into greater demand for routine and cognitive employment than in previous trends, leading to a smaller decline of the routine employment share (from -1.7%p in Scenario 2 to -1.1%p in Scenario 2) and even higher increases in the cognitive employment share (from +1.1%p in Scenario 1 to +1.4%p in Scenario 2).

Equation (13) provides an idea as to why the replacement of contact-intensive tasks reduces the demand for manual workers. Because $\sigma < 1$ in our calibrated model, an increase in M_j translates into a fall of $\tilde{M}_j$ ($:= M_j^{\sigma-1}$), which leads to a

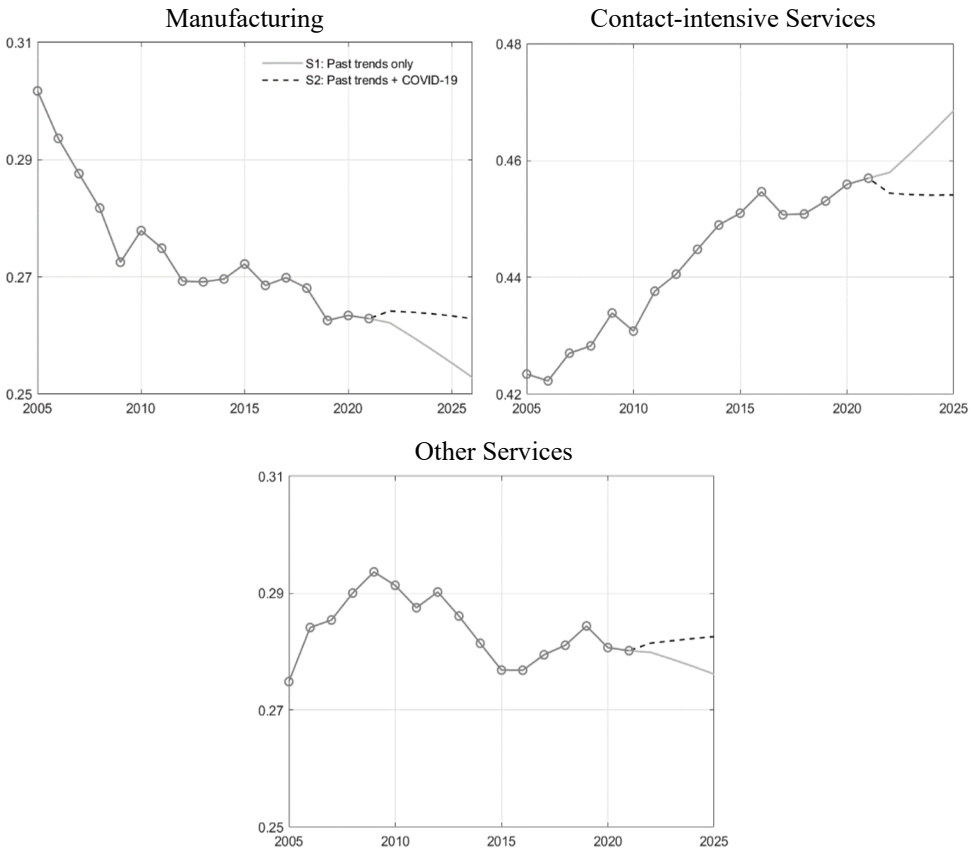

FIGURE 6. INDUSTRIAL STRUCTURE UNDER THE TWO SCENARIOS

Note: The line marked with circles is the observed employment share in data; the black dotted line is Scenario 1, and the gray solid line is Scenario 2.

Source: Author's calculations.

reduction in L_j in Equation (13). Because m_j is higher for manual workers than for other occupations, manual workers experience lower demand compared to other types of employment. In other words, manual workers tend to have tasks that are difficult to complete from home (relatively lower wfh_j) and hence are substituted more by technological changes that replace tasks that cannot be done at home.

I now turn to the industrial structure. Figure 6 shows the industrial employment structure under the two scenarios. In the data, the manufacturing employment share fell (-1.5%p from 2010 to 2021) and services employment increased through the process of structural transformation (circle-demarcated line). Within the service industry, the increase of line employment share focused on contact-intensive services (+2.6%p), whereas the share of other services (mostly high-skilled) experienced a decline (-1.1%p).

When the previous trend continues (Scenario 1), the manufacturing employment share decreases by -1.0%p over the next five years, while the employment share of contact-intensive services increases by +1.5%p and the employment share of other services falls by -0.5%p. However, as the replacement of contact-intensive tasks

accelerates after the pandemic (Scenario 2), the demand for contact-intensive services will be reduced by -0.3%p over the next five years a -1.8%p reduction from +1.5%p in Scenario 1. As the demand for contact-intensive services decreases, the decline in manufacturing will ease, shifting from -1.0%p in Scenario 1 to -0.003%p in Scenario 2. Also, the demand for other services will boost the employment share of these workers by +0.3%p.

Discussion

The simulation results demonstrate that the acceleration of contact-intensive replacement technological changes (or CBTC) would alleviate the structural changes in employment observed in the past, such as job polarization. This would occur because jobs with more significant portions of contact tasks (i.e., remote work being more difficult) are different from jobs that involve routine tasks, which have been replaced heavily by earlier technological changes, also known as the IT revolution.

It is important to note that these results should not be interpreted as meaning that routine tasks will not be replaced in the future. Instead, they suggest that a broader range of jobs, both routine tasks and contact-related tasks, may be in danger after the pandemic given the more recent technological changes that have occurred. I highlight the potential acceleration of the former type of automation due to the pandemic and present related implications with regard to occupational or industrial employment structures.

The CBTC scenario (Scenario 2) includes technological changes reflecting past trends as well as the acceleration of contact-intensive task replacement. Although a contact-intensive task is different from a routine task, they are not mutually exclusive. In other words, jobs intensive in routine tasks may or may not be intensive in contact tasks. For a more precise interpretation, I classify jobs by both routineness and contact-intensiveness in Table 5. I classify jobs with a work-from-home index below average as contact-intensive jobs and those with a work-from-home index above average as non-contact-intensive jobs. This classification of routine and non-routine jobs follows the literature, e.g., Acemoglu and Autor (2010).

Before the pandemic, a widely accepted view with regard to the labor market structure was that routine jobs had disappeared, regardless of their degree of contact-intensiveness. Our simulation is based on the possibility that contact-intensiveness can serve as an additional dimension of future technological changes due to the COVID-19 pandemic. Therefore, among routine jobs, the share of routine and contact-intensive jobs will decrease further, adding to the previous decline. In

TABLE 5—OCCUPATIONAL CLASSIFICATION BY ROUTINENESS AND CONTACT-INTENSIVENESS

	Contact-Intensive	Non-Contact-Intensive
Routine	Craft and related trades workers, Sales workers, Equipment, machine operating and assembling workers.	Clerks
Non-Routine	Service workers, elementary workers	Managers, professionals, and related workers

Note: 1) Contact-intensive jobs are those for which the wfh index is below average, and non-contact-intensive jobs are those for which the wfh index is above average, 2) The classification of routine and non-routine jobs follows Acemoglu and Autor (2010).

TABLE 6—LABOR FORCE COMPOSITION BY OCCUPATIONAL GROUPS IN 2020

(Unit: %)

	Manual	Routine	Cognitive
Age $\geq$ 60	31.4	18.1	6.3
Less than high school	77.6	56.0	13.0
Temporary and daily workers	45.0	15.3	9.9

Source: Economically Active Population Census (2020).

addition, the share of non-routine and non-contact-intensive jobs will increase more rapidly than in the past. Most interesting is that the demand for non-routine and contact-intensive jobs, i.e., manual jobs, shifts from increasing to decreasing with the widest gap between the two scenarios, as highlighted in Section 5.C.

Table 6 compares the employment composition of manual, routine, and cognitive jobs in 2020 in Korea. Manual jobs have a higher proportion of temporary and daily workers than other jobs (45% vs. 15% or 10%), and the share of low-educated (up to high school) workers is also higher than in the other cases (78% vs. 56% or 13%). Meanwhile, more elderly people (over age 60) work manual jobs than in other cases (31% vs. 18% or 6%), meaning means that the reduced demand for manual workers due to the pandemic will burden mostly socio-economically vulnerable workers, which calls for policies supporting vulnerable groups in the labor market.

VI. Conclusion

I study how COVID-19 affected the labor market through the lens of a general equilibrium model with multiple industries and occupations. I calibrate the model with Korean data and identify industrial and occupational COVID-19 shocks that derive employment dynamics in 2020 and 2021, when COVID-19 hit the Korean labor market.

I find that COVID-19 shocks correlate significantly with both infection risk and ease of work-from-home by occupation and industry. As the pandemic progressed, however, the correlation with infection risk weakened, whereas the correlation with the easiness of work-from-home strengthened. Moreover, the relationship is more robust in the occupational dimension than in the industrial dimension.

Based on this finding, I investigate how much, and in which direction, labor market structure would be affected if future technological changes accelerated the replacement of contact-intensive tasks (i.e., tasks that cannot be done at home). The simulation results show that the upward trend in manual workers' employment share will shift to a declining trend due to the pandemic. This result stands in contrast with the earlier trend of job polarization in which only routine workers showed a declining employment share. The analysis suggests that whether or not a job requires contact-intensiveness can play an essential role in shaping the future labor market structure; moreover, if it occurs, such a change calls for policies that support socio-economically vulnerable groups, distributed mainly in manual jobs.

APPENDIX

A. *Detailed Parameterization*

1. Classifications of Industry and Occupation

The classification of industries is mainly based on the classification of national accounts by economic activity; it is subsequently linked to the KSIC. I exclude agriculture, forestry and fishing and the public. Occupational classification is based on the KSOC, and I also exclude skilled workers in agriculture, forestry and fisheries, as in these cases it is difficult to connect with the data on infection risk and the work-from-home index later. Table A1 compares the classification in the model and the data.

TABLE A1—CLASSIFICATION OF INDUSTRY AND OCCUPATION

Industry		
i	KSIC	Economic Activities (NA)
1	C	Manufacturing
2	D, E	Electricity, gas and water supply
3	F	Construction
4	G, I	Wholesale and retail trade, accommodation and food services
5	H	Transportation and storage
6	K	Finance and insurance
7	L	Real estate
8	J	Information and communication
9	N	Business support services
10	P	Education
11	Q	Human health and social work
12	R, S	Cultural and other services
13	M	Professional, scientific and technical services
Occupation		
j	KSOC	Name
1	1	Managers
2	2	Professionals and related workers
3	3	Clerks
4	4	Service workers
5	5	Sales workers
6	7	Craft and related trades workers
7	8	Equipment, machine operating and assembling workers
8	9	Elementary workers

Source: KSIC, KSOC, National Accounts.

2. Estimation of production function parameters

From the equilibrium condition in equation (4), we have the following relationship:

$$\log\frac{p_i Y_i}{p_I Y_I} = \frac{1}{\varepsilon}\log\frac{\gamma_i}{\gamma_I} + \frac{\varepsilon - 1}{\varepsilon}\log\frac{Y_i}{Y_I},$$

I estimate the above equation by the iterated feasible generalized non-linear least squares (IFGNLS) method following Herrendorf, Rogers, and Valentinyi (2013). The sample period is from 2005 to 2019, and the nominal and the real value added by economic activity from the National Accounts correspond to $p_i Y_i$ and Y_i, respectively. The estimation results are in Table A2.

TABLE A2—ESTIMATION RESULTS: FINAL PRODUCTION

Parameter	Estimates
ε	0.503 (0.002)
$\gamma 1$	0.076 (0.001)
$\gamma 2$	0.075 (0.002)
$\gamma 3$	0.080 (0.001)
$\gamma 4$	0.079 (0.000)
$\gamma 5$	0.071 (0.001)
$\gamma 6$	0.072 (0.001)
$\gamma 7$	0.071 (0.001)
$\gamma 8$	0.079 (0.000)
$\gamma 9$	0.077 (0.000)
$\gamma 10$	0.080 (0.000)
$\gamma 11$	0.078 (0.000)
$\gamma 12$	0.081 (0.001)
$\gamma 13$	0.082 (0.001)
AIC	-980.79

Note: Standard errors in parenthesis.

Source: Author's calculations.

3. Calibration

The elasticity of substitution between occupations (σ) governs how employment responds to a change in occupation-specific productivity (M_j). I set the elasticity of substitution between occupations to 0.65, an average value of estimates in previous studies (Aum, Lee, and Shin, 2018; Aum, 2020; Lee and Shin, 2017; Duernecker and Herrendorf, 2020).

Other parameters have been identified through the method of moments so that the data and endogenous variables of the model are similar in 2019. I calibrate the values of ν_{ij} to match employment by industry and by occupation; in all cases α_i matches labor income shares by industry and A_i matches capital stock by industry

as well as the aggregate level of output, in the year 2019. Because the model does not have aggregate shocks to generate aggregate fluctuations, it takes any variations in the aggregate variable exogenously. Therefore, I normalize total employment in the year 2019 to one.

To be specific, the detailed procedure for the calibration is as follows.

1) Normalize $M_{j,2019} = 1$ for all j.

2) Set an arbitrary value of $A_{I,2019}$.

3) Find ν_{ij} from equation (9), $M_{j,2019} = 1$, and employment by occupation and industry in 2019; that is, $\nu_{ij} = L_{ij,2019} / L_{i,2019}$.

4) From equation (10), we have $\tilde{V}_{i,2019} = \left(\sum_j \nu_{ij}\right)^{\frac{1}{\sigma-1}}$.

5) Determine α_I from $1 - labor\,share_{I,2019}$ in the data. Then, $\alpha_i = 1/[1+(1-\alpha_I)k_{I,2019}/(\alpha_I k_{i,2019})]$ from equation (11).

6) The industry-specific productivity $A_{i,2019}$ is then

$$A_{i,2019} = \left[\left(\frac{L_{I,2019}}{L_{i,2019}}\right)\left(\frac{\tilde{V}_{i,2019}^{(1-\alpha_i)(\varepsilon-1)}}{\tilde{V}_{I,2019}^{(1-\alpha_I)(\varepsilon-1)}}\right)\left(\frac{\alpha_i}{\alpha_I}\right)^{\varepsilon}\left(\frac{k_{i,2019}^{\alpha_i(\varepsilon-1)-\varepsilon}}{k_{I,2019}^{\alpha_I(\varepsilon-1)-\varepsilon}}\right)\left(\frac{\gamma_i}{\gamma_I}\right)\right]^{\frac{1}{1-\varepsilon}} \times A_{I,2019}$$

from equation (12).

7) Iterate over $A_{I,2019}$ until the aggregate output in the model is equal to the data.

In our model, the time-varying exogenous variables are occupation-specific productivity M_j and industry-specific productivity A_i as well as aggregate variables. To have changes in the values of M_j and A_i corresponding to structural changes in the labor market before the pandemic, we identify the best matches of $M_{j,2010}$ and $A_{i,2010}$ to the observed changes in employment by industry and occupation between 2010 and 2019.

Specifically, from equation (9),

$$\frac{\tilde{M}_{j,2010}}{\tilde{M}_{1,2010}} = \frac{\nu_{i1}L_{ij,2010}}{\nu_{ij}L_{i1,2010}},$$

for all $i \in (1, \cdots, I)$. Denoting $Mr_{j,2010}^{i} = \nu_{i8}L_{ij,2010}^{data} / \left(\nu_{ij}L_{i8,2010}^{data}\right)$, I establish the occupation specific productivity in 2010 via

$$\frac{\tilde{M}_{j,2010}}{\tilde{M}_{8,2010}} = \frac{\sum_i L_{ij,2010}^{data} Mr_{j,2010}^{i}}{\sum_i L_{ij,2010}^{data}},$$

with $M_{8,2010} = 1$.

Lastly, the $A_{i,2010}$ values are obtained using the equation

$$A_{i,2010} = \left[\left(\frac{L_{I,2010}}{L_{i,2010}} \right) \left(\frac{\tilde{V}_{i,2010}^{(1-\alpha_i)(\varepsilon-1)}}{\tilde{V}_{I,2010}^{(1-\alpha_I)(\varepsilon-1)}} \right) \left(\frac{\alpha_i}{\alpha_I} \right)^{\varepsilon} \left(\frac{k_{i,2010}^{\alpha_i(\varepsilon-1)-\varepsilon}}{k_{I,2010}^{\alpha_I(\varepsilon-1)-\varepsilon}} \right) \left(\frac{\gamma_i}{\gamma_I} \right) \right]^{\frac{1}{1-\varepsilon}} \times A_{I,2010},$$

where $A_{I,2010}$ is set to match the aggregate output in the model and that in the data in 2010.

Given the calibrated values of α_i, we can compute the value of the rate of return on capital (R) in the model. The rate of return on capital implies that $\beta = 0.987$, with a depreciation rate (δ) of 0.05, which is the consumption of fixed capital divided by the net capital stock in 2019 in the Korean National Accounts.

Table A3 summarizes the calibrated parameter values.

TABLE A3—CALIBRATED PARAMETERS

Occupation intensity within industry (ν_{ij})								
Industry	Occupation							
	1	2	3	4	5	6	7	8
1	0.022	0.114	0.218	0.004	0.027	0.162	0.350	0.103
2	0.017	0.123	0.269	0.008	0.004	0.067	0.354	0.158
3	0.036	0.083	0.122	0.001	0.010	0.496	0.084	0.168
4	0.008	0.042	0.113	0.263	0.407	0.025	0.013	0.128
5	0.008	0.025	0.151	0.011	0.009	0.029	0.603	0.165
6	0.020	0.603	0.253	0.002	0.021	0.044	0.006	0.050
7	0.054	0.099	0.520	0.003	0.310	0.001	0.004	0.010
8	0.020	0.367	0.274	0.002	0.018	0.031	0.060	0.227
9	0.014	0.047	0.219	0.075	0.065	0.064	0.073	0.442
10	0.023	0.741	0.120	0.056	0.000	0.002	0.014	0.043
11	0.005	0.546	0.091	0.219	0.001	0.002	0.016	0.120
12	0.003	0.196	0.104	0.346	0.029	0.158	0.036	0.127
13	0.018	0.569	0.337	0.008	0.018	0.014	0.020	0.017

Industrial capital income share and industry-specific productivity			
Industry	α_i	$A_{i,2010}$	$A_{i,2019}$
1	0.613	0.057	0.064
2	0.895	1.627	1.087
3	0.121	3.084	2.702
4	0.155	0.356	0.277
5	0.618	0.491	0.530
6	0.591	2.283	1.811
7	0.409	4.525	5.612
8	0.947	0.037	0.032
9	0.134	6.411	5.984
10	0.333	1.307	1.696
11	0.211	4.712	1.746
12	0.287	2.502	2.462
13	0.313	6.231	5.176

TABLE A3—CALIBRATED PARAMETERS (CONT'D)

Occupation-specific productivity								
	Occupation							
	1	2	3	4	5	6	7	8
$M_{j,2010}$	0.271	0.965	1.321	0.715	0.354	0.582	0.876	1.000
$M_{j,2019}$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Source: Author's calculations.

4. Data Construction

The data for the output, capital, and labor income shares are obtained from the value added by economic activity (Tables 10.2.1.3, 10.2.1.4), the net capital stock (Tables 14.7.1, 14.7.2), employee compensation (Table 10.3.1.2) by industry, and the operational surplus of households (Table 10.4.2) in the Economic Statistics System (ECOS) of the Bank of Korea. In particular, I compute the labor income shares by industry from the compensation of employees divided by value added net of operational surplus of households by industry. Because the Bank of Korea provides data on the operational surplus of households at the aggregate level only, I distribute this data to each industry based on the share of self-employed in each industry.

The data for employment come from the Economically Active Population Survey (EAPS) from MDIS (Microdata Integrated Service). Employment by industry and occupation were based on the average number of employed persons from March to August of 2019 in the Economically Active Population Survey (EAPS). I restrict employment data from March to August because the COVID-19 shock started in March of 2020 and the microdata from the 2021 EAPS were available only until August at the time of the analysis. Therefore, employment in 2010, 2019, 2020, and 2021 in the model correspond to the average number of employed persons from March to August of 2010, 2019, 2020, and 2021, respectively.

Finally, the aggregate level of output comes from the Gross Domestic Product, Table 10.2.2.4, in ECOS.

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Does Learning Matter for Wages in Korea? International Comparison of Wage Returns to Adult Education and Training†

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This study compares the wage equation in Korea to those in other countries, focusing on the wage returns to adult education and training (AET) participation. It is found that the wage compensation structure in Korea is associated mainly with job characteristics such as tenure and workplace size rather than with worker characteristics such as AET participation and cognitive abilities. It is also found that Korea's AET participation is skewed toward non-job-related AET, relative to the situations in other countries. These findings imply that the link between a worker's productivity and wage should be strengthened in order to incentivize workers to invest in AET relevant to the labor market.

Key Word: Adult Education and Training, Lifelong Learning, Wage Education. Skills
JEL Code: J24, J31, P46

I. Introduction

In recent years, there has been growing interest in subsidizing adult education and training (henceforth AET) to facilitate individuals' efforts to adapt to the rapid technological progress. For example, the French government has implemented what is termed the Compte Personnel de Formation (Individual Learning Account when translated into English) since 2015, where a certain amount to be spent on training expenses is deposited annually to all workers and to the unemployed. The Singapore government has also promoted their SkillsFuture Credit since 2016, which provides all citizens over the age of 25 with a learning voucher. According to data from the OECD (2019), similar programs, albeit on a smaller scale, are in place in a number of advanced economies, including the U.S., Germany, and Scotland in the U.K.

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The ongoing digital transformation by COVID-19 and the resulting labor market mobility are expected to reinforce the argument for subsidizing AET participation. Indeed, Korea's AET legislation (the Lifelong Education Act and the Workers Vocational Competency Development Act) was amended in 2021 to allow the government to offer financial support for AET participation to all adult citizens. However, before considering the expansion of financial support, it is necessary to examine whether and the degree to which AET participation is compensated for in the labor market. Human capital theory predicts that the wage return to education and training is a major factor determining a worker's participation in such programs. To the extent that AET participation is less valued in the labor market, expanding government support for it may result in subsidizing education and training that are less relevant to the labor market.

This study estimates and compares the wage returns to AET participation in Korea relative to those in other countries. For the purpose, the study employs data from the OECD Survey of Adult Skills, designed to measure the cognitive skills of nationally representative groups 16 to 65 years old across countries, collecting various types of information about the respondents, including their education and training history and their labor market outcomes. This feature of the dataset allows the mitigation of the potential ability bias problem when estimating the wage returns to AET participation by directly controlling for the respondents' cognitive abilities as measured in the survey. Using the data, I find evidence that Korea's true wage return to AET participation is likely negligible and that the wage compensation structure in Korea is primarily determined by job tenure and workplace size relative to those in other major countries such as the U.S., Japan, and Germany.

This study contributes to the literature (e.g., Hanushek *et al*., 2015; Lee *et al*., 2015; Kim, 2019) on estimating wage equations by country with its use of data from the OECD Survey of Adult Skills. Although previous studies focused on estimating the wage returns to cognitive skills as measured in the survey, the present study mainly examines wage returns to AET participation, which has not been discussed in the literature. Additionally, this study employs a range of information pertaining to worker characteristics (e.g., type of employment contract, workplace size, and years of tenure) when estimating wage equations, unlike previous studies that focused exclusively on basic worker characteristics such as age, gender, years of schooling, and years of labor market experience. Estimating wage equations with extended worker characteristics enables a unique comparison of Korea's wage compensation structure with those of other countries; such a comparison may have important policy implications but remains unreported thus far in the literature.

The remainder of this paper proceeds as follows. Chapter II introduces the OECD Survey of Adult Skills and defines the samples and variables used in the analysis. Chapter III compares AET participation rates and wage returns to AET participation as well as the determinants of AET participation in Korea with those in other countries. Chapter IV summarizes the results and draws conclusions based on them.

II. Data

The data for this study are from the OECD Survey of Adult Skills, which is a

cross-sectional survey of nationally representative samples of the 16-to-65-year-old population in 33 countries, including Korea. The survey was conducted in 24 countries, including Korea from August of 2011 to March of 2012, followed by an additional survey in nine countries from April of 2014 to March of 2015. In this study, all 33 countries are analyzed, but detailed regression analysis results are presented only for four major countries (Korea, the U.S., Japan, and Germany).[1]

Although the main objective of the OECD Survey of Adult Skills is to measure cognitive skills such as literacy, numeracy, and the computer-based problem-solving skills of the adult population,[2] it also collects data on respondents' demographic backgrounds, educational attainment, job characteristics, and labor market outcomes.[3] This allows valid estimates of the wage returns to AET participation after controlling for various characteristics that may affect wages, including a worker's cognitive abilities, for a representative sample of each country.

The sample for this study is restricted in the following way. Initially, a total of 208,620 individuals were observed in the OECD Survey of Adult Skills data. Among them, I dropped 28,383 individuals who were still in their first cycle of formal school education as of the survey date. In other words, I restricted the sample to the adult education/training population (or AET population) defined by the survey. In addition, I removed 1,378 individuals for whom the key variables of this study, AET participation status and corresponding job relevance, are missing. The resulting sample consists of 178,859 individuals.

Table 1 presents descriptive statistics of the sample for this study. The main variable of interest is the AET participation status or whether the respondent participated in education or training within the last 12 months. The variable covers not only formal courses for the purpose of obtaining degrees or certificates but also informal courses such as open and distance education, on-the-job training, seminars and workshops, and other courses and private lessons. According to Table 1, approximately 44.7% of the respondents reported that they had participated in education and/or training within the last 12 months. For those who thus responded positively (i.e., that they had participated in education (or training) courses within the last 12 months), the survey inquired further as to whether the courses were job-related.[4] Job relevance was assessed to determine whether the main content of the participated education and/or training is to improve one's employability and/or job performance, not necessarily related to a specific job. Table 1 also shows that approximately 37.3% of the respondents reported that they had participated in job-related courses, while about 7.4% reported their participation in non-job-related education.

[1]The OECD Survey of Adult Skills is a biennial survey. The second round of the survey will begin in 2022. This study has a limitation in that it relied on data from the first round of the survey, which is the most recently available data but which may not accurately reflect the current state of the labor market in each country, including Korea.

[2]In that sense, the OECD Survey of Adult Skills can be understood as an extension of the OECD Program for International Student Assessment (PISA), which measures academic achievement in the areas of reading, math, and science of 15-year-olds in major countries.

[3]As of today, to the best of the author's knowledge, the OECD Survey of Adult Skills is the only data source that collects education history and labor market outcomes across countries in a consistent manner.

[4]The OECD Survey of Adult Skills only queries participants about the job-relevance of AET participation only in relation to the last act of participation among those reported by them. Due to this survey structure, job-related AET participation and non-job-related AET participation are mutually exclusive in the data used here.

TABLE 1—SUMMARY STATISTICS

Variables (units)	N	Mean	SD
Adult education and training (yes=1)	178,859	0.447	0.497
Job-related AET	178,859	0.373	0.484
Non-job-related AET	178,859	0.074	0.262
Hourly wage (log)	101,513	3.851	2.095
Female (yes=1)	178,859	0.506	0.500
Age (years)	178,859	42.97	12.46
Schooling (years)	176,847	12.62	3.430
Numeracy score (10 percentile scores)	178,809	4.846	2.911
Tenure (years)	109,659	9.016	9.435
Permanent contract (yes=1)	107,465	0.624	0.484
Public sector (yes=1)	128,069	0.211	0.408
Workplace size (yes=1)			
10 workers or less	108,987	0.247	0.431
11~50 workers	108,987	0.293	0.455
51~250 workers	108,987	0.237	0.425
251~1,000 workers	108,987	0.130	0.336
1,001 workers or more	108,987	0.094	0.292
Occupation (yes=1)			
Armed forces	126,409	0.005	0.071
Senior officials & managers	126,409	0.086	0.280
Professionals	126,409	0.186	0.389
Technicians & associate professionals	126,409	0.152	0.359
Clerks	126,409	0.092	0.289
Service workers & Sales workers	126,409	0.186	0.389
Skilled agricultural & fishery workers	126,409	0.020	0.141
Craft & related trades workers	126,409	0.116	0.320
Machine operators & assemblers	126,409	0.082	0.274
Elementary occupations	126,409	0.076	0.264
Industry (yes=1)			
Agriculture, forestry & fishing	126,034	0.027	0.163
Mining & quarrying	126,034	0.005	0.073
Manufacturing	126,034	0.158	0.365
Electricity, gas, & steam supply	126,034	0.007	0.086
Water, sewerage, & waste	126,034	0.007	0.082
Construction	126,034	0.075	0.263
Wholesale & retail trade	126,034	0.134	0.340
Transportation & storage	126,034	0.057	0.231
Accommodation & food service	126,034	0.047	0.212
Information & communication	126,034	0.035	0.184
Financial & insurance	126,034	0.034	0.181
Real estate	126,034	0.010	0.101
Professional, scientific & technical	126,034	0.048	0.213
Administrative & support service	126,034	0.045	0.208
Public administration & defense	126,034	0.066	0.249
Education	126,034	0.081	0.273
Health & social work	126,034	0.110	0.313
Arts, entertainment & recreation	126,034	0.017	0.130
Other service	126,034	0.028	0.165
Households as employers	126,034	0.007	0.083
Extraterritorial organizations & bodies	126,034	0.000	0.011

Note: 1) The units of each variable are indicated in parentheses, 2) All statistics are calculated using sampling weights.

Source: Data from the OECD Survey of Adult Skills.

The other variables used in this study include each respondent's hourly wage (in natural log), gender, age, years of schooling, cognitive ability measure (numeracy score), years of current employer tenure, employment contract type (permanent or temporary), sector (public or private), workplace size (five categories), occupation (ten categories), and industry (21 categories). The numeracy score, measured by a test in the survey, was used as a proxy for a respondent's cognitive ability. This study sets the unit of the numeracy score to 10 percentile scores computed within the respondent's own country. When estimating the wage returns to adult education and training, I further restricted the sample to 98,115 workers for whom hourly wages and all of the characteristics in Table 1 could be observed. Descriptive statistics for the restricted sample are presented in Table A1 in the appendix.

III. Empirical Analysis

A. *Adult Education and Training (AET) Participation Rates*

Before estimating the wage returns to the AET participation, I begin by comparing the AET participation rates by country. Columns (1), (2), and (3) of Table 2 present the participation rates of all AET, job-related AET, non-job-related AET, respectively. Numbers in square brackets in each column indicate the ranking of a given country out of all 33 countries. Column (4) in Table 2 indicates the number of observations for each country. The countries in Table 2 are arranged in descending order of their AET participation rates in column (1). All statistics in Table 2 were computed using the sampling weights of the OECD Survey of Adult Skills.

Column (1) in Table 2 shows that Anglo-Saxon and Scandinavian countries tend to have high AET participation rates. New Zealand (66.8%) has the highest AET participation rate among the 33 countries, followed by Denmark (66.1%) and Finland (65.9%). On the other hand, the AET participation rates in eastern and southern European countries are relatively low. Russia (19.9%) has the lowest rate, followed by Greece (20.5%), Turkey (22.8%), and Italy (24.3%). The AET participation rate of Korea is 50.0%, placing Korea 16th among the 33 countries, similar to the rate of Israel (50.4%) and Austria (48.8%).

Comparing columns (2) and (3) of Table 2, it can be seen that Korea's AET participation tends to be biased toward non-job-related AET. In Korea, 38.0% of the Respondents reported that they had participated in job-related AET, ranking the country 21st out of the 33 countries. On the other hand, 12.0% reported that they had participated in non-job-related AET, second highest out of the 33 countries. To summarize the results in Table 2, AET participation of Korea, relative to the rates of other countries, tends to be skewed toward AET with low job relevance. Table A2 in the appendix shows replicated results relative to those in Table 2 for the restricted sample of 98,115 workers for which the wage equations are estimated in the following sub-section. The results in Table A2 also confirm that AET participation by Korean workers is skewed toward non-job-related AET.

TABLE 2—ADULT EDUCATION AND TRAINING (AET) PARTICIPATION RATE

	AET		Job-related AET		Non-job-related AET		N
New Zealand	0.668	[1]	0.574	[2]	0.094	[9]	5,266
Denmark	0.661	[2]	0.580	[1]	0.081	[15]	6,519
Finland	0.659	[3]	0.553	[4]	0.106	[8]	4,834
Sweden	0.653	[4]	0.525	[6]	0.129	[1]	3,878
Netherlands	0.643	[5]	0.529	[5]	0.114	[5]	4,449
Norway	0.638	[6]	0.560	[3]	0.078	[16]	4,198
United State	0.596	[7]	0.505	[7]	0.090	[11]	4,326
Canada	0.576	[8]	0.487	[9]	0.089	[13]	23,711
Singapore	0.566	[9]	0.478	[11]	0.088	[14]	4,560
England (UK)	0.556	[10]	0.489	[8]	0.066	[23]	4,706
Australia	0.550	[11]	0.484	[10]	0.065	[25]	6,815
Germany	0.531	[12]	0.457	[12]	0.074	[19]	4,611
Estonia	0.527	[13]	0.417	[15]	0.110	[6]	6,634
Ireland	0.505	[14]	0.430	[13]	0.074	[18]	5,414
Israel	0.504	[15]	0.388	[20]	0.116	[3]	4,444
Korea	0.500	[16]	0.380	[21]	0.120	[2]	5,783
Czech Republic	0.488	[17]	0.422	[14]	0.067	[22]	4,949
Austria	0.488	[18]	0.398	[17]	0.090	[12]	4,474
Northern Ireland (UK)	0.487	[19]	0.415	[16]	0.071	[20]	3,409
Belgium	0.482	[20]	0.390	[19]	0.092	[10]	4,316
Slovenia	0.481	[21]	0.365	[22]	0.116	[4]	4,623
Chile	0.471	[22]	0.394	[18]	0.077	[17]	4,481
Spain	0.462	[23]	0.353	[23]	0.109	[7]	5,332
Japan	0.419	[24]	0.352	[24]	0.068	[21]	4,646
Cyprus	0.376	[25]	0.316	[25]	0.060	[27]	3,964
France	0.358	[26]	0.316	[26]	0.042	[30]	6,167
Poland	0.351	[27]	0.287	[28]	0.064	[26]	6,361
Lithuania	0.334	[28]	0.274	[29]	0.059	[28]	4,626
Slovak Republic	0.328	[29]	0.292	[27]	0.036	[33]	4,955
Italy	0.243	[30]	0.201	[30]	0.042	[32]	4,254
Turkey	0.228	[31]	0.162	[32]	0.066	[24]	4,742
Greece	0.205	[32]	0.162	[31]	0.042	[29]	4,449
Russian Federation	0.199	[33]	0.157	[33]	0.042	[31]	2,963
Total	0.447		0.373		0.074		178,859

Note: 1) Countries are listed in descending order of the adult education and training (AET) participation rate, 2) Numbers in brackets denote the ranking of a given country's AET participation rate among the 33 countries listed.

Source: Data from the OECD Survey of Adult Skills.

B. *Estimating Wage Returns to the AET Participation*

In order to estimate the wage returns to AET participation across countries, I consider the following regression equation:

$$\ln(wage_{ic}) = \beta_0 + \beta_1 AET_{ic} + X_{ic}\gamma + \delta_c + \varepsilon_{ic} \tag{1}$$

where $\ln(wage_{ic})$ indicates the natural logarithm of the hourly wage rate of worker i in country c, AET_{ic} is an indicator for whether worker i reported any

participation in AET within the last 12 months,[5] X_{ic} denotes a vector of covariates of worker i, in this case gender, age, years of schooling, years of current employer tenure, a dummy for permanent-contract worker, numeracy scores in units of ten percentile scores within country c, a dummy for public-sector worker, a list of dummies for the size of the workplace (less than ten workers, 11~250 workers, 251~1000 workers, 1001 workers or more), a list of dummies for ten occupation categories, and a list of dummies for 21 industry categories. δ_c represent a list of dummies for each country c, or country fixed effects. Finally, ε_{ic} is an error term.

β_1 in equation (1) identifies the difference in log hourly wages between those who participated in AET and those who did not participate in AET within country c, controlling for the worker characteristics included in X_{ic}. I estimate equation (1) with the ordinary least square (OLS) method, clustering standard errors at the country level.

The estimation result of equation (1) is summarized in column (1) of Table 3. I found that AET participation is associated with a 7.0% increase in hourly wages, conditional on the country and the worker characteristics. Columns (2) to (5) of Table 3 show the estimation results of equation (1) for Korea and for the three major countries of the U.S., Japan, and Germany, respectively. The estimated wage return to AET participation is 11.4% in Korea, which is higher than those of the 33 countries (7.0%) higher than Germany (8.0%), and similar to that of Japan (11.3%). The estimated wage return to AET participation in the U.S. is statistically insignificant.

Figure 1 shows the distribution of the β_1 estimates in equation (1) across all 33 countries, including the four major countries analyzed in Table 3. Korea's estimate (0.114) is denoted by the vertical line. It can be seen that the estimate for Korea is located in the upper part of the distribution. This suggests that Korea's estimated wage return to AET participation tends to be larger than those of other countries.

Although equation (1) controls for various worker characteristics, including a worker's cognitive ability, there may be unobserved factors that affect both hourly wages and AET participation. This can lead to selection bias in β_1 in equation (1). In other words, based on the estimation results in Table 3, it is difficult to distinguish whether AET participation increases hourly wages or whether high- wage workers are more likely to participate in AET than low-wage workers.

Considering the potential endogenous selection into AET participation, I estimate the following regression equation:

$$\ln(wage_{ic}) = \theta_0 + \theta_1 AETJR_{ic} + \theta_2 AET_{ic} + X_{ic}\pi + \rho_c + \omega_{ic} \tag{2}$$

where $AETJR_{ic}$ is an indicator for whether worker i reported that he or she had participated in job-related AET within the last 12 months. All other variables and the parameters in equation (2) are defined as those in equation (1). Unlike equation (1), equation (2) includes $AETJR_{ic}$ as an additional explanatory variable. With the inclusion of $AETJR_{ic}$, θ_2 in equation (2) identifies the difference in log hourly

[5]It should be noted that equation (1) ignores differences in AET intensity (e.g., duration), quality, or any other AET experience longer than 12 months ago.

TABLE 3—WAGE RETURNS TO AET PARTICIPATION

Country	(1) All	(2) Korea	(3) U.S.	(4) Japan	(5) Germany
AET	0.070***	0.114***	-0.013	0.113***	0.082***
	(0.012)	(0.029)	(0.031)	(0.026)	(0.019)
Female	-0.125***	-0.219***	-0.075	-0.252***	-0.072***
	(0.016)	(0.032)	(0.047)	(0.030)	(0.022)
Age	0.005***	0.004**	0.007***	0.003**	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Schooling	0.031***	0.032***	0.043***	0.015***	0.033***
	(0.003)	(0.006)	(0.007)	(0.005)	(0.006)
Tenure	0.009***	0.020***	0.008***	0.010***	0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Permanent	0.051***	0.098***	0.026	0.156***	0.216***
	(0.012)	(0.027)	(0.027)	(0.030)	(0.037)
Numeracy	0.023***	0.008	0.027***	0.022***	0.022***
	(0.002)	(0.005)	(0.007)	(0.005)	(0.004)
Public	-0.073***	-0.053	-0.067	0.019	0.069**
	(0.018)	(0.040)	(0.042)	(0.057)	(0.029)
11~50 workers	0.071***	-0.005	0.108***	0.061*	0.059*
	(0.018)	(0.034)	(0.039)	(0.036)	(0.035)
51~250	0.121***	0.050	0.189***	0.123***	0.139***
	(0.013)	(0.040)	(0.039)	(0.035)	(0.034)
251~1,000	0.198***	0.076	0.290***	0.216***	0.217***
	(0.026)	(0.048)	(0.085)	(0.040)	(0.037)
1,001 or more	0.284***	0.256***	0.348***	0.282***	0.332***
	(0.020)	(0.048)	(0.051)	(0.065)	(0.039)
Occupation	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y
Country	Y	N	N	N	N
Observations	98,155	2,961	2,249	3,127	3,081
R-squared	0.923	0.321	0.418	0.285	0.473

Note: 1) The dependent variable is the natural logarithm of hourly wage, 2) All statistics are calculated using sampling weights, 3) Robust standard errors are in parentheses, 4) In column (1), country fixed effects are additionally controlled and the standard errors are clustered at the country level.

Source: Data from the OECD Survey of Adult Skills.

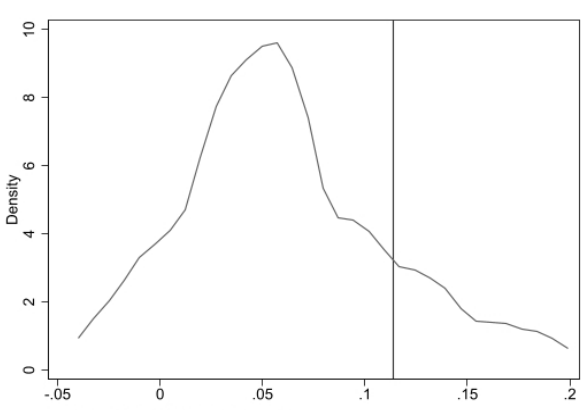

FIGURE 1. DISTRIBUTION OF WAGE RETURNS TO AET PARTICIPATION ACROSS 33 COUNTRIES

Note: The wage return estimate in Korea (0.114) is indicated by the vertical line.

Source: Data from the OECD Survey of Adult Skills.

wages between those who participated in *non-job-related* AET and those who did not participate in any type of AET within country c, controlling for the worker characteristics in X_{ic}, θ_1 in equation (2) identifies the difference in log hourly wages between those who participated in *job-related* AET and those who participated in *non-job-related* AET after controlling for the other covariates. Put differently, θ_1 refers to the additional wage returns that receiving *job-related* AET has over *non-job-related* AET participation. It may be reasonable to assume that receiving *job-related* AET will be better compensated in terms of wages than *non-job-related* AET in the labor market. Thus, if AET indeed causally increases hourly wages, any potential wage effect of *job-related* AET would be greater than that of *non-job-related* AET, and thus θ_1 is likely to be positive. In other words, a finding that θ_1 is close to zero for a given country suggests that the true wage return to AET participation is likely negligible for that country.

Column (1) of Table 4 summarizes the estimation results of equation (2) for the

TABLE 4—WAGE RETURNS TO AET PARTICIPATION BY JOB RELEVANCE

Country	(1) All	(2) Korea	(3) U.S.	(4) Japan	(5) Germany
AET, job-related	0.088***	-0.006	0.113***	0.028	0.074**
	(0.023)	(0.039)	(0.042)	(0.050)	(0.030)
AET	-0.008	0.119***	-0.114**	0.089*	0.016
	(0.030)	(0.044)	(0.047)	(0.050)	(0.033)
Female	-0.123***	-0.219***	-0.072	-0.251***	-0.068***
	(0.026)	(0.032)	(0.047)	(0.030)	(0.022)
Age	0.005***	0.004**	0.007***	0.003**	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Schooling	0.031***	0.032***	0.043***	0.015***	0.032***
	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
Tenure	0.008***	0.020***	0.008***	0.010***	0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Permanent	0.050	0.098***	0.025	0.156***	0.215***
	(0.035)	(0.027)	(0.027)	(0.030)	(0.037)
Numeracy	0.023***	0.008	0.027***	0.022***	0.022***
	(0.002)	(0.005)	(0.007)	(0.005)	(0.004)
Public	-0.073	-0.053	-0.065	0.020	0.070**
	(0.050)	(0.040)	(0.042)	(0.057)	(0.029)
11~50 workers	0.071***	-0.005	0.111***	0.061*	0.058*
	(0.010)	(0.034)	(0.039)	(0.036)	(0.035)
51~250	0.119***	0.050	0.190***	0.123***	0.138***
	(0.013)	(0.040)	(0.039)	(0.035)	(0.034)
251~1,000	0.196***	0.076	0.288***	0.216***	0.215***
	(0.025)	(0.048)	(0.085)	(0.040)	(0.037)
1,001 or more	0.282***	0.256***	0.350***	0.282***	0.330***
	(0.020)	(0.048)	(0.051)	(0.065)	(0.039)
Occupation	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y
Country	Y	N	N	N	N
Observations	98,155	2,961	2,249	3,127	3,081
R-squared	0.923	0.321	0.420	0.285	0.474

Note: 1) The dependent variable is the natural logarithm of hourly wage, 2) All statistics are calculated using sampling weights, 3) Robust standard errors are in parentheses, 4) In column (1), country fixed effects are additionally controlled and the standard errors are clustered at the country level.

Source: Data from the OECD Survey of Adult Skills.

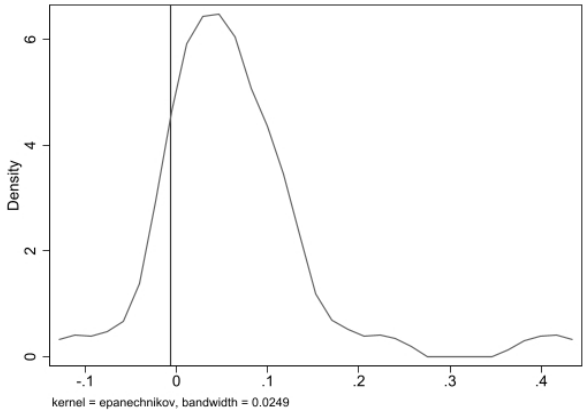

FIGURE 2. DISTRIBUTION OF ADDITIONAL WAGE RETURNS TO JOB-RELATED AET PARTICIPATION OVER NON-JOB-RELATED AET PARTICIPATION ACROSS 33 COUNTRIES

Note: The additional wage return estimate in Korea (-0.006) is indicated by the vertical line.

Source: Data from the OECD Survey of Adult Skills.

entire sample from 33 countries. The estimated θ_1 is -0.008 and is statistically insignificant, indicating that workers who received non-job-related AET earned as much as those who did not participate in any AET. On the other hand, the estimated θ_1 is 0.088 and statistically significant at the 1% level, implying that workers who received job-related AET earned about 8.8% more than those who participated in non-job-related AET. The fact that job-related AET is better compensated than non-job-related AET suggests that there is a positive wage return to AET participation.

The country-specific results in columns (3) to (5) for the U.S., Japan, and Germany also suggest that there are positive wage returns to AET participation in each of the three countries. The estimated values of θ_1, capturing the additional wage return to job-related AET over non-job-related AET, are all positive, despite the imprecise estimation for Japan. The size of the additional wage returns of receiving job-related AET over non-job-related AET is largest in the U.S. at 11.3%, with German also at 8.2%; in Japan, although statistically insignificant, at 2.8% the size is non-negligible.

In contrast, the result for Korea in column (2) reveals that there is no additional wage return of receiving job-related AET over non-job-related AET. The estimated θ_1 is -0.006, which is close to zero and statistically insignificant. This indicates that workers who received job-related AET earn just as much as workers who received non-job-related AET in Korea, which casts doubt on the existence of a positive wage return to AET participation in Korea.

Figure 2 presents the distribution of the θ_1 estimates in equation (2) across all 33 countries, with Korea's estimate (-0.006) represented by the vertical line. This figure shows that the estimate for Korea is relatively close to the bottom of the distribution, suggesting that the additional wage return on job-related AET participation over non-job-related AET participation in Korea is typically lower than in many other countries.

C. *Korea's Unique Wage Compensation Structure*

The estimation results in Table 4 also reveal several differences in the estimated wage equations between Korea and other countries. First, the estimated wage returns to job tenure in Korea are substantially greater than those of the major countries. It is estimated that an additional year of job tenure is associated with approximately a 2.0% increase in the hourly wage in Korea, more than double the corresponding amount for all 33 countries (0.8%) and in the U.S. (0.8%), Japan (1.0%), and Germany (1.0%).

Second, the estimated wage returns to cognitive ability (numeracy score) in Korea are substantially smaller than those of the other countries. When a worker's cognitive ability increases by ten percentile scores, hourly wages tend to increase by 2.7% in the U.S., 2.2% in Japan and Germany, and 2.3% in the 33 countries as a whole. On the other hand, there is no statistically significant increase in hourly wage in Korea. Third, the estimated wage returns to the workplace size in Korea show a more extreme pattern than those in other countries. Looking at the results for the 33 countries in column (1) of Table 4, hourly wages tend to increase gradually as the workplace size increases. Compared to the reference group of workers in workplaces with fewer than ten employees, the estimated wage returns to working in firms with eleven to 50 employees, those with 51 to 250 employees, those with 251 to 1,000 employees, and those with 1,001 or more employees are 7.1%, 11.9%, 19.6%, and 28.2%, respectively. Similar corresponding wage gap patterns according to the workplace size are confirmed in the cases of the U.S., Japan, and Germany. On the other hand, the results for Korea in column (2) show that only workers in workplaces with 1,001 or more employees show a statistically significant wage premium of 25.6% compared to the reference group, while the hourly wage levels of workers at smaller workplaces are statistically insignificant relative to those of the reference group.

D. *Characteristics of AET Participating Workers*

To summarize the main findings thus far, although Korea has a larger wage gap according to AET participation (Table 3), it is unclear whether AET participation in Korea causally increases hourly wages (Table 4). This suggests the possibility that high-wage workers tend to participate more actively in AET than low-wage workers in Korea. To compare the characteristics of workers participating in AET in Korea with the corresponding rates in other countries, I estimate the following regression equation:

$$AET_{ic} = \alpha + X_{ic}\tau + \mu_c + \varphi_{ic} \tag{3}$$

where AET_{ic} and X_{ic} are correspondingly defined as in equations (1) and (2). μ_c and φ_{ic} are country fixed effects and the error term, respectively. I estimate equation (3) with the OLS method or the linear probability model, clustering standard errors at the country level.

Column (1) in Table 5 summarizes the OLS estimation results for the entire sample

from 33 countries. The results generally show that the AET participation rate is higher for men than for women, higher among the younger than the elderly, higher as the levels of education and cognitive skills increase, and higher among those employed in the public sector and/or large-sized workplaces. These results are generally consistent with economic theory or empirical findings. For example, human capital theory predicts that younger workers have a greater incentive to participate in education because they have a longer period to recoup the human capital investment. The theory also predicts that on-the-job training investments more commonly occur in stable employment relationships, often characterized as those in public sector and/or large enterprises. It has also been reported that college graduates are the most active AET participants in most countries (OECD, 2021).

The country-specific results in columns (2) to (5) in Table 5 reveal that Korea's AET participation is mainly associated with job characteristics, rather than worker characteristics, relative to other countries. First, permanent-contract workers in Korea are approximately 4% points more likely to participate in AET than temporary-contract workers, whereas no statistically significant difference was observed for the other major countries assessed here. Second, the gap in the AET

TABLE 5—DETERMINANTS OF AET PARTICIPATION

Country	(1) All	(2) Korea	(3) U.S.	(4) Japan	(5) Germany
Female	-0.023**	0.007	-0.019	-0.053**	-0.022
	(0.009)	(0.020)	(0.021)	(0.021)	(0.021)
Age	-0.004***	-0.004***	-0.001	-0.003***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Schooling	0.017***	0.031***	0.022***	0.025***	0.010**
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
Tenure	0.001	0.005***	-0.001	0.002*	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Permanent	0.008	0.040**	-0.017	-0.001	-0.019
	(0.009)	(0.020)	(0.021)	(0.022)	(0.024)
Numeracy	0.016***	0.008**	0.021***	0.010***	0.020***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Public	0.035**	0.100***	0.062**	0.020	0.019
	(0.017)	(0.029)	(0.029)	(0.040)	(0.028)
Size: 11~50	0.059***	0.133***	0.037	0.054**	0.024
	(0.011)	(0.023)	(0.032)	(0.023)	(0.027)
51~250	0.106***	0.196***	0.070**	0.074***	0.107***
	(0.013)	(0.028)	(0.033)	(0.026)	(0.029)
251~1,000	0.133***	0.214***	0.050	0.120***	0.137***
	(0.025)	(0.031)	(0.037)	(0.033)	(0.032)
1,001 or more	0.161***	0.311***	0.099***	0.081**	0.139***
	(0.026)	(0.030)	(0.037)	(0.040)	(0.036)
Occupation	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y
Country	Y	N	N	N	N
Observations	98,155	2,961	2,249	3,127	3,081
R-squared	0.234	0.302	0.198	0.172	0.215

Note: 1) The dependent variable is an indicator for AET participation within the last 12 months, 2) All statistics are calculated using sampling weights, 3) Robust standard errors are in parentheses, 4) In column (1), country fixed effects are additionally controlled and the standard errors are clustered at the country level.

Source: Data from the OECD Survey of Adult Skills.

participation rate between public and private sector workers tends to be substantially larger in Korea (about 10.0% points) than in the three major countries (about 6.2% points in the U.S.; statistically insignificant in Japan and Germany). Third, the disparity in AET participation rates by workplace size is significantly greater in Korea than in the three major countries. The gap in the AET participation rate between workplaces with more than 1,000 employees and those with ten or fewer employees amounts to approximately 31.1% points in Korea but only 9.9% points in the U.S., 8.1% points in Japan, and 13.9% points in Germany. Park (2019) argued that because government subsidies for AET in Korea are mainly financed by the Employment Insurance Fund, AET participation is biased toward permanent-contract workers in the public sector and at large corporations, where the employment insurance coverage rate is high. The finding that AET participation in Korea is largely concentrated among permanent-contract workers in the public sector and/or large-sized workplaces, as shown in Table 5, may be related to the country's AET financing structure, as indicated in Park (2019).

IV. Conclusion

There are three important findings from this study. First, AET participation in Korea tends to be skewed toward non-job-related AET relative to other countries. Second, the wage return to AET participation is unclear in Korea compared to other major countries such as the U.S., Japan, and Germany. It was also found that the wage structure in Korea is mainly linked to job characteristics such as job tenure and workplace size rather than to worker characteristics such as a worker's cognitive ability and his/her participation in AET, compared to the situations in the other major countries. Finally, the main participants in AET in Korea are permanent-contract workers in the public sector and/or at large-scale workplaces.

The wage compensation structure in Korea as observed in this study may explain why the country's AET participation lacks relevance to the labor market. Because job-related AET is not sufficiently compensated for in the labor market, a worker may not be fully incentivized to participate in job-related AET, leading to skewed participation in non-job-related AET. This implies that in order to incentivize workers to acquire knowledge and skills relevant to the rapidly changing labor market, it is not enough to expand financial support for AET alone; the link between worker productivity and labor market compensation, i.e., wages, must also be strengthened.

APPENDIX

TABLE A1—SUMMARY STATISTICS FOR THE RESTRICTED SAMPLE

Variables (units)	N	Mean	SD
Adult education and training (yes=1)	98,155	0.569	0.495
Job-related AET	98,155	0.506	0.500
Non-job-related AET	98,155	0.063	0.243
Hourly wage (log)	98,155	3.902	2.126
Female (yes=1)	98,155	0.463	0.499
Age (years)	98,155	41.20	11.44
Schooling (years)	98,155	13.29	3.120
Numeracy score (10 percentile scores)	98,155	9.012	9.403
Tenure (years)	98,155	0.635	0.481
Permanent contract (yes=1)	98,155	5.269	2.881
Public sector (yes=1)	98,155	0.248	0.432
Workplace size (yes=1)			
10 workers or less	98,155	0.232	0.422
11~50 workers	98,155	0.300	0.458
51~250 workers	98,155	0.243	0.429
251~1,000 workers	98,155	0.131	0.337
1,001 workers or more	98,155	0.094	0.292
Occupation (yes=1)			
Armed forces	98,155	0.005	0.072
Senior officials & managers	98,155	0.075	0.264
Professionals	98,155	0.196	0.397
Technicians & associate professionals	98,155	0.156	0.363
Clerks	98,155	0.103	0.304
Service workers & Sales workers	98,155	0.182	0.386
Skilled agricultural & fishery workers	98,155	0.009	0.092
Craft & related trades workers	98,155	0.109	0.312
Machine operators & assemblers	98,155	0.087	0.282
Elementary occupations	98,155	0.078	0.268
Industry (yes=1)			
Agriculture, forestry & fishing	98,155	0.014	0.118
Mining & quarrying	98,155	0.006	0.079
Manufacturing	98,155	0.175	0.380
Electricity, gas, & steam supply	98,155	0.008	0.091
Water, sewerage, & waste	98,155	0.007	0.085
Construction	98,155	0.065	0.247
Wholesale & retail trade	98,155	0.129	0.335
Transportation & storage	98,155	0.058	0.234
Accommodation & food service	98,155	0.046	0.208
Information & communication	98,155	0.036	0.185
Financial & insurance	98,155	0.034	0.181
Real estate	98,155	0.006	0.079
Professional, scientific & technical	98,155	0.042	0.200
Administrative & support service	98,155	0.043	0.202
Public administration & defense	98,155	0.076	0.265
Education	98,155	0.093	0.290
Health & social work	98,155	0.121	0.327
Arts, entertainment & recreation	98,155	0.014	0.118
Other service	98,155	0.022	0.146
Households as employers	98,155	0.005	0.068
Extraterritorial organizations & bodies	98,155	0.000	0.011

Note: 1) The units of each variable are indicated in parentheses, 2) All statistics are calculated using sampling weights.

Source: Data from the OECD Survey of Adult Skills.

TABLE A2—AET PARTICIPATION RATE FOR THE RESTRICTED SAMPLE

	AET		Job-related AET		Non-jon-related AET		N
Finland	0.777	[1]	0.687	[3]	0.090	[7]	3,120
New Zealand	0.767	[2]	0.699	[2]	0.069	[15]	3,129
Netherlands	0.764	[3]	0.671	[4]	0.093	[6]	2,849
Denmark	0.762	[4]	0.702	[1]	0.060	[24]	4,156
Sweden	0.740	[5]	0.628	[9]	0.113	[2]	2,706
England (UK)	0.727	[6]	0.670	[5]	0.057	[25]	2,406
Norway	0.723	[7]	0.658	[6]	0.065	[19]	2,679
United State	0.706	[8]	0.633	[8]	0.072	[13]	2,249
Australia	0.697	[9]	0.642	[7]	0.055	[26]	4,078
Northern Ireland (UK)	0.687	[10]	0.616	[10]	0.071	[14]	1,585
Canada	0.682	[11]	0.606	[11]	0.076	[12]	14,204
Singapore	0.660	[12]	0.581	[13]	0.079	[10]	3,085
Ireland	0.651	[13]	0.590	[12]	0.061	[22]	2,668
Estonia	0.641	[14]	0.537	[16]	0.104	[4]	3,755
Czech Republic	0.626	[15]	0.559	[14]	0.067	[18]	2,454
Israel	0.625	[16]	0.507	[19]	0.118	[1]	2,206
Korea	0.604	[17]	0.506	[20]	0.098	[5]	2,961
Germany	0.604	[18]	0.541	[15]	0.063	[21]	3,081
Spain	0.602	[19]	0.515	[18]	0.087	[9]	2,367
Slovenia	0.592	[20]	0.486	[23]	0.106	[3]	2,182
Austria	0.591	[21]	0.504	[21]	0.087	[8]	2,696
Chile	0.588	[22]	0.528	[17]	0.060	[23]	2,153
Belgium	0.577	[23]	0.501	[22]	0.077	[11]	2,610
Poland	0.507	[24]	0.439	[25]	0.067	[16]	3,114
Japan	0.496	[25]	0.443	[24]	0.053	[28]	3,127
Cyprus	0.485	[26]	0.439	[26]	0.046	[29]	2,071
Slovak Republic	0.468	[27]	0.430	[27]	0.038	[31]	2,429
France	0.458	[28]	0.428	[28]	0.030	[32]	3,524
Lithuania	0.441	[29]	0.377	[29]	0.063	[20]	2,648
Turkey	0.427	[30]	0.360	[30]	0.067	[17]	1,448
Greece	0.371	[31]	0.316	[31]	0.055	[27]	1,187
Italy	0.335	[32]	0.306	[32]	0.029	[33]	1,816
Russian Federation	0.270	[33]	0.230	[33]	0.040	[30]	1,412
Total	0.569		0.506		0.063		98,155

Note: 1) Countries are listed in descending order of the adult education and training (AET) participation rate, 2) Numbers in brackets denote the ranking of a given country's AET participation rate among the 33 countries listed.

Source: Data from the OECD Survey of Adult Skills.

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Factors for the Decline of the Self-employed in Korea: A Search and Matching Model Approach†

By JIWOON KIM*

This paper studies potentially relevant factors affecting changes in the number of self-employed in Korea during the period of 1986-2018. The number of self-employed had increased steadily until 2002 but started to decrease around that time and had continued to decline. The increasing trend in the number of self-employed during 1986-2001 is mostly explained by demographic changes, whereas the declining trend during 2002-2018 cannot be explained by demographic factors. In this study, I consider four institutional factors that potentially affect the decrease in the number of self-employed after 2002: i) a decrease in the job-separation rate of wage workers, ii) an increase in the income tax rate applied to the self-employed, iii) an increase in minimum wages, iv) an expansion of unemployment insurance benefits. Using a search and matching model with the self-employed, I quantify the effects of these four factors on the decrease in the number of self-employed during 2002-2018. Quantitative results show that the impact of the increase in the minimum wage is relatively large, whereas the effects of the other three factors are limited. The increase in the minimum wage accounts for approximately 17.5% (0.169 million) of the decrease in the number of self-employed during 2002-2018 (0.964 million).

Key Word: Self-employed, Institutional Factors, Minimum Wages, Occupational Choice
JEL Code: E24, J24

I. Introduction

Self-employed businesses have played an important role as a basis of economic growth through business dynamics and as a social safety net in Korea. Recently, social concerns related to these businesses have increased to a large extent, as they

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were hit the hardest by the COVID-19 shock. Many government programs have been implemented to support them, and more programs are being discussed. Nonetheless, basic research on the self-employed sector is still rare in Korea. This is disappointing, in particular considering that the Korean economy relies on the self-employed more heavily than in other OECD countries (Lee *et al*., 2020).

As shown in Figure 1, the number of self-employed in Korea increased steadily until 2002 but started to decrease around that time and has continued to show a relatively rapid decline. Based on the Economically Active Population Survey (henceforth, EAPS), the number of self-employed increased from 7.07 million in 1986 to a peak of 8.03 million in 2002, after which the trend began to decrease, with the number decreasing to 6.74 million in 2018.

The purpose of this study is to discuss potential factors affecting changes in the number of self-employed in Korea and to understand the economic effects of these factors. First, the effect of demographic changes on the self-employed is examined. I find that the increasing trend of self-employment during 1986-2001 is mostly explained by demographic changes. On the other hand, the declining trend in self-employment during 2002-2018 cannot be explained by demographic factors. Next, I consider four institutional factors that potentially affect the decrease in the number of self-employed after 2002: 1) a decrease in the job-separation rate of wage workers, 2) an increase in the income tax rate applied to the self-employed, 3) an increase in minimum wages, and 4) an expansion of unemployment insurance benefits. Because the job-separation rate is closely related to labor market regulations, it can be viewed as an institutional factor in a broad sense.[1] Lastly, using a search and matching model with the self-employed, I quantify the effects of the four factors on the decrease in the number of self-employed during 2002-2018.

The four factors may reduce the number of self-employed in the following channels. A decline in the job-separation rate for wage workers can decrease the

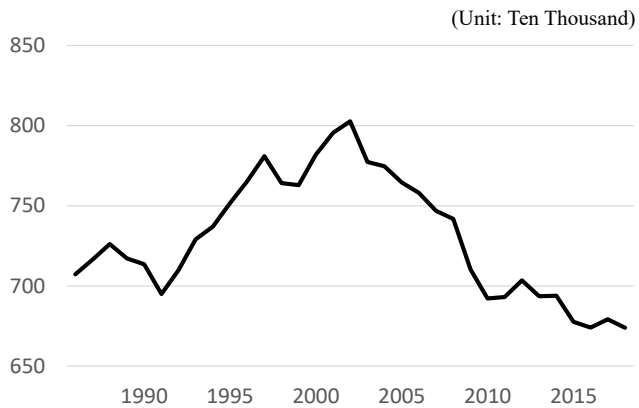

FIGURE 1. NUMBER OF SELF-EMPLOYED

Source: Statistics Korea, EAPS, 1986-2018.

[1]Although the job-separation rate is affected by employment regulation related to dismissal, it may also be influenced by other factors, such as voluntary quitting by workers and labor demand by firms. Therefore, job-separation rates cannot be considered a purely institutional factor in this study. The analysis results related to the job-separation rate should be interpreted with this limitation in mind.

number of self-employed because it reduces potential entrants to self-employment when other conditions remain the same. A higher income tax rate on self-employed businesses can also reduce their expected profitability and thus discourage entry into self-employment. An increase in the minimum wage can lead to a decline in the number of self-employed because it raises the value of being wage workers and lowers the value of being self-employed who hire employees. An expansion of unemployment insurance benefits increases the value of wage workers and thus discourages the unemployed from becoming self-employed when other conditions remain the same.

In Korea, the job-separation rate of wage workers decreased by 3.8%p and the effective income tax rate rose by 1.4%p during the period of 2002-2018. The ratio of the minimum wage to the median wage increased by 25.2%p and the ratio of unemployment benefit recipients to the unemployed rose by 6.2%p during the period. These facts suggest that the four institutional factors considered in this study are potentially relevant to account for the downward trend of self-employment.

In frictional labor markets, however, additional channels that affect the relative values of wage workers and self-employed should be considered in addition to the simple channels mentioned above. For example, a drop in the job-separation rate has the potential to increase the value of the self-employed by reducing costs related to replacement hiring in frictional labor markets. If this effect is large enough, the number of self-employed can increase.

As another example, an expansion of unemployment insurance benefits can increase the number of self-employed in frictional labor markets. In a frictional labor market, the unemployed cannot find a job immediately when desired. An extension of unemployment benefits lengthens the duration of unemployment, and long-term unemployed are more likely to become self-employed rather than wage workers, as their assets become depleted. If this effect is large enough, the expansion of unemployment benefits can lead to an increase in the number of self-employed. Therefore, this study quantifies the effect of the four institutional factors on the number of self-employed using a search and matching model that explicitly reflects labor market friction and the occupation choices between wage workers and the self-employed.

The main contribution of this study is that it quantifies the effect of institutional factors on changes in the number of self-employed in Korea during 2002-2018 using a calibrated structural model. Although a few studies exist on the trend of self-employed in Korea (Ryoo and Choi, 1999; 2000; Hong and Oh, 2018), they do not explicitly quantify the effects of potential factors on changes in the number of self-employed. On the other hand, Cheon (2003), Sung (2002), and Kim (2013) empirically examine factors that have the potential to affect the choice between wage workers and self-employed in Korea. However, these studies do not examine trend changes in relation to the self-employed in Korea.

To quantify the effects of institutional factors on changes in the number of self-employed, I build a search and matching model that reflects the choice between wage workers and the self-employed. Although there is no significant difference from the standard search and matching model in terms of the main components of the model, there is a contribution in that the model is revised to contain the four institutional factors for the main quantitative analysis of the paper.

This paper proceeds as follows. Section II documents several facts related to the trend change in the number of self-employed in Korea during 1986-2018. Section III provides four institutional factors that potentially affect the decline in the number of self-employed since 2002. Section IV quantifies the effect of the four institutional factors on the downward trend in the number of self-employed during 2002-2018 using a calibrated labor market search and matching model that reflects the occupational choice between wage workers and self-employed. Section V concludes the paper.

II. Trends in the Number of Self-employed in Korea

A. *Definition of the Self-employed*

The definition of self-employed in this paper includes only the self-employed in non-agricultural sectors. Economic growth is accompanied by changes in the industrial structure, and as the economy grows, the proportion of agriculture among all industries decreases. Therefore, a decreasing trend of self-employed in the agricultural sector can be interpreted as a result of changes in the industrial structure. As shown in Figure A1 in the Appendix, the number of self-employed in the agricultural sector has been steadily decreasing since 1986 in Korea. The characteristics of the self-employed in the agricultural sector and those in non-agricultural sectors are quite different, and a decreasing trend with regard to the number of self-employed in the agricultural sector is a common phenomenon in most advanced countries, including Korea. For these reasons, these workers were excluded from the analysis.

The self-employed are composed of self-employed without employees, self-employed with employees, and unpaid family workers. In Korea, the proportion of self-employed without employees is much higher than that of self-employed with employees and unpaid family workers. However, there are no significant differences in these trends, as shown in Figure A2 in the Appendix. In general, the increasing trend was maintained until around 2002, after which the rate of increase slowed or began to decrease. In this study, unpaid family workers were excluded from the analysis because their characteristics are closer to those of wage workers. In addition, it is difficult properly to reflect unpaid family workers in the structural model in Section IV. For these reasons, unpaid family workers are also excluded from the analysis.

Figure 2 shows the trend of the self-employed excluding unpaid family workers in non-agricultural sectors. The number of self-employed, which was 2.99 million in 1986, increased gradually, peaking at 5.05 million in 2006 and then showing a decreasing trend, with a decrease to 4.79 million in 2018.

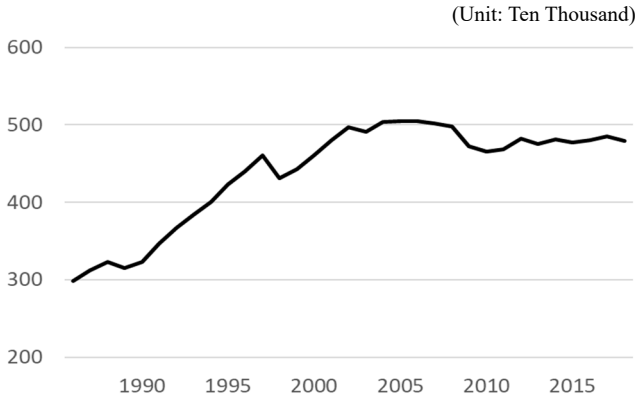

FIGURE 2. SELF-EMPLOYED EXCLUDING UNPAID FAMILY WORKERS IN NON-AGRICULTURAL SECTOR

Source: Statistics Korea, EAPS, 1986-2018.

B. *Effects of Demographic Changes*

The number of self-employed varies by gender and age group, as shown in Figure A3 and Figure A4 in the Appendix. The total number of self-employed is the sum of the number of self-employed in each subgroup defined by gender and age. Therefore, demographic changes (or changes in population distribution) may affect changes in the total number of self-employed. To quantify the effect of demographic changes explicitly, the number of self-employed can be decomposed as follows:

$$S_t = \sum_{i \in I} S_t^i = \sum_{i \in I} \frac{S_t^i}{P_t^i} \frac{P_t^i}{P_t} P_t$$

The number of self-employed for a specific subgroup (i) each year (S_t^i) is expressed as the product of ① the proportion of the self-employed in each subgroup's population (S_t^i / P_t^i), ② the proportion of each subgroup's population in the total population (P_t^i / P_t), and ③ the total number of the population (P_t). The series of artificial self-employed can be constructed by changing only one of ①, ②, and ③ and fixing the other two at the level of 1986. Then, each artificial series of self-employed can be compared with the actual series of self-employed.

$$S_{1,t} = \sum_{i \in I} \frac{S_t^i}{P_t^i} \frac{P_{1986}^i}{P_{1986}} P_{1986}$$

$$S_{2,t} = \sum_{i \in I} \frac{S_{1986}^i}{P_{1986}^i} \frac{P_t^i}{P_t} P_{1986}$$

$$S_{3,t} = \sum_{i \in I} \frac{S_{1986}^i}{P_{1986}^i} \frac{P_{1986}^i}{P_{1986}} P_t$$

$S_{1,t}$ represents the number of artificial self-employed whose demographic structure is controlled. In other words, it shows the trend of the number of self-employed that changes due to factors other than the demographic structure, and the statistics mainly reflect the choice of economic agents given that exogenous demographic changes were controlled. On the other hand, $S_{2,t}$ and $S_{3,t}$ show the effects of changes in the proportion of each subgroup's population and the effects of changes in the total population, respectively. They show the effects of exogenous demographic changes on changes in the number of self-employed.

In this study, for each male and female, thirteen age groups (15-19 years old, 20-24 years old, …, 70-74 years old, and 75 years old or over) are constructed by dividing the total population into five-year-age units. Therefore, in total, 26 subgroups were constructed for the analysis. After calculating the proportion of self-employed and the population of each subgroup using raw data from the EAPS, the number of artificial self-employed was computed using the methodology described above. Figure 3 compares the series of actual self-employed to the series of artificial self-employed.

The increasing trend of the number of self-employed after 1986 was mostly explained by demographic changes. The series S_3, which reflects only the change in the overall population, has continuously increased since 1986. The series S_2, which reflects only the change in the proportion of each subgroup's population, also shows an increasing trend. However, for S_2, the rate of increase has slowed since the mid-2000s, showing a gradual decline. On the other hand, the series S_1, where population structures were controlled, showed a generally moderate increase until 2002 with a rapid decrease after 2002. Specifically, the number of artificial self-employed decreased from 3.3 million to 2.33 million during 2002-2018, representing a 29.2% drop compared to 2002.

In sum, the increase in the number of self-employed before 2002 is largely explained by changes in the demographic structure, especially the increased population overall. On the other hand, the declining trend of the actual self-employed since 2002 is not explained by demographic factors. Because the increasing trend of self-employment before 2002 is mostly explained by demographic changes, the

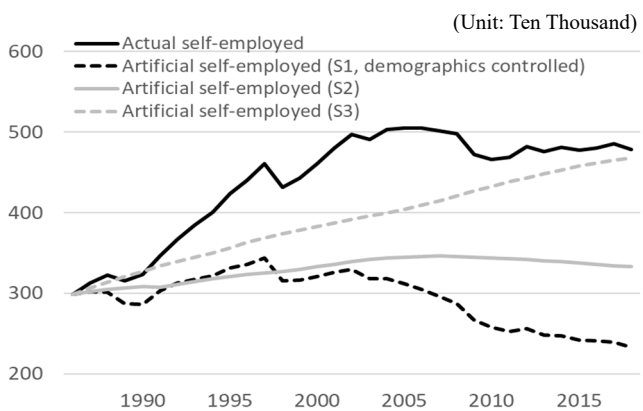

FIGURE 3. ACTUAL AND ARTIFICIAL SERIES OF SELF-EMPLOYED

Source: Statistics Korea, EAPS, 1986-2018.

analysis using a structural model will focus on the declining trend during 2002-2018, which cannot be explained by the demographic structure.

III. Institutional Factors Affecting the Decline in the Self-employed during 2002-2018

In this study, I consider the following four institutional factors that may have affected the decline in self-employment after 2002[2]: 1) a decrease in the job-separation rate of wage workers, 2) an increase in the income tax rate applied to the self-employed, 3) an increase in minimum wages, and 4) an expansion of unemployment insurance benefits (an increase the ratio of unemployment benefit recipients to the unemployed). Because the job-separation rate is closely related to labor market regulations, it can be viewed as an institutional factor in a broad sense.

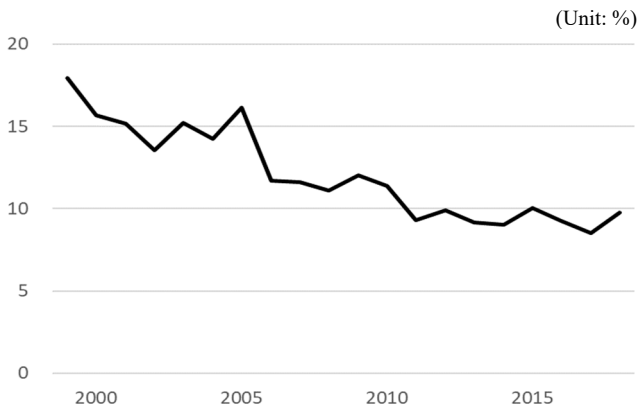

FIGURE 4. JOB-SEPARATION RATE FOR WAGE WORKERS

Source: Korea Labor Institute, KLIPS, 1999-2018.

A. *Decrease in the Job-separation Rate for Wage Workers*

The job-separation rate for wage workers refers to the transition probability from wage workers to non-wage workers, that is, the exit probability of wage workers. A decline in the job-separation rate for wage workers can decrease the number of self-employed because it reduces potential entrants to self-employment when other conditions remain the same. Figure 4 shows the job-separation rate for wage workers calculated by data from the Korean Labor and Income Panel Study (henceforth KLIPS). The job-separation rate of wage workers decreased by 3.8%p from 13.6% in 2002 to 9.8% in 2018.

[2]Factors that affect an increase the exit rate of the self-employed, such as business closure costs, can also be considered. However, according to Lee *et al.* (2020), the decrease in the number of self-employed since 2002 is mainly due to a decrease in the entry rate rather than an increase in the exit rate. Therefore, potential factors that directly affect the exit rate from self-employment are not considered in this study.

B. *Increase in the Income Tax Rate for the Self-employed*

A higher tax rate on self-employed businesses can reduce their expected profitability and thus discourage entry into self-employment. Although the income tax is not directly considered, several previous studies, such as Torrini (2005), Buehn and Schneider (2012), and Kang and Yoo (2018), showed that changes in tax rates and the degree of tax avoidance had a significant effect on the number of self-employed. Figure 5 shows the effective income tax rate for the self-employed, as calculated using the Tax Statistics provided by the National Tax Service. The effective income tax rate is calculated by dividing the determined tax amount by the total income. The effective income tax rate rose 1.4%p from 13.5% in 2002 to 14.9% in 2018.[3]

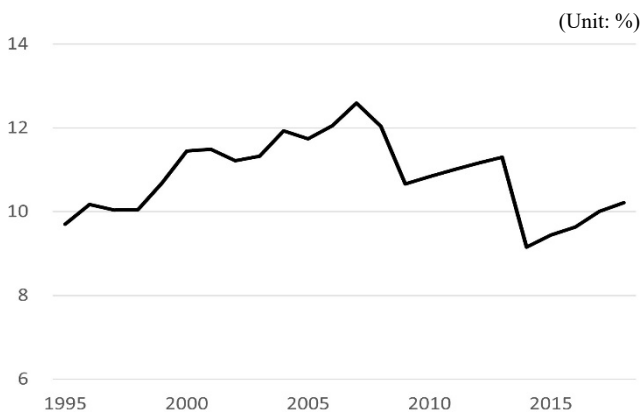

FIGURE 5. EFFECTIVE INCOME TAX RATE FOR THE SELF-EMPLOYED

Source: National Tax Service, Tax Statistics, 1995-2018.

C. *Increase in Minimum Wages*

An increase in the minimum wage can lead to a decline in the self-employed because it raises the value of being wage workers and lowers the value of being self-employed with employees. Kang and Yoo (2018) showed that 43.5-45.2% of the decrease in the proportion of the self-employed in Korea between 2000 and 2011 can be explained by the increase in the ratio of the minimum wage to the median wage.

Figure 6 shows the ratio of the minimum wage to the median wage. The ratio increased by 25.2%p from 33.4% in 2002 to 58.6% in 2018. The increase in the minimum wage may have affected the decrease in the number of self-employed since 2002.

[3]The income tax rate applied to wage workers decreased from 11.2% in 2002 to 10.2% in 2018. This may have reduced the number of self-employed by increasing the value of wage workers. For convenience of the analysis, this study focuses on changes in the income tax rate for the self-employed, as such changes directly affect the self-employed. However, if the income tax rate relative to wage workers is explicitly reflected in the analysis, the effect of the income tax rate for the self-employed on the decline in the number of self-employed is expected to be larger in the quantitative analysis.

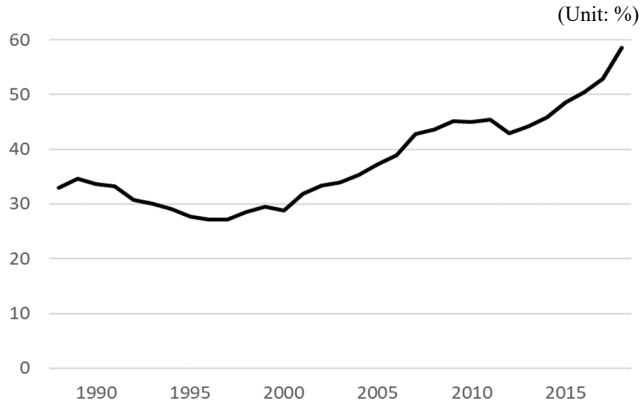

FIGURE 6. RATIO OF THE MINIMUM WAGE TO THE MEDIAN WAGE

Source: OECD, OECD Statistics, 1988-2018.

D. *Expansion of Unemployment Insurance Benefits*

Because unemployment insurance is compulsory for wage workers, an expansion of unemployment insurance benefits increases the value of wage workers and thus discourages the unemployed from becoming self-employed. The wage replacement rate and maximum benefit duration of unemployment insurance benefits did not change significantly after 1995. However, the coverage of unemployment insurance gradually expanded, leading to a steady increase in the proportion of unemployment benefit recipients among the total unemployed. Figure 7 shows the ratio of unemployment benefit recipients to the unemployed. The ratio rose by 6.2%p from 4.6% in 2002 to 10.8% in 2018.

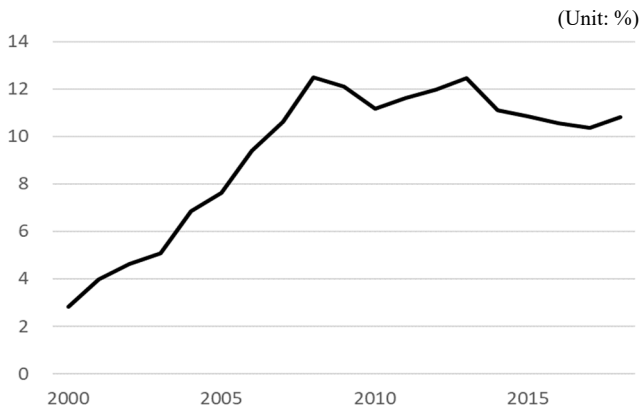

FIGURE 7. RATIO OF UNEMPLOYMENT INSURANCE RECIPIENTS TO THE UNEMPLOYED

Source: Statistics Korea, EAPS, 2000-2018; Korea Employment Information Service (2019).

IV. Effects of Institutional Factors on the Decrease in Self-employed during 2002-2018

In this section, I build a search and matching model that reflects occupational choices between wage workers and the self-employed to quantify the effects of the four potential factors discussed in the previous section on the decline in the number of self-employed. Based on the artificial series of self-employed in Figure 3 (S_1), in which the demographic structure is controlled, the number of self-employed decreased by 29.2% (0.964 million) between 2002 and 2018. Therefore, the model quantifies the degree to which the changes in the four potential factors can explain the decrease in the self-employed during this period.

A. *Search and Matching Model with Occupational Choices*

Environment

The period in the model is one year. The population of the model economy is assumed to be one. Risk-averse economic agents are divided into employed (wage workers, self-employed) and unemployed.[4] Again, the self-employed are divided into self-employed without employees and self-employed with employees.[5] The unemployed look for a job to become wage workers each period or choose to become self-employed. The unemployed can become wage workers with a probability of p ($p<1$) or can become self-employed with a probability of one for as long as they want to. The unemployed have the same productivity (x) as wage workers, and the productivity as wage workers is normalized to one.[6] On the other hand, the unemployed have productivity (z) as the self-employed, and the productivity as the self-employed changes stochastically each period. With regard to becoming a wage worker, there is no uncertainty in labor income related to productivity because the productivity as a wage worker (x) is constant. On the other hand, for those who seek to become self-employed, there is uncertainty in business income due to the uncertainty in the productivity of the self-employed (z). If the unemployed remain unemployed, they will receive unemployment benefits (b) with probability (π).

Wage workers receive the minimum wage ($\underline{w}$) with a probability of γ and they receive the median wage (w) with a probability of $1-\gamma$. The self-employed decide on how many vacancies ($v \geq 0$) are posted every period based on their productivity. Given that fixed costs (κ_f) are incurred when posting vacancies, the self-employed

[4]In fact, the labor force participation rate increased by 1%p in 2018 compared to 2002 in Korea, but people not in the labor force were assumed to be constant and were not explicitly reflected in the model for convenience of the analysis.

[5]Unpaid family workers are excluded for simplicity in this model.

[6]The reason that productivity as a wage worker is assumed to be constant in this study is to simplify the problem of the self-employed. When the self-employed hire multiple workers and workers' productivity are heterogeneous, wage determination becomes very complicated in the model. In this study, the wage determination process is simplified through the simple assumption that productivity as a wage worker is identical and that the self-employed receive the minimum wage or the median wage in a probabilistic manner, whereas the internal consistency of the model is partially abandoned. Therefore, this model has a limitation in that the productivity and income distribution of wage workers are not explicitly reflected.

without employees can exist in equilibrium due to the fixed costs. The self-employed pay τ proportion of their net output, excluding labor costs, as income tax. Finally, wage workers and the self-employed become unemployed with an exogenous probability of χ_w and χ_s, respectively, each period. It is assumed that direct movement between wage workers and the self-employed is impossible and that the choice between wage workers and the self-employed is possible only when they become unemployed.

Maximization Problems for Economic Agents

The state variables for the unemployed and wage workers are represented by $s^u = s^w = (z,a)$, and the state variables for the self-employed are represented by $s^s = (z,a,n)$. Here, z is the productivity of the self-employed, a is the amount of net assets, and n is the number of employees excluding the self-employed.

1) Unemployed

The value function for the unemployed is given by

$$V^u(z,a) = \max_{c,a'} u(c) + \beta E \begin{bmatrix} p\max\left(V^w(z',a'), -\eta + V^s(z',a',0)\right) \\ +(1-p)\max\left(V^u(z',a'), -\eta + V^s(z',a',0)\right) \end{bmatrix}$$

$$s.t. \quad c + a' = (1+r)a + \pi b + T$$

$$z' \sim iid, U\left(\underline{z}, \overline{z}\right), \quad a' \geq 0$$

The unemployed observe their state variables at the beginning of each period and optimally choose the amount of consumption and net assets to maximize their utility from consumption given their budget constraints.[7] The unemployed receive unemployment insurance benefits with probability π.[8] The unemployed distribute income from net assets, unemployment benefits, and transfers from the government (T) to consumption and savings. The productivity of the self-employed (z) is independently and identically distributed (iid) and is assumed to follow a uniform distribution with the support of $\left[\underline{z}, \overline{z}\right]$.

There exist borrowing constraints in this economy, and the maximum amount that can be borrowed is assumed to be zero following Han *et al*. (2017). The unemployed

[7]In this study, the model includes only the extensive margin of labor supply without the intensive margin. Therefore, the inclusion of leisure in the utility function has little effect on the quantitative results. Moreover, we have a problem in the calibration when leisure is included in the utility function. Additional parameters related to leisure cannot be calibrated independently from the job-finding rate.

[8]In reality, unemployment benefits can only be claimed if the unemployed have a long enough history of employment insurance and they lost their job involuntarily. However, in this study, the complicated unemployment benefit system in Korea is simplified to meet the purpose of this study, and it is assumed that the unemployed can receive unemployment benefits probabilistically. Through this type of simplified modeling, the exogenous expansion of the unemployment benefits (increase in the ratio of unemployment benefit recipients to the unemployed) can be reflected in the model relatively easily.

can become a wage worker with an exogenous probability of p by searching for jobs[9] or can become self-employed without employees with a probability of one for as long as they want to be. It is assumed that the unemployed become self-employed without employees when they choose to become self-employed. For wage workers, there is no uncertainty in their labor income related to productivity because their productivity as wage workers is constant. On the other hand, for the self-employed, there is uncertainty in their business income due to the uncertainty in their productivity as the self-employed.

When the unemployed become self-employed without looking for a job, start-up costs (η) are incurred, and start-up costs include both monetary and non-monetary costs. For convenience of the analysis and parameterization, start-up costs are modeled as a disutility occurring during the start-up process rather than as explicit monetary costs in the budget constraints. It is assumed that there are no monetary and non-monetary costs for job search activities. If the unemployed look for a job but cannot find a job, they remain unemployed. V^w and V^s represent the value function for wage workers and for the self-employed, respectively.

2) Employed: Wage Workers

The value function for wage workers is given by

$$V^w(z,a) = \max_{c,a'} u(c) + \beta E\left[\chi_w V^u(z',a') + (1-\chi_w)V^w(z',a')\right]$$
$$s.t.\quad c + a' = \gamma \underline{w} + (1-\gamma)w + (1+r)a + T$$
$$z' \sim iid, U\left(\underline{z},\overline{z}\right),\ \ a' \geq 0$$

Among the employed, wage workers observe their state variables at the beginning of each period and optimally choose the amount of consumption and net assets to maximize the utility from consumption under their given budget constraints. Wage workers distribute income from labor income, net assets, and transfers from the government to consumption and savings. It is assumed that wage workers receive the minimum wage ($\underline{w}$) with probability γ and the median wage (w) with probability $1-\gamma$ to reflect the ratio of the minimum wage to the median wage in the model in a simple manner.

In this study, the median wage is normalized to 1 ($w=1$). Therefore, the minimum wage can also be interpreted as the ratio of the minimum wage to the median wage. Because γ proportion of wage workers receive the minimum wage on average, γ can be interpreted as the influence rate of the minimum wage.[10] In this way, the

[9]For convenience of the analysis, it is assumed that the job-finding rate is determined outside the model as an exogenous parameter in this model. However, in reality, the probability of finding a job for each unemployed person can vary depending on the productivity of the unemployed and the total number of vacant jobs. In this study, it is assumed that productivity as wage workers is identical for all the unemployed and that changes in the number of vacant jobs do not affect the probability of finding a job. In this regard, we should take this simplification into account when interpreting the analysis results.

[10]The influence rate of the minimum wage represents the proportion of wage workers receiving the minimum

expected earned income of wage workers becomes $\gamma\underline{w}+(1-\gamma)w$. Wage workers experience exogenous job separation at the end of each period with a probability of χ_w and become unemployed.[11] They remain wage workers with a probability of $1-\chi_w$.

3) Employed: Self-employed

The value function for the self-employed is given by

$$
\begin{aligned}
V^s(z,a,n) &= \max_{c,a',v} u(c)+\beta E\left[\chi_s V^u(z',a')+(1-\chi_s)V^s(z',a',n')\right] \\
s.t.\quad c+a' &= \kappa_f I_{(v>0)}+\kappa_v v \\
&= (1-\tau)\left[f(z,1+n)-n(\gamma\underline{w}+(1-\gamma)w)\right]+(1+r)a+T \\
z' &\sim iid,\ U\left(\underline{z},\overline{z}\right),\ \ a'\geq 0 \\
n' &= (1-\chi_w)n+qv
\end{aligned}
$$

Among the employed, the self-employed observe their state variables at the beginning of each period and optimally set the amount of consumption and net assets, and the number of vacancies (v) to maximize the utility from consumption under their given budget constraints. The self-employed distribute income from after-tax business income, net assets, and transfers from the government to consumption and savings.

The production function of the self-employed is given by $f(z,1+n)$ and it is assumed that the output varies depending on the productivity (z) for the self-employed and the number of employees (n), which change each period. The total labor input of each firm is $1+n$ by adding the self-employed person and the number of employees. The price of the final product (output) is normalized to 1, which implies that the output becomes sales. The total wage cost is $n(\gamma\underline{w}+(1-\gamma)w)$, as the average wage paid to each employee is $\gamma\underline{w}+(1-\gamma)w$ and the number of employees equals n. Business income is defined as sales excluding wage costs, and τ proportion of business income is paid as income tax.

The number of vacancies in the current period leads to the number of employees in the next period (n') with a certain probability q ($q<1$), an exogenous job-filling rate. Reflecting the exogenous job-separation rate of wage workers, it is assumed that the number of employees decreases by χ_w regardless of whether a business closure occurs. There is a fixed cost (κ_f) that must be paid for any positive number of vacancies and a variable cost (κ_v) that increases according to the number of vacancies posted. I assume a fixed cost for vacancies to reflect explicitly the self-

wage.

[11] For convenience of the analysis, this model does not distinguish between voluntary and involuntary unemployment of wage workers. This simplification is consistent with the assumption that the unemployed collect unemployment benefits probabilistically regardless of voluntary or involuntary unemployment in the maximization problem of the unemployed.

employed without employees in the model. This factor can be interpreted as explicit and implicit fixed costs in the hiring process. The self-employed experience an exogenous business closure at the end of each period with a probability of χ_s and become unemployed.[12] The self-employed remain self-employed with a probability of $1-\chi_s$.

Stationary Recursive Equilibrium

This model is a partial equilibrium model in which the real wage (w) and the real interest rate (r) are given exogenously. In this model, the state variables for the unemployed, wage workers, and the self-employed are given as $s^u=(z,a)$, $s^w=(z,a)$, $s^s=(z,a,n)$, respectively. Correspondingly, the state space for each economic agent is defined as S^u, S^w, and S^s and the state variable for the overall economy is defined as S.

The *stationary recursive equilibrium* of the model is 1) a set of value functions (a value function for the unemployed (V^u), a value function for wage workers (V^w), and a value function for the self-employed (V^s)), 2) a set of policy functions (a policy function for consumption and assets of the unemployed, a policy function for the occupational choice of the unemployed, a policy function for the consumption and assets of wage workers, and a policy function for consumption, assets, and vacancies of the self-employed), 3) transfer income from the government (T), and 4) a distribution function of economic agents ($\mu(S)$) such that the following hold:

1. Given exogenous wages (w) and interest rates (r), the policy functions for each economic agent are solutions to the relevant maximization problems.

2. Given the exogenous income tax rate (τ), the government's transfer income (T) satisfies the government's budget constraint

$$\tau\int f(z,1+n)\mu(S^s)dS=T$$

3. The distribution function of economic agents is time-invariant.

$$\mu_{t+1}(S)=\mu_t(S)\ \ for\ all\ S\ and\ t.$$

B. *Calibration*

Functional Forms

I use a standard utility function in the form of constant relative risk aversion (CRRA), which is widely used in macroeconomic studies.

[12]For convenience of the analysis, this model does not distinguish between voluntary and involuntary business closures of the self-employed. This simplification is consistent with the assumption that the unemployed collect unemployment benefits stochastically regardless of the types of previous jobs in the maximization problem of the unemployed.

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

The production function for the self-employed is defined as follows:

$$f(z, 1-n) = e^{z}(1+n)^{\alpha} \qquad (0 < \alpha < 1)$$

Here, n becomes zero for the self-employed without employees who perform production activities alone. On the other hand, for the self-employed with employees (employers), production activities are carried out using the number of employees including themselves. If the self-employed have higher productivity, more production is possible given the same number of employees.

Calibration of the Parameters

Parameters in this model can be divided into two groups: 1) parameters calculated outside the model or borrowed from previous studies, and 2) parameters determined inside the model in the process of matching the target statistics. Because this study quantifies the declining trend of self-employed between 2002 and 2018, the model is calibrated based on 2002. Therefore, most of the parameters and target moments used for calibration were set as of 2002, and values close to those in 2002 were used as much as possible when data were not available.

1) Parameters Calibrated Outside of the Model

The parameter for the relative risk aversion (σ) in the utility function is set to 2, a value widely used in macroeconomic studies. The elasticity parameter (α) in the production function is set to 0.85 following Atkeson and Kehoe (2005). Productivity (z) of the self-employed is assumed to be independently and identically distributed and the minimum value of productivity ($\underline{z}$) is set to 1.492, as this value guarantees positive consumption for the self-employed. That is, consumption for the self-employed can be less than zero when the productivity of the self-employed is lower than this value.

The median wage (w) is normalized to be one and the minimum wage ($\underline{w}$) is set to 0.334, which is the ratio of the minimum wage to the median wage in 2002. The influence rate of the minimum wage (γ) is set to 0.028, which is the influence rate in 2002. The exogenous job-separation rate for wage workers and the probability of business closures are set to 0.136 and 0.133, respectively, based on the exit probabilities of wage workers and self-employed in 2002 from the KLIPS data.

The real interest rate (r) is assumed to be 2.39% using the interest rate of the one-year Treasury Bond in 2002 (5.19%) and the CPI inflation rate in 2002 (2.8%). The annual time discount factor is set to 0.9767 to be consistent with the annual real interest rate of 2.39%. The wage replacement rate of unemployment insurance benefits is assumed to be 50% because the replacement rate has long been maintained

TABLE 1— PARAMETERS CALIBRATED OUTSIDE THE MODEL

Parameter	Explanation	Value	Remarks
	Utility function, production function		
σ	Degree of risk aversion	2.000	Many macroeconomic studies
α	Elasticity parameter in prod. function	0.850	Atkeson and Kehoe (2005)
	Labor market		
$\underline{z}$	Minimum value for z	1.492	Set to guarantee positive consumption
w	Median wage	1.000	Normalized to one
$\underline{w}$	Minimum wage	0.334	Minimum wage/Median wage, 2002
γ	Influence rate of the minimum wage	0.028	Influence rate of min. wage, 2002
χ_w	Job-separation rate for wage workers	0.136	Exit rate (13.6%) for wage workers, 2002
χ_s	Probability of business closures	0.133	Exit rate (13.3%) for self-employed, 2002
	Real interest rate, time discount factor		
r	Real interest rate (annual)	0.0239	Real interest rate, 2002
β	Time discount factor (annual)	0.9767	Real interest rate, 2002
	Unemployment insurance		
b	Unemployment benefits	0.167	Annual wage replacement rate, 2002
π	Probability of receiving UI benefits	0.046	UI recipients /Unemployed, 2002
	Tax		
τ	Income tax rate for the self-employed	0.135	Effective income tax rate, 2002

Note: UI denotes unemployment insurance.

at around 50%.[13] Considering that a period in the model is one year and that the average duration of receiving unemployment benefits is approximately four months, annual unemployment benefits (b) are calculated and found to be 0.167 by multiplying one third of the median wage by 50%.

The probability of receiving unemployment benefits (π) is set to 0.046, which is the ratio of unemployment benefit recipients to the unemployed in 2002. Lastly, the effective income tax rate for the self-employed (τ) is set to 0.135, which is the actual tax rate in 2002. The parameters calibrated outside of the model are listed in Table 1.

2) Parameters Calibrated in the Model

Six parameters are determined to match the target moments in the model. As the target moments, six labor market statistics are used. The job-finding rate for the unemployed (p), referring to the probability of finding jobs as wage workers, is determined to match the proportion of the employed among the labor force (87.9%) in 2002 from the EAPS. Because the population out of the labor force is excluded from the model, the proportion of employed among the total population in the model corresponds to the proportion of employed among the labor force in the data.[14]

[13]The wage replacement rate is defined as the ratio of the monthly unemployment benefit to the three-month average wage before the job loss. Because only median wages are included in the model, the wage replacement rate in the model may be slightly different than that in the data, which uses average wages. Given that the difference between the average wage and median wage is not large in the data, errors related to this approximation would be small.

[14]In this study, workers in the agricultural sector and unpaid family workers are excluded. Therefore, the

The job-filling rate for the self-employed (q) is set to match the ratio of vacancies to the unemployed (V / U), i.e., market tightness, in the data. Although the matching function is not explicitly reflected in this study, the job-filling rate can be expressed as a function of the job-finding rate and the market tightness using a property of the constant returns to scale matching function: $q = p / (V / U)$. Therefore, the job-filling rate can be computed using the calibrated job-finding rate and value for the market tightness (0.93) in Kim (2020).

The parameter for disutility from becoming self-employed (η) is determined to match the proportion of the self-employed among the employed (24.6%) in 2002 from the EAPS. The parameter for fixed costs for posting vacancies (κ_f) is set to match the proportion of the self-employed without employees among the employed (16.8%) in 2002 from the EAPS. On the other hand, the parameter for variable costs for posting vacancies (κ_v) is determined to match the proportion of employees hired by the self-employed with 1-9 employees among the employed (53.9%) in 2004 from the EAPS.[15] Lastly, the maximum value for the productivity of the self-employed ($\bar{z}$) is set to match the labor income share (58.4%) in 2002 from the National Income Accounts in Korea.

The six parameters calibrated in the model are summarized in Table 2. The annual job-finding rate and job-filling rate are set to 0.925 and 0.995, respectively. These values imply that 92.5% of the unemployed will become wage workers within one year and that 99.5% of vacant jobs will be filled within one year. The parameter for disutility from becoming self-employed is set to 3.350 and the parameters for fixed and variable costs for posting vacancies are set to 2.955 and 0.014, respectively. Considering that the annual median wage in this model is normalized to one, fixed costs for posting vacancies can be interpreted as the annual salaries of three workers. The variable cost of posting vacant jobs is determined to be relatively low. The upper limit of productivity of the self-employed is parameterized as 2.014.

Table 3 compares the target moments calculated in the model with those in the data. Although most of the target moments in the model are matched quite well, the ratio of the self-employed without employees to the employed and the share of

TABLE 2—PARAMETERS CALIBRATED IN THE MODEL

Parameters	Explanation	Value	Target moments
p	Job-finding rate for the unemployed	0.925	E/LF (0.879), EAPS, 2002
q	Job-filling rate for the self-employed	0.995	V/U (0.930), Kim (2020)
η	Disutility from becoming self-employed	3.350	SE/E (0.246), EAPS, 2002
κ_f	Fixed costs for posting vacancies	2.955	SEwo/E (0.168), EAPS, 2002
κ_v	Variable costs for posting vacancies	0.014	E(1-9)/E (0.539), EAPS, 2004
$\bar{z}$	Maximum value for z	2.014	Labor share (0.584), NIA, 2002

Note: 1) E, U, LF, V, SE, SEwo denote the employed, the unemployed, labor force, vacancies, the self-employed, and the self-employed without employees, respectively, 2) E(1-9) represents the number of employees hired by the self-employed with 1-9 employees, 3) NIA stands for the National Income Accounts in Korea.

proportion of the employed among the labor force in the target moments is slightly different than that for the entire population.

[15]Because the values for the number of employed by size of employment are available only after 2004 in the Korean Statistical Information Service (KOSIS), the value for 2004 is used in this study.

TABLE 3—TARGET STATISTICS: MODEL VS. DATA

Target statistics	Model	Data
E/LF	0.880	0.879
V/U	0.930	0.930
SE/E	0.246	0.246
SEwo/E	0.148	0.168
E(1-9)/E	0.447	0.539
Labor share	0.561	0.584

Note: 1) E, U, LF, V, SE, SEwo denote the employed, the unemployed, labor force, vacancies, the self-employed, and the self-employed without employees, respectively, 2) E(1-9) represents the number of employees hired by the self-employed with 1-9 employees.

TABLE 4—MAIN STATISTICS IN THE EQUILIBRIUM

Target statistics	Model
Consumption	1.200
Assets	2.215
Employed	0.879
Wage workers	0.663
Self-employed	0.216
Unemployed	0.120

employees hired by the self-employed with 1-9 employees cannot be matched very closely. Both target moments are related to the distribution of the size of employment. The differences appear to occur because the assumption of the probability distribution of productivity for self-employed does not accurately describe the actual case in the data.

In this model, for convenience of the analysis, the probability distribution is assumed to be a uniform distribution. However, a Pareto distribution can be used for the probability distribution of productivity, similar to Buera *et al*. (2011), to gain a better fit of the distribution of the size of employment. However, the focus of this study is the trend change in the number of self-employed, the sum of the number of self-employed without employees and that with employees, not the distribution of employees hired by the self-employed. Therefore, problems related to the assumption of the probability distribution may not be significant.

Table 4 shows the main statistics in the stationary recursive equilibrium. The averages of consumption and assets are 1.200 and 2.215, respectively. In the model economy, 66.3% of the total population are wage workers and 21.6% are self-employed. Because the proportion of the unemployed among the population in the model is 12.0% and the model excludes workers who are not in the labor force, the unemployment rate in the basic economy is 12.0%. In this study, workers in the agricultural sector and unpaid family workers are excluded from the model and data. Therefore, the proportion of the employed among the labor force is lower than that calculated using the entire sample. Similarly, the proportion of the unemployed in the labor force, the unemployment rate, is higher than that calculated using the entire sample.

In the model, the most important decision for the unemployed is the occupational

choice between being a wage worker and self-employed. Given that the probability of being a wage worker is fixed, the more productive unemployed as self-employed are likely to become self-employed. Among the self-employed, those with relatively low productivity become self-employed without employees, and those with high productivity become self-employed with employees. On the other hand, because the cost of unemployment becomes relatively large as the amount of assets is small, the unemployed with a small amount of assets will choose self-employment when other conditions remain the same. Therefore, the unemployed with a small amount of assets can become self-employed even if their productivity is low.[16]

C. *Quantitative Analysis*

Based on the number of self-employed computed in Section 2, where the demographic structure is controlled, the number of self-employed in 2018 decreased by approximately 29.2% (0.964 million) compared to that in 2002. I quantify how much the four potential factors proposed in Section 3 can explain the change in the number of self-employed from 2002 to 2018.

Table 5 shows the changes in the parameters used in each policy experiment. In policy experiment 1 (P1), which examines the effect of the decrease in the job-separation rate for wage workers on the decrease in the self-employed, the exogenous job-separation rate changed from 13.6% in 2002 (baseline economy) to 9.8% in 2018. In policy experiment 2 (P2), which examines the effect of the increase in the income tax rate for the self-employed on the decrease in the self-employed, the income tax rate changed from 13.5% in 2002 to 14.9% in 2018.

In policy experiment 3 (P3), which examines the effect of an increase in the minimum wage on the decrease in the number of self-employed, the ratio of the minimum wage to the median wage changed from 33.4% in 2002 to 58.6% in 2018.[17] Lastly, in policy experiment 4 (P4), which examines the effect of the expansion of the unemployment insurance benefits on the decrease in the number of self-employed, the ratio of unemployment insurance recipients to the unemployed changed from 4.6% in 2002 to 10.8% in 2018.

TABLE 5—INPUTS FOR POLICY EXPERIMENTS

(Unit: %)

Parameters	2002 (baseline)	2018
P1. Decrease in job-separation rate for wage workers	13.6	9.8
P2. Increase in the income tax rate for the self-employed	13.5	14.9
P3. Increase in minimum wages (min. wages / median wages)	33.4	58. 6
P4. Increase in UI recipients/unemployed	4.6	10.8

Note: UI denotes unemployment insurance.

[16]Alternatively, one can build a model with the unemployed at both extremes of productivity without the role of assets. Poschke (2019) assumes that there is no distinction between the productivity as wage workers and the self-employed. In this case, the job-finding rate depends on individual productivity; thus, the unemployed with very high productivity as well as those with very low productivity choose to become self-employed in equilibrium.

[17]Given the influence rate of 2.8% in 2002, the increase in the minimum wage during 2002-2018 raises the labor cost per worker (or the average wage) by approximately 0.7% for the self-employed.

TABLE 6—QUANTITATIVE RESULTS FOR POLICY EXPERIMENTS

Target statistics	Baseline	P1	P2	P3	P4
Employed	0.880	0.903	0.879	0.879	0.880
Wage workers	0.663	0.687	0.666	0.674	0.663
Self-employed	0.216	0.217	0.214	0.205	0.216
Unemployed	0.120	0.097	0.121	0.121	0.120
Increase in SE compared to baseline economy	-	+0.24%	-1.00%	-5.11%	+0.12%

Note: SE represents the self-employed.

Table 6 shows the quantitative results for each policy experiment. In policy experiment 1 (P1), the number of self-employed increased by 0.24% compared to that in the baseline economy. If the job-separation rate of wage workers decreases, the inflow of wage workers to the unemployed will decrease and thus will reduce the number of unemployed who will potentially become self-employed. At the same time, however, from the viewpoint of the self-employed, a decrease in the job-separation rate for wage workers has the effect of reducing the turnover rate of their employees. A lower job separation reduces the demand for replacement hiring and the relevant vacancy costs, increasing the value of the self-employed. In the calibration of this study, the latter effect is larger than the former and the number of self-employed persons increases slightly. A notable change compared to the baseline economy is that the unemployment rate decreased by 0.023%p due to a decrease in the job separation from wage workers.

In policy experiment 2 (P2), the number of self-employed decreases by 1.00% in the base economy. An increase in the effective income tax rate reduces the after-tax business income for the self-employed, thereby lowering the value of the self-employed. The fact that an increase in the income tax rate for the self-employed leads to a decrease in the number of self-employed is consistent with the results of previous studies by Torrini (2005), Buehn and Schneider (2012), and Kang and Yoo (2018). It is noteworthy that although a 1.4%p increase in the effective income tax rate for the self-employed appears to be insufficient to explain the decline in self-employment during 2002-2018, the effect is relatively large in terms of elasticity.

The increase in the measured income tax rate in this study is likely to be underestimated for the following reasons. First, as the business income of the self-employed has been gradually reported more transparently mainly due to the expansion of credit card use (Kim and Hong, 2012), the business income of the self-employed in the past was likely underestimated. In this case, the effective income tax rate of the self-employed in the past may be overestimated, and thus the increase in the income tax rate for the period 2002-2018 may be underestimated. Second, the tax system has been changed in the direction of reducing tax exemptions and tax deductions for the self-employed since the 2000s (Kim and Hong, 2012), causing entries into self-employment to decrease and exits from self-employment to increase. Because the measured income tax rate for the self-employed is calculated only based on the self-employed who exist in the market despite the relatively large tax burdens, the measured income tax rate can be underestimated.

Given the high elasticity, the actual effect of the increase in the income tax rate on the decrease in the self-employed can be expected to be more significant considering

that the increase in the income tax rate in this study can be underestimated. In other words, the actual increase in the income tax rate can be higher than that in this paper, and thus the impact of the increase in the income tax rate on the decline in the number of self-employed people may be increased considerably.

In policy experiment 3 (P3), the number of self-employed decreased by 5.11% compared to that in the baseline economy. This value corresponds to approximately 17.5% (0.169 million) of the decrease in the number of self-employed during 2002-2018 (0.964 million). In other words, the minimum wage increase explains 17.5% of the decrease in the number of self-employed during 2002-2018.[18]

This result for the minimum wage is consistent with the empirical results of Kang and Yoo (2018). Using linear regression estimates for panel data of OECD countries, they show that 43.5-45.2% of the decrease in the proportion of self-employed between 2000 and 2011 could be explained by the increase in the minimum wage. Although the estimated effect is less than half of that in Kang and Yoo (2018), this paper's result supplements their empirical results in that the detailed features of the Korean labor market and the occupational choices between wage workers and self-employed are explicitly reflected in a structural model.

Intuitively, an increase in the minimum wage leads to a decrease in the number of self-employed people, especially those who have employees. In addition, the effect of the increase in the minimum wage on the self-employed without employees will be limited. Considering those who reduce their number of employees and engage in self-employment alone, the number of self-employed without employees can be expected to increase. Consistent with this prediction, in the results of this study, the number of self-employed with employees decreased significantly (-37.7%) while the number of self-employed without employees increased (16.6%).

Figure 8 shows the recent changes in the self-employed by type. A notable change since 2018 is that the number of self-employed with employees decreased significantly, whereas the number of self-employed without employees increased. The result of the experiment in this paper implies that the drastic change in the composition of the self-employed since 2018 may be closely related to the rapid increase in the minimum wage during 2018-2019.[19]

Finally, in policy experiment 4 (P4), the number of self-employed increases by 0.12% compared to that in the baseline economy. When the probability of receiving unemployment benefits increases, the value of the unemployed increases, which reduces the incentive to become a wage worker or self-employed. On the other hand, as the duration of unemployment increases due to the generous unemployment benefits, assets held gradually decrease. Therefore, the incentive to become self-

[18]It is also noteworthy that the total number of employed did not show a significant difference compared to the baseline economy because the number of wage workers increased as the number of self-employed decreased. Theoretically, an increase in the minimum wage raises the value of wage workers and, at the same time, lowers the value of the self-employed due to an increase in labor costs. Therefore, more unemployed people will choose wage workers rather than self-employed, which will increase the number of wage workers and decrease the number of self-employed. However, in this model, a decrease in labor demand caused by an increase in the minimum wage does not lead to a decrease in the job-finding probability because the job-finding probability of the unemployed is assumed to be given exogenously. Therefore, it should be noted that if the job-finding probability decreases due to a decrease in labor demand caused by an increase in the minimum wage, the unemployment rate may further increase and the number of total employed may decrease.

[19]The increasing rates of the minimum wage in 2018 and 2019 were 16.4% and 10.9%, respectively, significantly exceeding the period average in 2010-2017 (5.7%).

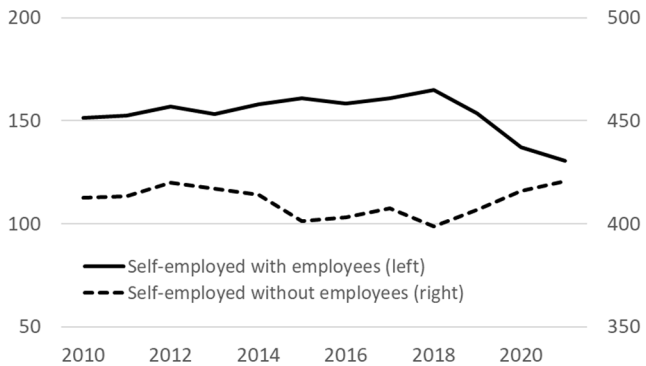

FIGURE 8. RECENT CHANGES IN THE NUMBER OF SELF-EMPLOYED BY TYPE

Source: Statistics Korea, EAPS, 2010-2021.

employed can be increased because the unemployed can always become self-employed with no uncertainty. In this study, the latter effect is larger than the former given the calibration of the model. Therefore, the expansion of unemployment insurance benefits resulted in a small increase in the number of self-employed. Although the share of unemployment insurance recipients more than doubled from 4.6% to 10.8%, 89.2% of the unemployed are still excluded from receiving unemployment benefits as of 2018. For this reason, the effect of changes in the ratio of unemployment insurance recipients to the number of self-employed appears to be limited.

In sum, while the decrease in the job-separation rate for wage workers and the expansion of unemployment insurance benefits slightly increased the number of self-employed, the increase in the effective income tax rate for the self-employed and the increase in the minimum wage reduced the number of self-employed by 1.00% and 5.11%, respectively. According to the quantitative results, 17.5% (0.169 million) of the decrease in the number of self-employed people during 2002-2018 (0.964 million) can be attributed to the increase in the minimum wage.

V. Concluding Remarks

This paper studies the potentially relevant factors affecting trend changes in the number of self-employed in Korea during the period of 1986-2018. The number of self-employed had increased steadily until 2002 but started to decrease around that year and has continued to decline up to the present. The increasing trend in self-employment during 1986-2001 is mostly explained by demographic changes, whereas the declining trend during 2002-2018 is not.

In this study, I consider four institutional factors that potentially affect the decrease in the number of self-employed after 2002: i) a decrease in the job-separation rate of wage workers, ii) an increase in the income tax rate applied to the self-employed, iii) an increase in minimum wages, iv) an expansion of unemployment insurance benefits. Using a search and matching model with the self-employed, I quantify the effects of these four factors on the decrease in the self-employed during 2002-2018.

The quantitative results show that the impact of the increase in the minimum wage is relatively large, whereas the effects of the other three factors are limited. The increase in the minimum wage accounts for approximately 17.5% (0.169 million) of the decrease in the number of self-employed during 2002-2018 (0.964 million).

The institutional factors considered in this study cannot sufficiently explain the decline in self-employment during 2002-2018. Approximately 80% of the decline in self-employment during that period is still attributable to institutional or non-institutional factors not addressed in this study. According to Hong and Oh (2018), the profit rate for the self-employed decreased by 16.8% between 2010 and 2015, whereas the real GDP increased by 15.9% during the same period. Although this estimate is not applicable for the entire period from 2002 to 2018, the decline in profitability may be related to the decline in the number of self-employed during the analysis period. They also show that the decline in the profit rate is attributed to a more rapid increase in costs than sales for the self-employed.

The decrease in demand due to the slowdown in the overall economic growth, the spread of online retail sales, and intensifying domestic and international competition can be considered as factors that reduce the sales of the self-employed. On the other hand, reduction in cost deductions for the self-employed and the spread of self-employment in the form of franchises[20] can be seen as factors that increase the costs of the self-employed. An analysis of the effects of these factors, not covered in this study, on the decline in the self-employed is left for future research.

This paper has several limitations. First, the four institutional factors considered in this study may change in different ways by age group or may have different effects on the change in the self-employed by age group. However, in this study, a detailed analysis by age group was not conducted. An empirical analysis of the effects of the institutional factors on the self-employed by age group or a structural analysis using an overlapping generation model is needed to investigate the heterogeneous effects of these factors on trend changes in the self-employed by age group. Second, according to the OECD panel analysis by Parker and Robson (2004), the higher the female labor force participation rate, the lower the number of self-employed because men are more likely to be self-employed. The rapid growth of the labor force participation rate for Korean women can have a significant impact on the decrease in the number of self-employed in Korea because the proportion of men among the self-employed is considerably high in Korea, as shown in Figure A3. Studies of the effects of changes in the labor force participation rate of women on the decline in the self-employed in Korea appear to be promising and important research topics.

[20]According to Hong and Oh (2018), sales by self-employed for the franchise type are much higher than those of other types of self-employed, whereas the profit rate of the self-employed for the franchise type is lower than those of other types of self-employed.

APPENDIX

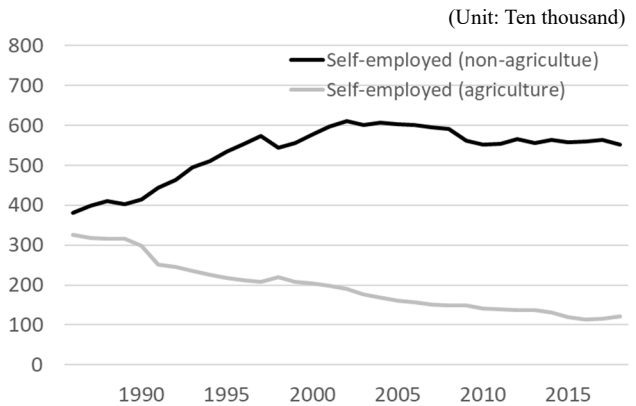

FIGURE A1. SELF-EMPLOYED: AGRICULTURE VS. NON-AGRICULTURE

Source: Statistics Korea, EAPS, 1986-2018.

FIGURE A2. SELF-EMPLOYED IN AGRICULTURE BY TYPE

Source: Statistics Korea, EAPS, 1986-2018.

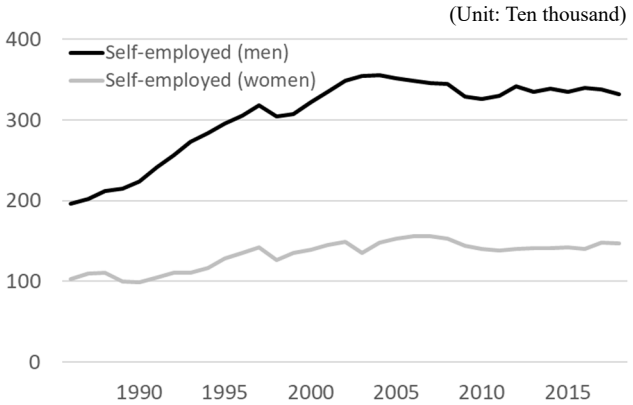

FIGURE A3. SELF-EMPLOYED BY GENDER GROUP

Source: Statistics Korea, EAPS, 1986-2018.

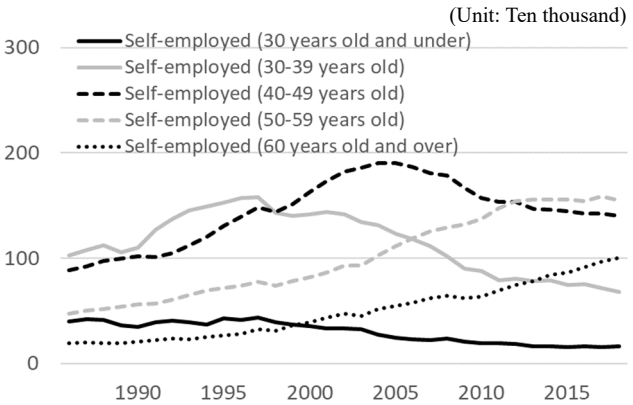

FIGURE A4. SELF-EMPLOYED BY AGE GROUP

Source: Statistics Korea, EAPS, 1986-2018.

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