Effects of Initial Labor Market Conditions on Job Polarization: Evidence from South Korea*

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Abstract

This paper investigates the extent to which initial conditions in the labor market influence the progress of job polarization in Korea. In particular, we compare two competing hypotheses: a specialization hypothesis and an inter-industry wage differentials hypothesis. Our findings indicate that job polarization is more pronounced in industries that have historically relied on routine tasks and have experienced a significant increase in ICT capital intensity between 2000 and 2019. In contrast, initial inter-industry wage differentials are not associated with job polarization in Korea during the same period.

Keywords: Job polarization, Initial conditions, Routine worker, Industry wage premium, ICT capital, Korea

JEL Classification: J20, J23, J31

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1. INTRODUCTION

What causes job polarization, a phenomenon in which the employment of middle-skilled workers has shrunk while that of high- and low-skilled workers has expanded?[1] Routine-replacing technological change (henceforth RRTC)[2] has been suggested to be an important factor for job polarization (Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014; and Michaels et al., 2014). More recently, offshoring (Goos et al., 2014) and demand shifts (Leonardi, 2015) have also been proposed as additional sources of job polarization. Based on the previous findings (Kim, 2012; Kim et al., 2019; and Park et al., 2022) that job polarization is closely associated with RRTC in Korea[3], the country selected for the empirical analysis in this study, we focus on testing hypotheses that argue the importance of initial labor market conditions in determining RRTC adoption in the spirit of Caballero and Hammour (1998) and Acemoglu (2002).

Specifically, we compare two hypotheses, a specialization hypothesis (Autor et al., 2003; and Autor and Dorn, 2013) and an inter-industry wage differentials hypothesis (Shim and Yang, 2018), suggesting that an initial industrial factor with a stable structure generates differences in firms' incentives to adopt RRTC across industries. The former contends that when firms adopt ICT (information and communication technology) capital as its price falls, productivity gains are proportional to the routine task intensity in the production function, which differs across industries. As a result, job polarization is more pronounced in industries (or regions) where routine workers

[1] For relevant studies, see Autor et al. (2006), Goos and Manning (2007), Autor et al.(2008), Dustmann et al. (2009), Goos et al. (2009), Acemoglu and Autor (2011), Autor and Dorn (2013), Goos et al. (2014), Michaels et al. (2014), Cortes (2016), and Jaimovich and Siu (2020) as examples.

[2] RRTC lowers the price of ICT capital, and hence middle-skilled workers performing primarily routine tasks are more likely to be replaced by ICT capital because the substitutability of labor and capital in routine tasks is greater than in other tasks (e.g., cognitive and manual).

[3] As we will demonstrate later, routine employment declined more in industries that rapidly adopted ICT capital (Fig 2). Based on this observation, our study centers on the hypothesis emphasizing the role of ICT capital in explaining job polarization.

have historically played an important role in production. On the contrary, the latter observes a persistent wage gap across industries, i.e., workers with the same observed productivity are paid differently when working in different industries. They contend that a high industry wage premium motivates firms to look for ways to lower production costs. Thus, firms in a high-wage industry are more likely to substitute ICT capital for routine workers than firms in a low-wage industry as ICT technology advances.

Although each of the two hypotheses sheds light on a different mechanism that facilitates job polarization, it is uncommon to find empirical research that considers both of them in a unified framework.[4] We aim to fill this gap in the literature by utilizing micro-level data from South Korea, which has seen rapid changes in the labor market, such as automation through robot adoption (Acemoglu and Restrepo, 2022).

As can be easily observed from Fig 1, South Korea has also experienced job polarization since the 1990s. The employment share of routine workers decreased from 73.2% to 58.9% between 1993 and 2019.[5] Fig 2 further shows the relationship between the changes in the share of routine employment and the growth in the intensity of ICT capital after 2000. The magnitude of the decline in routine employment was even greater in industries where ICT capital per worker increased more. This indicates that RRTC could also be behind the job polarization in Korea.

[Figure 1]

[Figure 2]

[4] To the best of our knowledge, the only exception is Shim and Yang (2018). Using U.S. data, they analyzed the impact of industrial factors (for example, industry wage premium, routine share, unionization rate) in the initial period on progress of job polarization.

[5] Unless otherwise noted, this paper measures employment in terms of total hours worked. According to Acemoglu and Autor (2011), we divide workers into three groups.

We first notice that the severity of job polarization is heterogeneous across industries in Korea (Fig A1), which allows us to utilize industry variation to study which hypothesis is more suitable for explaining patterns of job polarization in Korea. For the empirical analysis, we primarily use (1) employment and wage data from the Survey on Labor Conditions by Employment Type (SLCET) from the Korea Ministry of Employment and Labor for 1993–2019, and (2) ICT capital stock data from the Korea Information Society Development Institute's industry-level Productivity Account (KISDI PA) for 2000–2019. Our empirical test is based on the Barro-type Growth equation, in which we regress employment growth by occupation and ICT capital intensity on the initial routine share and the initial industry wage premium, along with control variables. To mitigate the endogeneity concerns, we instrument our key variables of interest with their historical counterparts. We also run a series of additional analyses using subsample, different measures for employment as the dependent variable, and an alternative occupational classification system.

The OLS results show that, between 2000 and 2019, the higher the initial routine share in industry, the greater the increase in ICT capital per worker and the greater the decline in routine employment relative to the other occupation groups. On the contrary, the initial industry wage premium has no significant effect on employment growth by occupation and ICT intensity growth. These outcomes still hold in the results of the instrumental variable (IV) analysis and the robustness checks. Overall, the empirical results support the specialization hypotheses to account for job polarization in Korea, which is different from Shim and Yang (2018), who found that inter-industry wage differentials caused heterogeneous patterns in job polarization across industries in the U.S.

This study adds to the literature on identifying the mechanism of job polarization by providing evidence on the effect of initial conditions on the progression of job polarization using data from countries other than the United States and Europe. Furthermore, this article is the first study to examine the causal relationship between industry-specific factors and job polarization in Korea.[6] Recently, Park et al. (2022) analyzed the relationship between initial characteristics of each region and job polarization between 2008 and 2019 in Korea. Our finding complements Park et al. (2022) by clarifying the impact of initial conditions on the evolution of job polarization in Korea.[7]

The remainder of the paper is structured as follows. Section 2 discusses empirical methodology, including the estimation model and data. Section 3 documents the main findings. Finally, Section 4 concludes the paper.

2. METHODOLOGY

2.1. Testable Implications of Two Hypotheses

This section derives testable implications of the two hypotheses on the progression of job polarization. Both hypotheses, as stated in the introduction, share the idea that the initial state of the industry can generate inter-industry variation in job polarization by inducing endogenous responses of firms to technological progress. The main distinction between the two is that the former emphasizes the role of industry-specific heterogeneous production functions, whereas the latter emphasizes the importance of uneven wage structure across industries in a non-competitive labor market.

[6] Most job polarization studies in Korea either document key features of job polarization (Jeon, 2007; and Kim, 2015) or empirically test the hypothesis of routine-replacing technological changes (Kim, 2012; and Kim et al., 2019).

[7] Our paper differs from Park et al. (2022) in several ways. First, we undertake an industry-level analysis to identify the role of initial conditions in job polarization. Second, we extended the analysis period (2000–2019) compared to Park et al. (2022)'s study period (2008–2019). Third, we employ an instrumental variables approach. Finally, we attempt to analyze the impact of an industry's initial conditions on employment changes by occupation and adoption of ICT capital across industries, which informs the channel of job polarization. The last two, in particular, allow us to more clearly apply a causal interpretation to the relationship between initial conditions and job polarization in the context of the routine-replacing technological change hypothesis.

First, according to the specialization hypothesis (Autor et al., 2003; and Autor and Dorn, 2013), when firms adopt ICT capital as the price of ICT capital falls, productivity gains are proportional to the routine task intensity in the production function that is uniquely assigned to each industry. For instance, Autor et al. (2003) introduced the following Cobb-Douglas production function, combining routine tasks with non-routine tasks.

$$Q_i = R_i^{\alpha_i} NR_i^{1-\alpha_i},$$

where Q_i is industry i's output, R is routine task, NR is non-routine task, α is routine task intensity, and $\alpha_i \in (0, 1)$. Therefore, the hypothesis predicts that as ICT technology develops, industries with higher routine task intensity substitute routine workers for ICT capital more sharply, thus showing more substantial job polarization.

Meanwhile, the inter-industry wage differentials hypothesis (Shim and Yang, 2018) argues that wage differentials generated by exogenous factors, rent sharing or efficiency wages as examples, and other factors create differences in incentives to replace labor across industries.[8] Accordingly, firms in industries with high-wage premia have greater incentives to reduce production costs, and as a result, they actively replace routine workers through the use of ICT capital, resulting in varying degrees of job polarization across industries.

The testable implications of the two hypotheses can be summarized as follows, based on their own theoretical predictions. Suppose that the price of ICT capital, which is common to all industries, falls continuously. Then,

[8] Dickens and Katz (1987) and Borjas and Ramey (2000) showed that the inter-industry wage gap in the U.S. has remained stable for a long time. According to Gibbons and Katz (1989) and Krueger and Summers (1988), wage differentials across industries in the United States cannot be explained entirely by unobserved worker heterogeneity. Dickens and Katz (1987) and Shim and Yang (2018) also found that an industry variable is a consistently significant factor in explaining wage differentials.

$$\text{Specialization hypothesis: } \frac{\partial^2 s_i}{\partial p \partial \alpha_i} < 0 \text{ and } \frac{\partial^2 \kappa_i}{\partial p \partial \alpha_i} < 0 \left(\frac{\partial s_i}{\partial p} < 0 \text{ and } \frac{\partial \kappa_i}{\partial p} < 0\right)$$

and

$$\text{Inter-industry wage differentials hypothesis: } \frac{\partial^2 s_i}{\partial p \partial \omega_i} < 0 \text{ and } \frac{\partial^2 \kappa_i}{\partial p \partial \omega_i} < 0.$$ [9]

The subscript i denotes industry; p is the price of ICT capital; α is the intensity of routine task; ω is the industry's wage premium; s is the non-routine share (non-routine labor input divided by routine labor input); κ is the ratio between ICT capital input and routine labor input.

In other words, industries with higher routine task intensity (specialization hypothesis) or higher wage premium (inter-industry wage differential hypothesis) in the initial period will show more significant increases in the non-routine share (prediction 1; job polarization). It will also show larger increases in the capital-routine worker ratio (prediction 2; channel of job polarization) over time.

2.2. Empirical Model

In this section, we present an empirical model to formally test the aforementioned testable implications derived from the two hypotheses in a unified econometric framework.

Before presenting our empirical model, we first address the measurement of key variables (industry's routine task intensity (α_i) and industry wage premium (ω_i)) for both hypotheses. We rely on proxies or estimates since our two variables of interest cannot be observed directly.

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[9] Since each of the two hypotheses is grounded in a distinct model with different features, the implications of each hypothesis are contingent upon the assumptions inherent in the respective underlying models. For instance, the specialization hypothesis assumes heterogeneous production functions ($\alpha_i \neq \alpha_j$) and a competitive labor market ($\omega_i = 0, \ \forall i$), while the inter-industry wage differentials hypothesis is based on a model featuring common production technology ($\alpha_i = \alpha, \forall i$) and a non- competitive labor market ($\omega_i \neq \omega_j$). Therefore, our examination seeks to empirically evaluate which model is more effective in describing the evolution of job polarization in Korea.

First, each industry's routine task intensity (α_i) is measured as the employment share of routine workers in the industry following Autor et al. (2003) and Autor and Dorn (2013).[10]

Second, the industry wage premium (ω_i) is estimated by the industry fixed effects in the Mincerian wage regression model, which controls a variety of socioeconomic characteristics (e.g. education, gender, age, and work experiences) that affect individual earnings:

$$log\ W_{\hbar,i,t} = \delta_t SC_{\hbar,i,t} + I_{i,t} + \varepsilon_{\hbar,i,t}, \tag{1}$$

where $W_{\hbar,i,t}$ is the wage rate of worker h in industry i in year t; $SC_{h,i,t}$, a vector of socioeconomic characteristics, includes worker's age (six age groups: 16–24, 25–34, 35–44, 45–54, 55–64 and at least 65 years), educational attainment (four educational groups: lower than high school graduates, high school graduates, 2-year college graduates, and 4-year college graduates), gender, occupation (three occupation groups: cognitive, routine, and manual), work experiences and years of service; $I_{i,t}$, the industry fixed effects, measures the industry wage premium.[11] The estimation results of the wage regression are reported in Table A1.[12] We also consider union's bargaining power as a potential factor influencing the extent of capital substitution for labor in the medium to long term.[13]

Finally, we estimate the following regression model:

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[10] They suggest the routine employment share in each industry (or region) in the initial period as a logical proxy for the intensity of routine tasks at the industry (or regional) level.

[11] See the notes in Table A1 for more information on the explanatory variables in the wage regression. We omit "Real estate," which has the lowest estimated coefficient value in the 1993 wage regression, so that every other coefficient for industry dummies has a positive sign in 1993.

[12] All individual socioeconomic characteristics coefficients are consistent with general prediction (Table A1). The industrial factor accounts for 13–18% of wage variations (Table A2). Interestingly, the industrial factor's explanatory power gradually decreases over time, implying that the nature of inter-industry wage differentials has changed. This topic is covered further in Section 3.3.

[13] In general, unions impose firms' production costs through collective bargaining in wage determination. Accordingly, the bargaining power of labor unions emerges as one of the main contributors to industry wage premium, which has the potential to facilitate the adoption of capital to replace labor in the face of technological progress. The positive correlation observed between industry wage premium and unionization rate supports this argument (Fig A2). On the other hand, if the union is involved in determining employment levels as well as wage rates, it may limit the substitution of capital for labor.

$$\Delta L_{i,j,t} = \beta_{j,q} X_{i,q,t_0} + \varepsilon_{i,j,t}, \tag{2}$$

$$\Delta K_{i,o,t} = \theta_{o,q} X_{i,q,t_0} + \varepsilon_{i,o,t}, \tag{3}$$

where $\Delta L_{i,j,t}$ is the annualized growth rate of employment for each occupational group j ($j \in$ {cognitive (*c*), routine (*r*), manual (*m*)} in industry *i* between the initial year (t_0) and final year (t). Similarly, $\Delta K_{i,o,t}$ is the annualized growth rate of capital stock per worker for each capital type *o* ($o \in$ {ict capital (*ict*), non-ict capital (*non-ict*)} in industry *i* between periods t_0 and t. X_{i,q,t_0} is the vector containing each industry's initial factor q ($q \in${routine share, industry wage premium, unionization rate}) in the initial year (t_0). We use Eq.(2) and Eq.(3) to evaluate the predictions (1) and (2), respectively. We estimate each equation separately for each occupational group and capital type.

If the specialization hypothesis can explain the inter-industry variation in job polarization, we would expect that the initial routine share is negatively related to the growth rate of routine employment relative to the other occupational groups ($\beta_{r,routine-share} < \beta_{c,routine-share}$ and $\beta_{r,routine-share} < \beta_{m,routine-share}$), which confirms the first testable implication (prediction (1)). It is also expected to have a positive relationship with the growth rate of ICT capital per worker ($\theta_{ict,routine-share} > 0$), which confirms the second testable implication (prediction (2)).[14] A similar interpretation can be applied to evaluate the inter-industry wage differentials hypothesis ($\beta_{r,wage\ premium} < \beta_{c,wage\ premium}$, $\beta_{m,wage\ premium}$ and $\theta_{ict,wage\ premium} > 0$).

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[14] Because the KIDSI PA data do not include information about workers' occupations, we use ICT capital per worker as a dependent variable when estimating Eq.(3) to test the second testable implications (i.e. prediction (2)). However, if a positive relationship is found between the growth of ICT capital per worker and the initial factor in a situation where prediction (1) holds, it ensures prediction (2).

2.3. Data

Main data are drawn from the Survey on Labor Conditions by Employment Type (SLCET) from the Korea Ministry of Employment and Labor for 1993–2019.[15] Establishments with 10 or more employees are selected as the sample for our analysis in order to produce a consistent sample. Additionally, we eliminate the categories "Agriculture, forestry and fishery," "Armed forces," and "Public administration."[16] We construct consistent industry series and occupation series using crosswalks from Korean Standard Industrial Classification (KSIC) and Korean Standard Classification of Occupations (KSCO), respectively.[17]

We also use the industry-level Productivity Account form the Korea Information Society Development Institute (KIDSI PA) for 2000–2019. Since the industry classification of the KIDSI PA is slightly different from the SLCET, we reclassify industries into more aggregated categories to ensure the compatibility between analyses using the SLCET and the KISDI PA data.[18]

We follow Acemoglu and Autor (2011) to categorize each occupation based on its primary task in the main analysis. As a robustness check, we reclassify workers into three groups (cognitive, routine, and manual) following Kim (2015) and perform exercises comparable to the main analysis.[19]

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[15] The SLCET is an annual survey of a wide range of working conditions such as working days, working hours, wages, etc. in a sample of about 33,000 establishments in Korea.

[16] The total number of individual observations used in our main analysis is 437,384 in 1993, 483,641 in 2000, 640,222 in 2010, and 794,584 in 2019.

[17] Crosswalks are used at the sub-major (2-digit) level for industry classification and at the sub-major (2-digit) or minor (3-digit) level for occupation classification.

[18] There are 29 industries (16 industries in the manufacturing sector; 13 industries in the non-manufacturing sector).

[19] Following Autor and Dorn (2013), Kim (2015) classified the KSCO code into three occupational groups (cognitive, routine, and manual). Autor and Dorn (2013) classified US Census occupation codes into three categories (cognitive, routine, and manual) based on task measures derived from the US Department of Labor's Dictionary of Occupational Titles (DOT). On the other hand, Acemoglu and Autor (2011) classified occupations into four groups and logically mapped these broad occupational categories into four task clusters (e.g., (1) managerial, professional, and technical occupations – non-routine cognitive tasks; (2) sales, clerical, and administrative occupations – routine cognitive tasks;

2.4. Estimation Implementation

We first note that we use the estimated value from the wage regression model for the industry wage premium, which is one of the key explanatory variables of the main regression model. To alleviate the concern that a heteroscedasticity can undermine the main estimation results because of the generated regressor problem, we weigh the regression by the employment size of each industry in the initial period.

We also have to consider potential endogeneity in estimating the main regression model,[20] so we use an instrumental variable (IV) approach in addition to OLS for the main regression. Following Autor and Dorn (2013) and Shim and Yang (2018), we use the historical counterparts of endogenous variables as instruments. The instrumental variable is the 1993 observation or estimate corresponding to each endogenous variable. Accordingly, the target period of the regression analysis is 2000 to 2019.

[Figure 3]

To check a persistency of each industrial factor, Fig 3 compares the values of each industrial factor between 1993 and 2000, 2000 and 2010, 2010 and 2019, and 1993 and 2019. For each time span, the correlation coefficient between the initial and terminal states of each industrial factor are also displayed. For all subset periods and the entire period, the correlation coefficient for routine share are very high (0.94–0.97 and 0.85). Within about ten years, the correlation coefficients for industry wage premium and unionization rate are high (0.72–0.91 for industry wage premium and

(3) production and operative occupations – routine manual tasks; and (4) service occupations – non-routine manual tasks).

[20] For example, a demand shock to a specific industry near the start of the period may affect both the initial conditions and subsequent employment growth by occupation (Autor and Dorn, 2013; and Shim and Yang, 2018).

0.79–0.96 for unionization rate). However, when the period is extended, the correlation for these factors weakens significantly (0.53 for industry wage premium and 0.67 for unionization rate between 1993 and 2019). Given the dynamics of industrial factors over the sample period, we estimate the model separately by roughly decade (2000–2010 and 2010–2019) within our target period for regression analysis, then pool the two periods as stacked variables with a time fixed effect.[21] The model is then estimated for the entire target period (2000–2019) to confirm whether any initial factor can affect job polarization over time.

3. EMPIRICAL RESULTS

3.1. Main Results

3.1.1. Job polarization and industry's initial conditions

Table 1 shows the results when we regress the employment growth rate by occupation on the initial factors by stacking Eq.(2) for each period (2000–2010, 2010–2019). The coefficients of both the OLS and IV estimations are presented in panels A and B, respectively. Estimates for cognitive workers are in columns 1 and 4, routine workers in columns 2 and 5, and manual workers in columns 3 and 6, respectively. The IV estimates (Panel B) show that the negative relationship between the growth rate of routine employment and the initial share of routine workers is larger than those between other occupational groups and the initial routine share ($\beta_{r,\ routine-share} < \beta_{c,\ routine-shar}$, $\beta_{m,\ routine-share}$).[22] For example, when the initial routine share increased by 10%p, the annualized growth rate of routine employment decreased by 1.86%p, whereas that of

[21] For instance, for each industry, the employment growth rate by occupation between 2000 and 2010 and between 2010 and 2019 is stacked on the left side in Eq.(2). We then regress these stacked variables on the level of industrial factors in 2000 and 2010, respectively. In estimating Eq.(3), we employ the same procedure.

[22] Both coefficients are significantly different from each other at the 1% significance level.

cognitive employment decreased by 1.21%p on average between 2000 and 2019. The initial routine share is not significantly related to the growth rate of manual employment. On the contrary, for the initial wage premium and the unionization rate, all estimates for the employment growth rate by occupational group are statistically insignificant. The OLS results (Panel A) are similar to the IV results (Panel B). These findings imply that the specialization hypothesis may be more relevant for job polarization in Korea than the inter-industry wage differential hypothesis.

[Table 1]

Table A3 shows the first-stage results, in which we instrument the industrial factors in 2000 and 2010, treated as endogenous regressors in the main regression model, with their historical counterparts (i.e., corresponding values in 1993), respectively.[23] Note that the instruments for the routine share have fairly high F-statistics (548.1 in 2000 and 21.4 in 2010). The first-stage F-statistics for the industry wage premium and the unionization rate in 2000 are also high (29.0 and 75.6, respectively), while drop significantly in 2010 (1.8 and 6.0, respectively).[24] The first-stage results alleviate concerns that IV estimates may suffer from a weak instruments problem, at least when the regressions with industrial factors are run in 2000.

[Table 2]

Table 2 shows the results of estimating Eq.(2) for each of the two periods separately (2000–2010 and 2010–2019). The OLS and IV estimation results are consistent with what was previously discovered using the pooled model: Compared to the other occupational groups, the initial routine

[23] When we focus on the coefficients of its own historical counterpart for each industrial factor, they are significant in 2000 and 2010. Each coefficient is close to one in 2000 and smaller in 2010. The decreasing magnitude is expected because initial conditions become less important over time.

[24] This is a natural consequence of the fact that the industry wage premium and the unionization rate are less persistent in expanded periods, which we show in Fig 3.

share significantly and negatively impacts the growth rate of routine employment for each period.[25] On the contrary, the initial industry wage premium and the unionization rate had no significant relationship with the employment growth by occupation.

3.1.2. ICT capital intensity and industry's initial conditions

This section examines the relationship between each initial factor and ICT capital adoption across industries. This enables us to study how the industrial factor is linked to the heterogeneous aspect of job polarization across industries.

Table 3 shows the results of regressing the growth rate of capital per worker by capital type (ICT/non-ICT) and the productivity on the initial factors using stacking Eq.(3) for each period (2000–2010 and 2010–2019). The coefficient is similar in both the OLS and IV regressions. According to the IV estimation (Panel B), industries with a higher initial routine share increased their ICT capital intensity more than others. (i.e., non-ICT capital intensity) ($\theta_{ict,\ routine-sha} > \theta_{non-ict,\ routine-shar}$).[26] For example, when the initial routine share increased by 10%p, the annualized growth rate of ICT capital per worker increased by approximately 2.07%p, whereas non-ICT capital per worker increased by approximately 1.16%p on average between 2000 and 2019. However, the initial industry wage premium is not related to the growth rate of any type of capital intensity. Interestingly, the higher the initial rate of unionization in industry, the lower the growth rate of ICT capital stock per worker, implying that unions may play a role in limiting technology adoption to replace labor.

[Table 3]

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[25] The negative relationship between the initial routine share and the subsequent routine employment growth across industries is larger in the 2000s than in the 2010s.

[26] Both coefficients are significantly different from each other at the 1% significance level.

Table 4 presents the estimation results of Eq.(3) separately for each period (2000–2010 and 2010–2019). Overall, the OLS and IV estimation results are consistent with the pooled model's. The initial routine share significantly affects the growth rate of ICT capital per worker for each period.[27] Meanwhile, the initial industry wage premium is not related to the changes in any type of capital intensity. The initial unionization rate negatively affects the growth of the ICT capital intensity, again in line with the results reported in Table 3.

[Table 4]

3.1.3. The effects of initial factors on job polarization in long-run perspective

In this section, we investigate the relationship between initial factors and job polarization over a longer period. Table 5 and Table 6 report the results of estimating the effect of the initial industrial factors on the growth rate of employment by occupation and the growth rate of capital intensity by capital type from 2000 to 2019, respectively. The IV estimates (Panel B) show that between 2000 and 2019, industries with a higher initial routine share experienced more obvious declines in routine employment relative to non-routine employment and more obvious increases in ICT capital intensity relative to non-ICT capital.[28] On the contrary, the initial wage premium does not affect the growth of ICT capital or the growth of employment by occupation, while the initial unionization rate has a negative relationship with the growth of ICT capital intensity. These

[27] In the 2000s, the magnitude of the positive relationship between initial routine share and subsequent growth of ICT capital per worker across industries was greater than in the 2010s. This is consistent with our previous findings, which show that the negative relationship between initial routine share and subsequent routine employment growth across industries is stronger in the 2000s than in the 2010s.

[28] Consistent labor productivity gains and ICT capital deepening in industries with initially high routine shares support the claim that the pronounced job polarization in these industries results from firms' adopting new technologies to replace labor as an endogenous response to their industry's initial conditions.

findings confirm that the initial share of routine workers had a major impact on job polarization over an even longer period in Korea.

[Table 5]

[Table 6]

3.2. Additional Analysis

In this section, we perform further empirical analyses to ascertain our findings in the main analysis. To start with, we re-estimate the main regression model (Eq.(2)) for the period 2000 to 2019 using subsamples, a different index of employment as the dependent variable, and an alternative occupational classification system. When we limit our sample to full-time employees (Table A4), replace the growth rate of hours worked as the dependent variable with the change in employment share or the growth rate of employees for each occupation (Table A5 and Table A6), and reclassify workers into three groups following Kim (2015) (Table A7)[29], the results do not differ from the main analysis.[30]

In addition, we consider the possibility that there exist cross-industry occupation-specific wage premiums in the data, which can potentially affect our findings (see Shim and Yang (2018) for more discussions). In such a case, the wage premium for the routine occupation differentiated by

[29] Kim (2015) made one variation by adapting the US occupational classification system proposed by Autor and Dorn (2013) to the Korean occupational code to improve the consistency of wage distribution and skill distribution in Korea. As a result, he classified some production workers (e.g., packing laborers, labeling laborers, product screening laborers) and sales workers (e.g., store sales workers, door-to-door salespersons, street sales related workers) as manual workers, owing to the fact that they were typically paid low wages in Korea. However, we do not adopt this modification by Kim (2015) to maintain an occupational classification scheme based on task content that governs the substitutability of labor and capital by occupation. To put it differently, when we apply the alternative occupation classification system based on Kim (2015), we classify the workers mentioned above as routine workers, as suggested by Autor and Dorn (2013) and Acemoglu and Autor (2011).

[30] There is one difference between the main results. When we use changes in routine employment share as the dependent variable between 2000 and 2019, the significance of the coefficient for the initial routine share in IV estimation is reduced (column 5 in Table A5).

industry could be more suitable for empirically testing the inter-industry wage differentials hypothesis, rather than using the (average) industry wage premium. Considering an occupation-specific industry wage premium, we estimate the following wage regression model, a variant of Eq.(1):

$$log\, W_{\hbar,i,t} = \delta_t SC_{\hbar,i,t} + \psi_{i,o,t} + \varepsilon_{\hbar,i,t}, \tag{4}$$

where $\psi_{i,o,t}$ is a dummy variable for each combination of industry and occupation (e.g., cognitive, routine, and manual). Fig A3. Industry Wage Premium and Occupation-Specific Industry Wage Premium (2000) depicts the cross-industry occupation-specific wage premiums in 2000. Cognitive occupations tend to receive the highest compensation, followed by routine and manual occupations (panel A). Moreover, the industry wage premium specific to each occupation generally increases in sync with the (average) industry wage premium.[31]

Subsequently, we estimate Eq.(2) and Eq.(3) using the routine-specific wage premium instead of the (average) industry wage premium. The results are nearly identical to those obtained in the main analysis, as presented in Table A8 and Table A9.[32] The initial routine-specific industry wage premium affects neither the ICT capital intensity growth nor the occupational employment growth.

[31] These patterns of occupation-specific wage premium across industries mirror those observed in the U.S., as reported by Shim and Yang (2018). We also estimate industry wage premium using samples segregated by occupation, not the entire sample. In other words, we take industry fixed effects by separately estimating Eq.(1) for each occupation. The estimated industry wage premiums for each occupation in this manner are similar to those obtained through estimating Eq.(4).

[32] Considering the patterns of occupation-specific wage premiums across industries, these results are somewhat predictable. In panel B of Fig A3. Industry Wage Premium and Occupation-Specific Industry Wage Premium (2000), routine-specific wage premium and non-routine-specific wage premium across industries exhibit similar patterns at comparable levels, implying a high correlation between routine-specific wage premium and the (average) industry wage premium across industries.

In contrast, the initial routine share is still negatively correlated with the routine employment growth and positively correlated with the ICT capital intensity growth.[33]

Therefore, our main results are robust in several dimensions, thus affirming our key finding: the initial routine share contributes significantly to the progress of job polarization in Korea.[34]

3.3. Discussion – Why is industry wage premium not associated with job polarization in Korea?

According to Shim and Yang (2018), in the US, the initial industry wage premium can explain why some industries experienced rapid job polarization than others. In contrast, in Korea, the higher the initial share of routine workers in the industry, the greater the decline in routine employment compared to other occupations. On the contrary, there is no significant relationship between the industry's initial wage premium and job polarization. In this section, we rationalize why the results are different.

First, one might speculate that the estimated industry wage premium could systematically reflect unobserved industry-specific human capital. Then, the estimated industry wage premium includes substantial compensation for heterogeneous labor productivity across industries and discriminatory compensation for homogeneous labor across industries. In this case, a strong positive relationship would be expected between the industry wage premium and labor productivity between industries. Fig 4 shows the correlation coefficient between the industry wage premium and labor productivity across industries in Korea for each year over 1993–2019.[35] At

[33] Additionally, we estimate Eq.(2) and Eq.(3) including non-routine-specific industry wage premium. There are no effects of the initial non-routine-specific industry wage premium on the occupational employment growth and the ICT intensity growth. Also, the findings of the main analysis remain unchanged.
[34] The result using only two groups of workers (routine/non-routine) is reported in Table A10. The result is also consistent with the main result. Table A11 shows the first-stage IV estimation results in additional analysis, which are similar to those in the main analysis (Panel A in Table A3).
[35] Labor productivity from 1993 to 1999 was computed using WORLD KLEMS data.

least in the early 2000s, the correlation between the industry wage premium and labor productivity across industries in Korea were quite low. Therefore, it is unlikely that our results were significantly distorted by unobservable labor heterogeneity across industries.

[Figure 4]

The alternative hypothesis is that the industry wage premium did not actually affect firms' incentives to reduce labor costs in the medium to long term. As previously stated, Fig 3 shows that the structure of inter-industry wage differentials in Korea is less stable than in the United States (see Dickens and Katz, 1987; Borjas and Ramey, 2000; Shim and Yang, 2018). We re-estimate the wage regression model with the individual union membership dummy and its interaction with industry fixed effects to roughly identify the influence of union bargaining power on the industry wage premium. Specifically, we estimate following equation:

$$log\, W_{h,i,t} = \delta_t SC_{h,i,t} + U_{h,t} + U_{h,t} \times I_{i,t} + I_{i,t} + \varepsilon_{h,i,t}, \tag{5}$$

where $\mathrm{U}_{\mathrm{h,t}}$ is a dummy variable indicating whether or not worker h is a union member in year t.

Fig 5 shows changes in the estimated industry fixed effects when we additionally control for variables related to the union membership in the wage regression model. In 1993 and 2000, the estimated industry fixed effects change significantly.[36] However, the magnitudes of the changes in the estimated industry fixed effects became smaller over time (2010 and 2019) suggesting that the impact of unions on the industry wage premium has diminished continuously since the 2000s.[37]

[36] This suggests that unions might have affected industry wage premiums until the early 2000s. Fig A4 shows that unions mainly comprise routine workers. Fig A5 indicates that the unionization rate in 1993 had a positive relationship with the growth rate of routine employment for 1993–2003. These facts, together with Fig 5, suggest that unions are one of the sources of the industry wage premium, while also preventing firms from replacing routine workers, who were mostly covered by unions throughout the 1990s and early 2000s. This could be partly related to our results that the industry wage premium is not related to job polarization.

[37] This is in line with the pattern of union membership in Korea. Fig A6 shows that the unionization rate has steadily declined since the 1990s and has recently rebounded slightly. We can also infer that the steady weakening of union power contributes to the decline in the explanatory power of the industrial factor in the wage variation over time, as shown in Table A2.

Numerous prior studies also have already documented a consistent decline in unionization rates since the 2000s, accompanied by a weakening of bargaining power for labor unions (Chung, 2008; Nho, 2011; and Nho and Kim, 2012). The reduced bargaining power of unions leads to a reduction in the extra costs that firms used to bear because of the substantial influence of the labor union.

In conjunction with the deterioration in the bargaining power of unions since the 2000s, the increased capacity of firms to use irregular workers during the same period appears to have alleviated the potential impact of unions' monopolistic position on labor costs.[38] It is widely recognized that, with the same level of productivity, the compensation of irregular workers is considerably lower than that of their regular counterparts (Kim and Park, 2006; Park and Kim, 2007; Hong et al., 2016; Jeon et al., 2018; and Keum and Choi, 2021).[39] Especially noteworthy is the empirical observation that within firms where labor unions exist, the wage disparity between regular and non-regular workers is even more pronounced.[40] This suggests that firms may have been smoothing out union-induced excess labor costs through the use of more affordable workers

[38] Irregular workers typically encompass contingent workers with no guaranteed employment continuity, atypical workers with alternative employment arrangements (e.g. dispatched workers and subcontract workers), and part-time workers (Kim and Park, 2006; and Nho, 2007). The sharp rise in irregular employment can be traced back to the institutional promotion of labor market flexibility in response to the Korea's 1997 financial crisis (Nho, 2007; and Jeon et al., 2018). Irregular workers in Korea accounted for approximately 36.3% of total employment in 2019, which is double the average for OECD countries (Keum and Choi, 2021).

[39] For a summary of empirical studies reporting on the wage gap between regular and irregular workers in Korea since the 2000s, see Keum and Choi (2021). Unionization rates for irregular workers are also much lower than for regular workers (Kim and Kim, 2013). Furthermore, irregular workers have very limited mobility toward regular employment in Korea. For more information on the dual structure in the Korean labor market, see Jeon et al. (2018).

[40] According to several studies using data from 2000 to 2010, it has been shown that wage differentials between regular and irregular employees are more significant in companies with labor unions (Kim and Park, 2006; Park and Kim, 2007; Lee and Kim, 2009; and Kim and Kim, 2013). Kim and Park (2006) additionally demonstrate, using the data from the 2003 establishment employment survey, that small and medium-sized enterprises (SMEs) with unions are more likely to employ irregular workers than SMEs without unions. Hong et al. (2016) also discover that wage premium associated with unions is diminished by outsourcing and subcontract firms, based on firm-level cross-sectional data in 2011. This raises the possibility that firms may have dealt with the excess labor cost burden associated with the presence of unions by leveraging economically efficient labor inputs in the secondary labor market, rather than adopting new technologies.

in the enlarged secondary labor market, implying that cross-industry wage differentials stemming from union bargaining power is becoming less important to a firm's overall costs.

In Fig 4, the correlation between the industry wage premium and labor productivity across industries has gradually increased since the early 2000s, reaching a value of around 0.5 by the mid-2000s. This also supports the argument that the implication of the inter-industry wage differentials on firms' costs may have altered with a change in key sources of industry wage premium since the 2000s.[41]

In short, with the change in the fundamentals of industry-specific wage premium, the structure of wage differentials across industries in initial period do not appear to be sufficiently robust to trigger a consistent response in the adoption of new technologies by firms.

[Figure 5]

4. CONCLUSION

This study tests two hypotheses (a specialization hypothesis and an inter-industry wage differentials hypothesis) that stress the industry's initial conditions as a promoter of job polarization. The specialization hypothesis is supported by empirical analysis using Korean data in explaining job polarization in Korea, but the inter-industry wage differentials hypothesis does not appear to hold. Our findings in favor of the specialization are consistent with those of Park et al. (2022), who found that job polarization was more pronounced in areas where routine workers

[41] It is beyond the scope of this paper to rigorously identify changes in the nature of the industry wage gap structure in Korea. However, we can first consider the possibility that workers' self-selection into industries with high wage premium has been enhanced since the 2000s. Second, efficiency wages could arise as one of key sources of inter-industry wage differentials after the 2000s. Some models based on efficiency wage theories suggest that higher wages can increase productivity by raising workers' effort level or workers' feelings of loyalty to their firm (for more descriptions of relevant models for efficiency wage theories, see Katz, 1986; and Krueger and Summers, 1988). In both cases, the mechanism proposed by Shim and Yang (2018) that industry wage premium forces firms to adopt routine-replacing technologies more aggressively may be mitigated.

were historically more important. This corroborates that path dependency is the driving mechanism behind job polarization in Korea.

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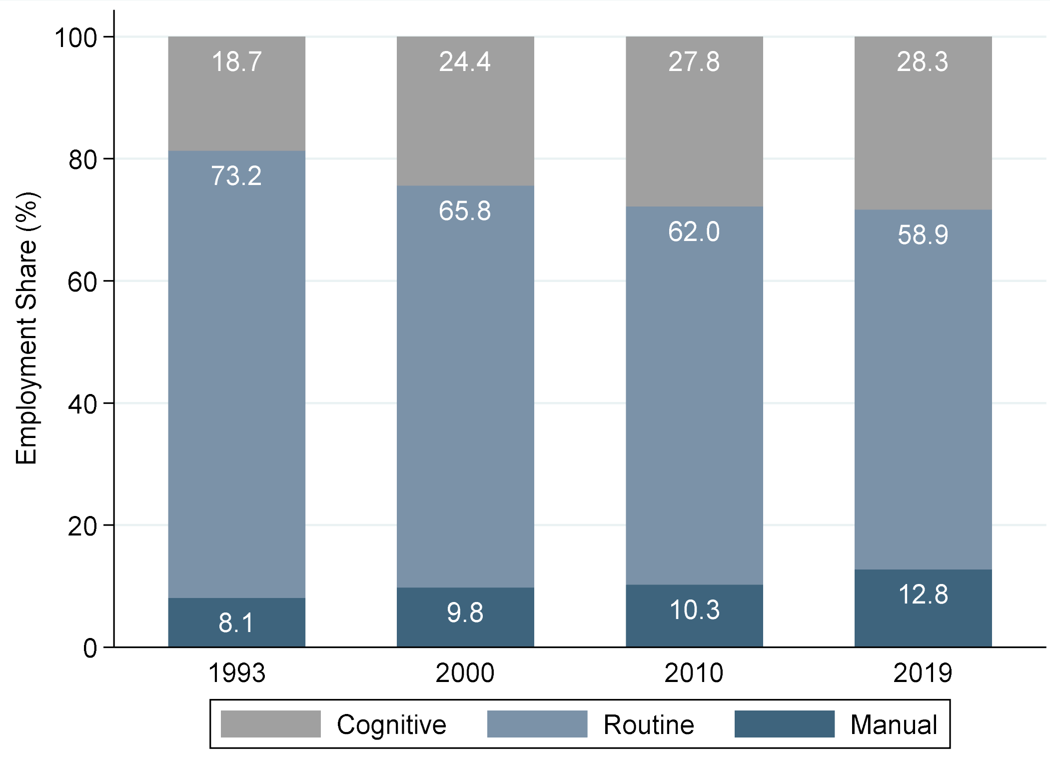
Figures

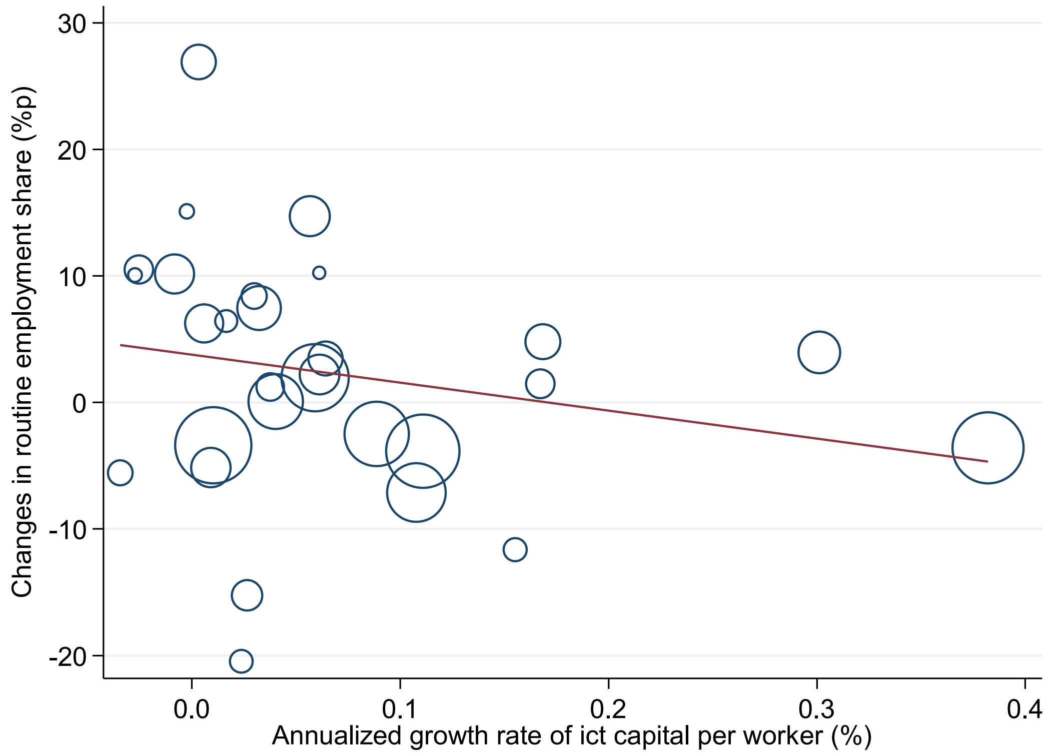
Fig 1. Employment Share by Occupation



Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure shows each occupation's share of total employment for the selected year.

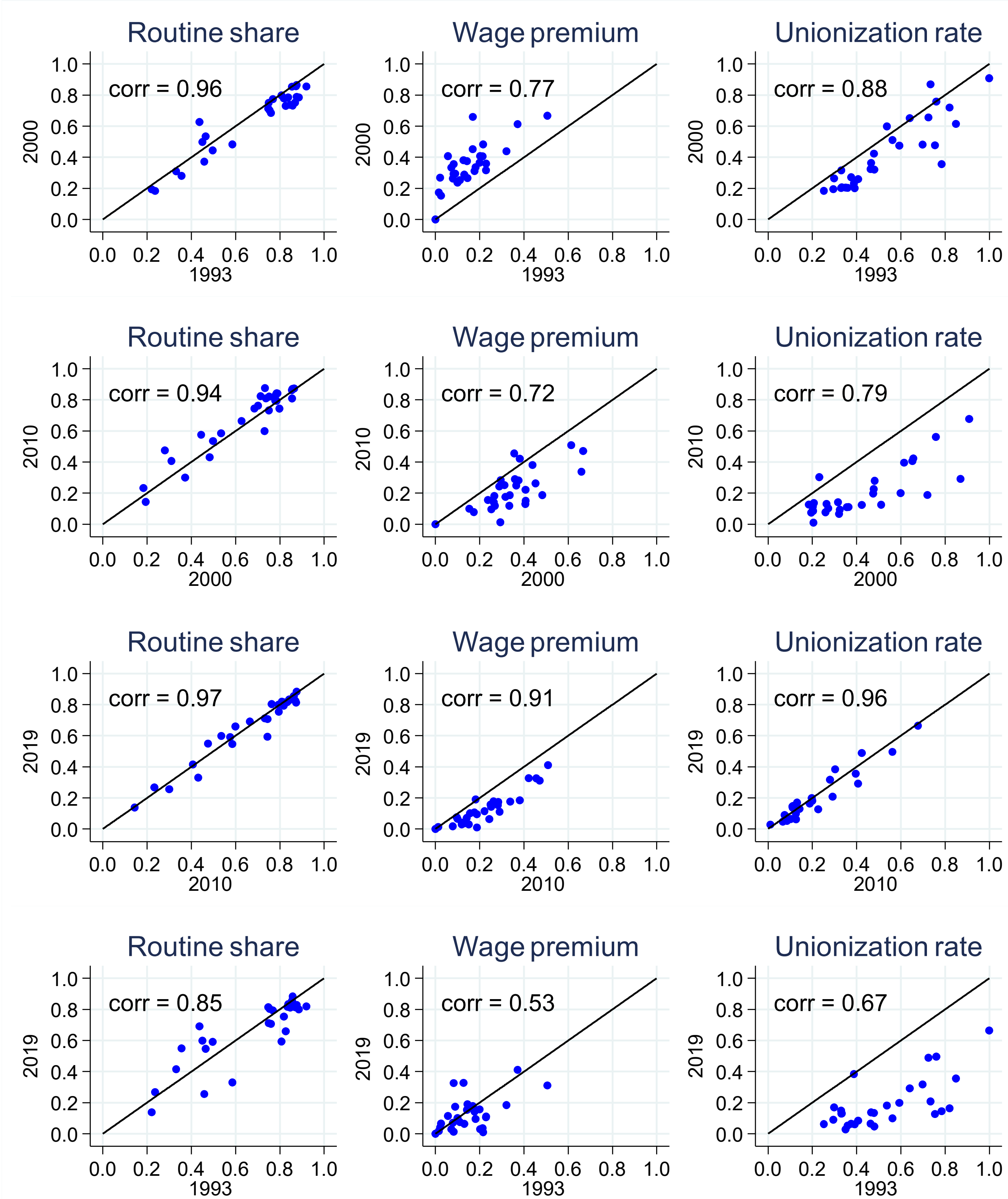
Fig 2. Changes in Routine Employment Share and Growth of ICT Capital Intensity by Industry (2000–2019)



Source: Survey on Labor Conditions by Employment Type (SLCET) and Productivity Account from the Korea Information Society Development Institute (KISDI PA).

Note: This figure shows the changes in routine employment share and the growth rate of ICT capital intensity in each industry between 2000 and 2019. The circle's size denotes the employment level of routine occupations in each industry in 2000.

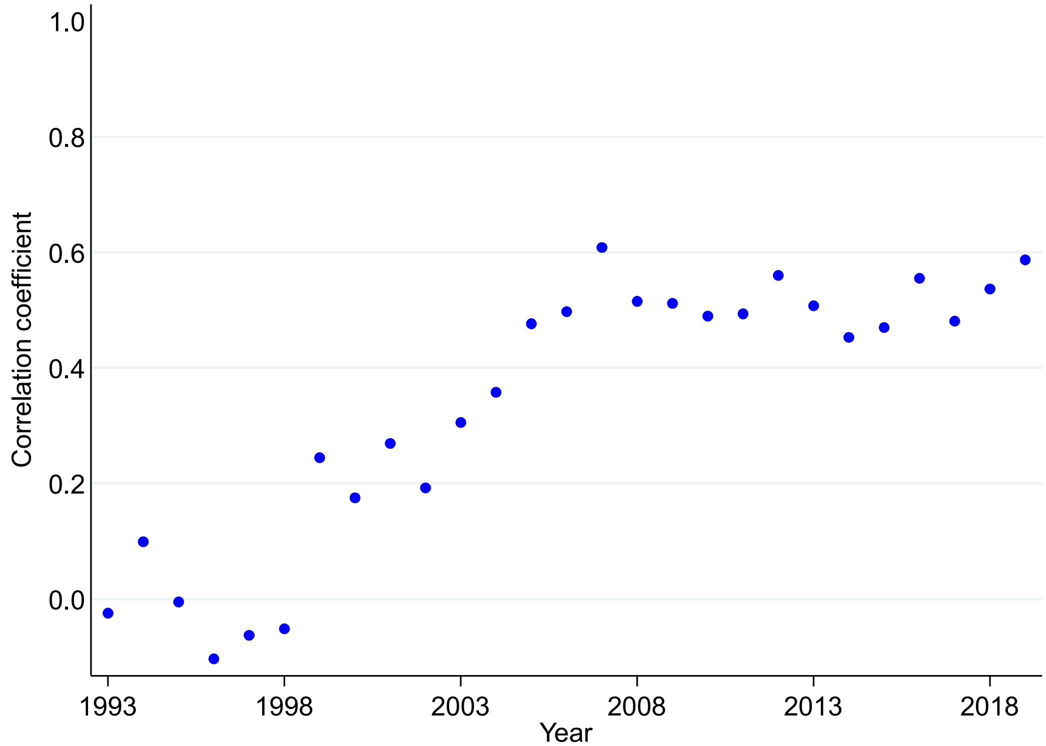
Fig 3. Industry's Initial Factors, Comparison by Period



Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure compares the values of each industry factor over time. The black line represents a 45-degree line.

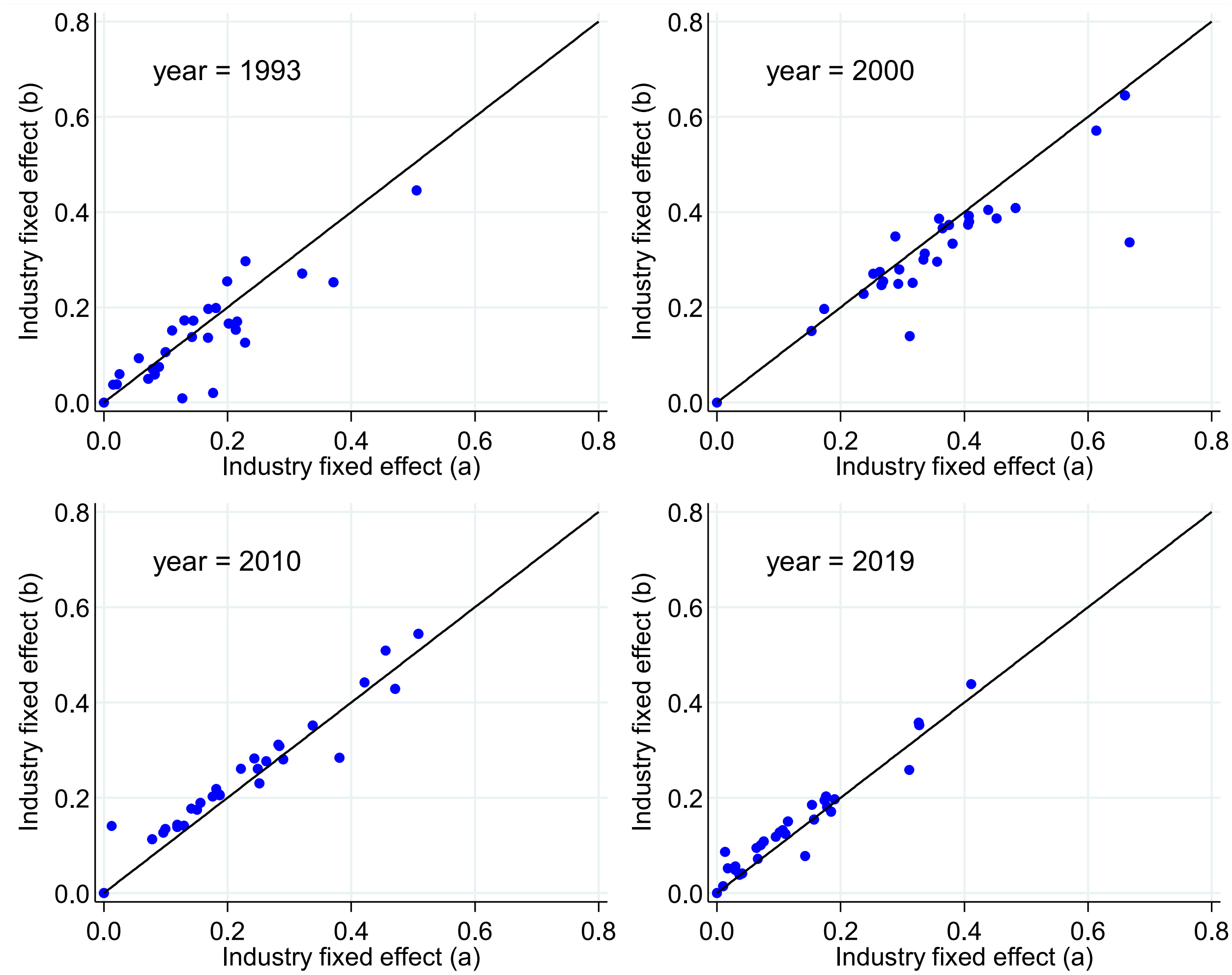
Fig 4. Correlation of Industry Wage Premium and Labor Productivity across Industries



Source: Survey on Labor Conditions by Employment Type (SLCET), Productivity Account from the Korea Information Society Development Institute (KISDI PA), and WORLD KLEMS.

Note: This figure shows the correlation coefficient of industry wage premium and labor productivity across industries in each year. Labor productivity is calculated by dividing value added by the number of workers in each industry.

Fig 5. Industry Fixed Effects in the Wage Regression



Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure shows the changes in the estimated industry fixed effects when we additionally control union membership related variables in the wage regression (Eq.(1)). The horizontal axis (industry fixed effect (a)) represents the estimated industry fixed effect in the wage regression model (Eq.(1), as shown in Section 2.2). The vertical axis (industry fixed effect (b)) represents the estimated industry fixed effect where we estimate the wage regression model including the individual union membership dummy and its interaction with the industry dummies (Eq.(5)). The black line represents a 45-degree line.

Tables

Table 1. Estimates of Employment Growth by Occupational Group (pooled two periods: 2000–2010 and 2010–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	−0.103**	−0.159**	−0.082	−0.121**	−0.186**	−0.099
	(0.045)	(0.069)	(0.068)	(0.051)	(0.076)	(0.060)
$Industry\ wage\ premium_{t0}$	0.051	0.025	0.112	−0.061	−0.077	0.213
	(0.061)	(0.051)	(0.074)	(0.093)	(0.112)	(0.158)
$Unionization\ rate_{t0}$	−0.023	−0.052	−0.026	0.029	−0.012	0.010
	(0.036)	(0.041)	(0.077)	(0.041)	(0.039)	(0.109)
R^2	0.213	0.289	0.107	0.147	0.257	0.065

Note: The models are estimated by pooling the two periods (2000–2010 and 2010–2019) as stacked variables. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept and time dummies. N = 58 (29 industries × 2 time periods). Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 2. Estimates of Employment Growth by Occupational Group
(by period: 2000–2010 and 2010–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
1. Period: 2000–2010						
$Routine\ share_{t0}$	−0.165*	−0.254*	−0.098	−0.195*	−0.278*	−0.118
	(0.085)	(0.144)	(0.087)	(0.099)	(0.152)	(0.078)
$Industry\ wage\ premium_{t0}$	0.116	0.003	0.226	−0.136	−0.155	0.349
	(0.102)	(0.104)	(0.149)	(0.143)	(0.173)	(0.242)
$Unionization\ rate_{t0}$	−0.057	−0.042	−0.035	0.056	0.038	−0.045
	(0.044)	(0.063)	(0.127)	(0.066)	(0.054)	(0.150)
R^2	0.355	0.355	0.208	0.183	0.317	0.168
2. Period: 2010–2019						
$Routine\ share_{t0}$	−0.041	−0.071***	−0.048	−0.054	−0.096***	−0.067
	(0.032)	(0.025)	(0.106)	(0.037)	(0.030)	(0.100)
$Industry\ wage\ premium_{t0}$	0.006	0.043	−0.012	0.089	0.006	−0.070
	(0.050)	(0.044)	(0.081)	(0.080)	(0.100)	(0.206)
$Unionization\ rate_{t0}$	0.003	−0.053**	−0.090	0.053	−0.050	0.037
	(0.036)	(0.023)	(0.076)	(0.045)	(0.051)	(0.156)
R^2	0.075	0.404	0.080	0.000	0.364	0.008

Note: The models are estimated separately for each decade (2000–2010 and 2010–2019). Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 3. Estimates of Capital Intensity Growth by Capital Type
(pooled two periods: 2000–2010 and 2010–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	ICT	Non-ICT	Productivity	ICT	Non-ICT	Productivity
$Routine\ share_{t0}$	0.200***	0.102***	0.101***	0.207***	0.116***	0.119***
	(0.061)	(0.027)	(0.030)	(0.061)	(0.031)	(0.033)
$Industry\ wage\ premium_{t0}$	0.032	0.098	0.120***	0.010	0.105	0.029
	(0.074)	(0.060)	(0.045)	(0.132)	(0.060)	(0.063)
$Unionization\ rate_{t0}$	-0.242***	−0.067*	−0.060	−0.228***	−0.045	−0.057
	(0.074)	(0.037)	(0.038)	(0.069)	(0.038)	(0.039)
R^2	0.447	0.256	0.264	0.444	0.201	0.214

Note: The models are estimated by pooling the two periods (2000–2010 and 2010–2019) as stacked variables. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include intercepts and time dummies. N = 58 (29 industries ×2 time periods). Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 4. Estimates of Capital Intensity Growth by Capital Type
(by period: 2000–2010 and 2010–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	ICT	Non-ICT	Productivity	ICT	Non-ICT	Productivity
1. Period: 2000–2010						
$Routine\ share_{t0}$	0.338***	0.118**	0.170***	0.332***	0.126**	0.179***
	(0.091)	(0.050)	(0.047)	(0.091)	(0.049)	(0.047)
$Industry\ wage\ premium_{t0}$	0.091	0.050	0.116	0.074	0.011	0.034
	(0.099)	(0.067)	(0.072)	(0.138)	(0.091)	(0.092)
$Unionization\ rate_{t0}$	−0.327***	−0.063	−0.080	−0.294***	−0.045	−0.065
	(0.091)	(0.055)	(0.069)	(0.091)	(0.061)	(0.070)
R^2	0.497	0.180	0.239	0.495	0.170	0.217
2. Period: 2010–2019						
$Routine\ share_{t0}$	0.059**	0.080***	0.029**	0.075**	0.104**	0.058*
	(0.026)	(0.023)	(0.012)	(0.027)	(0.040)	(0.029)
$Industry\ wage\ premium_{t0}$	0.039	0.150	0.142**	0.028	0.031	0.052
	(0.034)	(0.090)	(0.066)	(0.061)	(0.075)	(0.084)
$Unionization\ rate_{t0}$	−0.110***	−0.039	−0.016	−0.139***	−0.043	−0.059
	(0.027)	(0.046)	(0.041)	(0.047)	(0.048)	(0.039)
R^2	0.357	0.387	0.411	0.332	0.212	0.200

Note: The models are estimated separately for each decade (2000–2010 and 2010–2019). Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 5. Estimates of Employment Growth by Occupational Group (2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	−0.124**	−0.232*	−0.113	−0.150**	−0.248*	−0.135
	(0.058)	(0.133)	(0.138)	(0.066)	(0.140)	(0.136)
$Industry\ wage\ premium_{t0}$	0.114	0.013	0.181	−0.066	−0.115	0.205
	(0.072)	(0.099)	(0.203)	(0.092)	(0.165)	(0.273)
$Unionization\ rate_{t0}$	−0.031	−0.042	0.012	0.052	0.013	0.012
	(0.031)	(0.048)	(0.159)	(0.053)	(0.044)	(0.177)
R^2	0.418	0.355	0.123	0.241	0.328	0.120

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

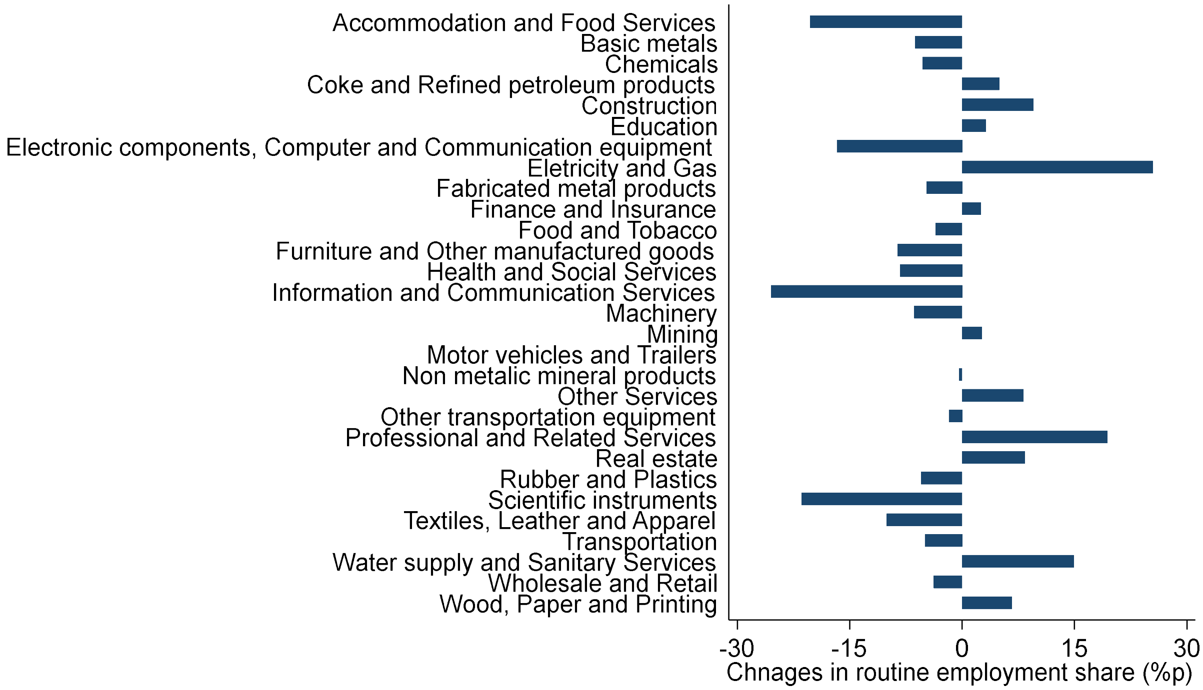
Table 6. Estimates of Capital Intensity Growth by Capital Type (2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	ICT	Non-ICT	Productivity	ICT	Non-ICT	Productivity
$Routine\ share_{t0}$	0.283***	0.128**	0.139**	0.289***	0.148**	0.151**
	(0.098)	(0.056)	(0.054)	(0.096)	(0.058)	(0.058)
$Industry\ wage\ premium_{t0}$	0.006	0.061	0.162*	0.000	0.025	0.071
	(0.116)	(0.081)	(0.079)	(0.151)	(0.103)	(0.103)
$Unionization\ rate_{t0}$	−0.300***	−0.055	−0.088	−0.281**	−0.052	−0.078
	(0.105)	(0.074)	(0.067)	(0.104)	(0.073)	(0.059)
R^2	0.459	0.110	0.137	0.457	0.103	0.117

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix

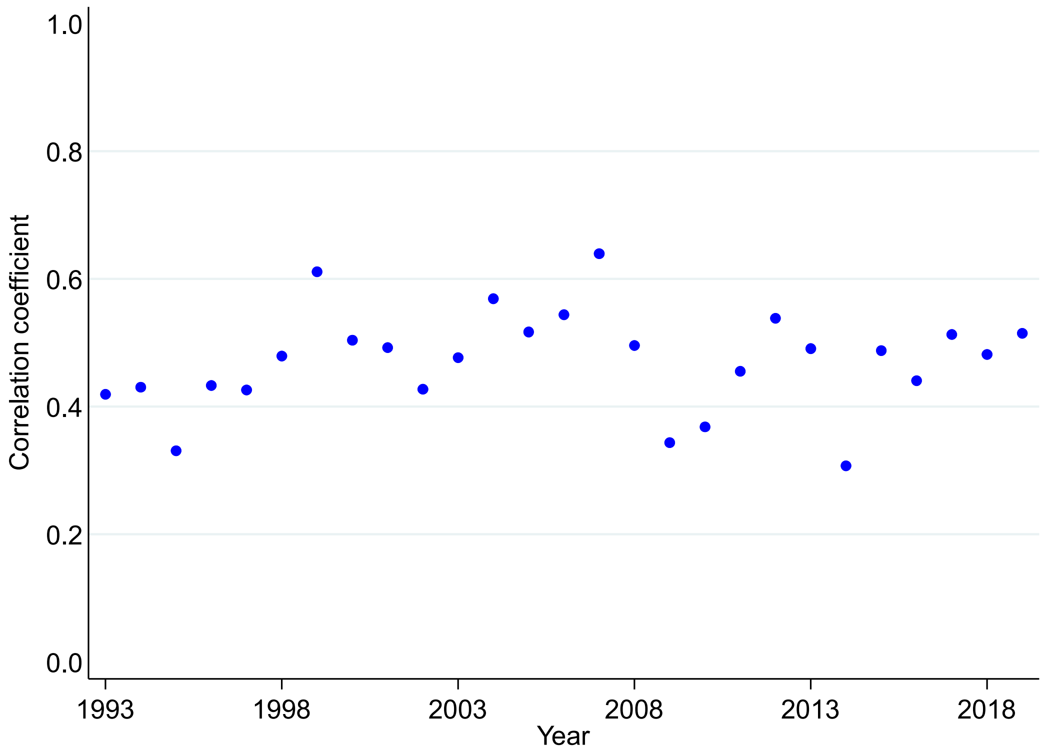
Fig A1. Changes in Routine Employment Share by Industry, 1993–2019



Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure shows the changes in employment share of routine workers in each industry between 1993 and 2019. The vertical axis denotes 29 industries. The horizontal axis denotes the changes in employment share of routine workers in each industry between 1993 and 2019.

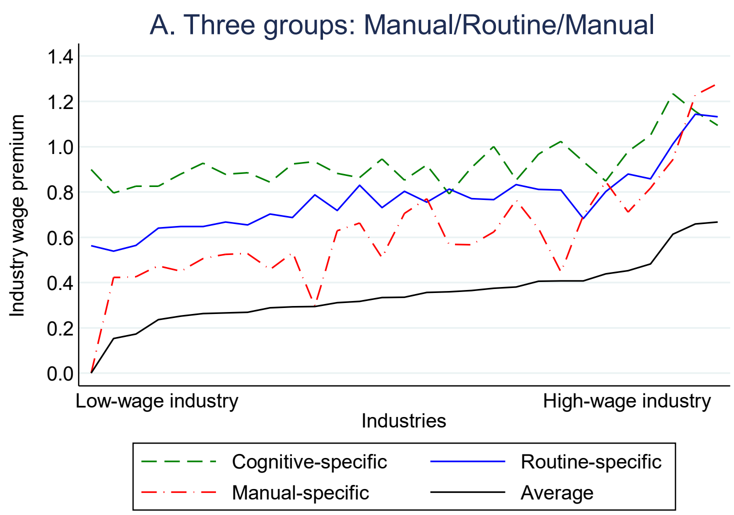
Fig A2. Correlation of Industry Wage Premium and Unionization Rate across Industries

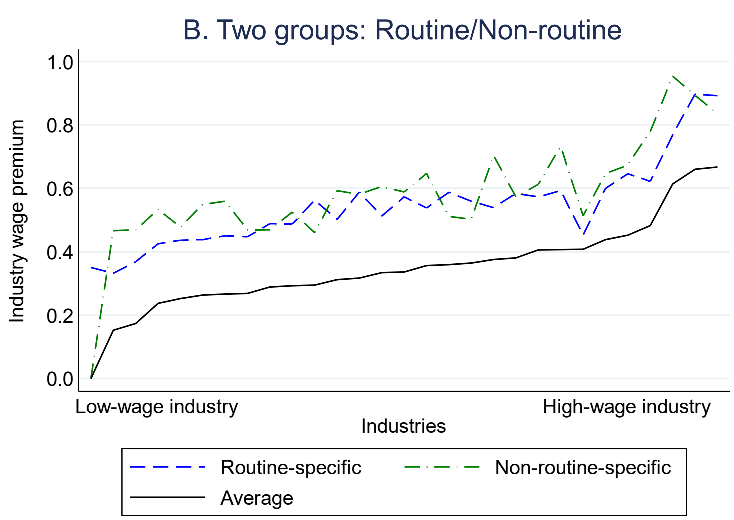


Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure shows the correlation coefficient of industry wage premium and unionization rate across industries in each year.

Fig A3. Industry Wage Premium and Occupation-Specific Industry Wage Premium (2000)

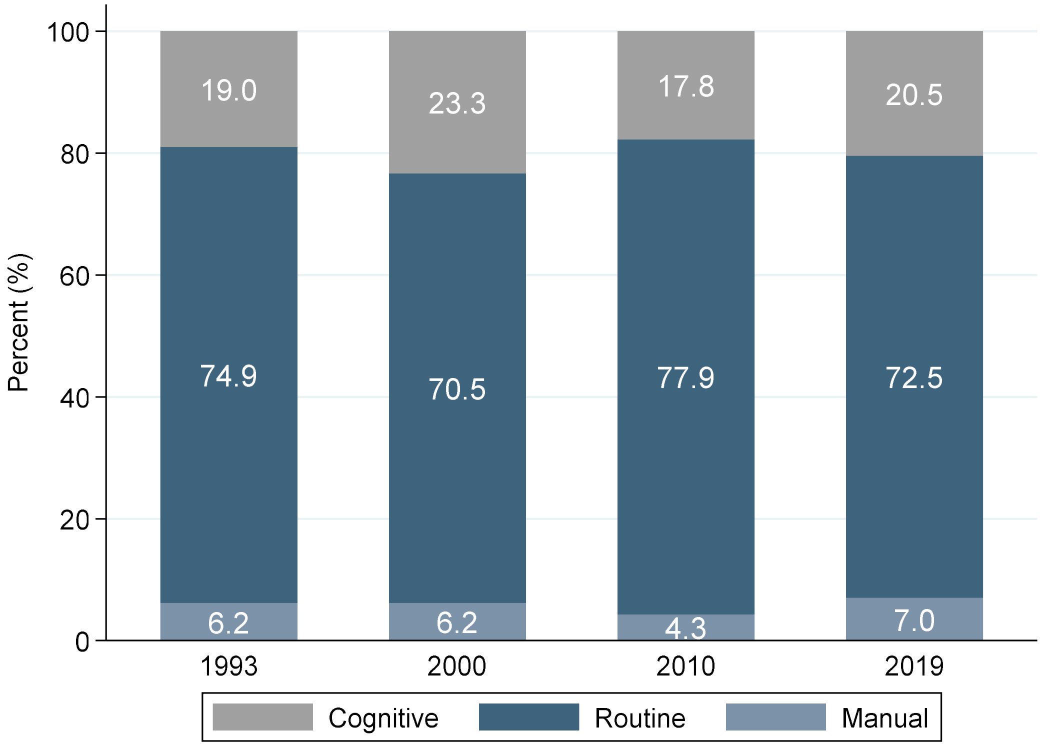




Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure shows the (average) industry wage premium and the occupation-specific industry wage premium in 2000. Panel A displays the industry wage premium specific to each occupation, categorized into three occupational groups (cognitive, routine, manual), while Panel B illustrates the industry wage premium specific to each occupation, grouped into two occupational categories (routine and non-routine). We order industries by the (average) industry wage premium in 2000.

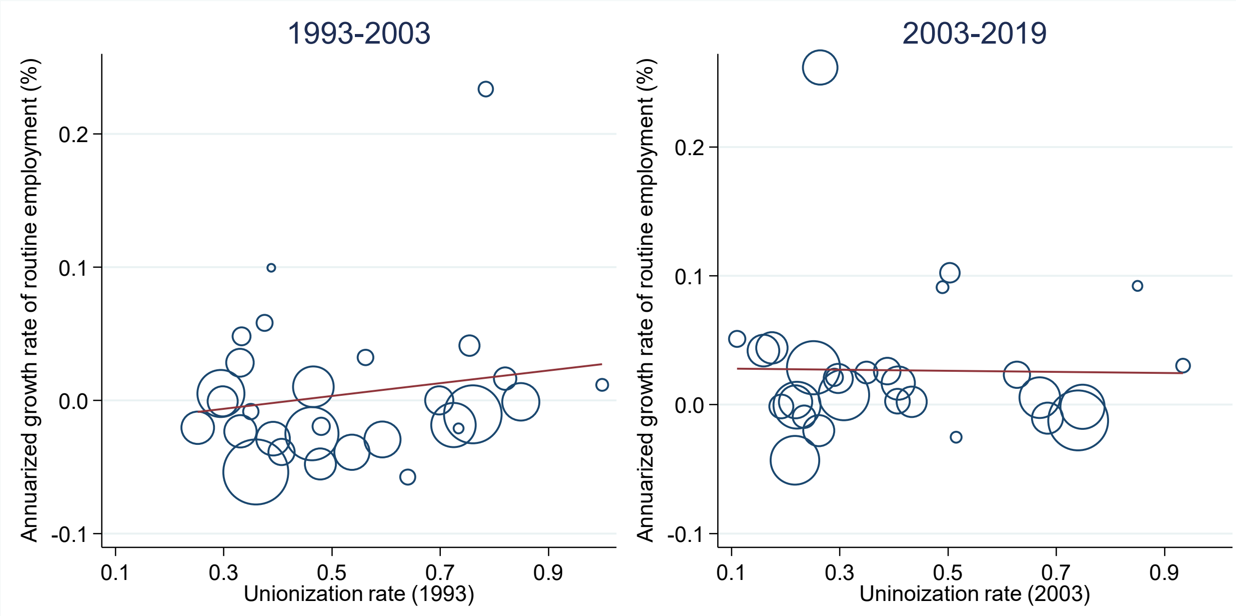
Fig A4. Occupational Composition of Total Union Membership



Source: Survey on Labor Conditions by Employment Type (SLCET).

Note: This figure shows each occupation's share of total union membership for the selected year.

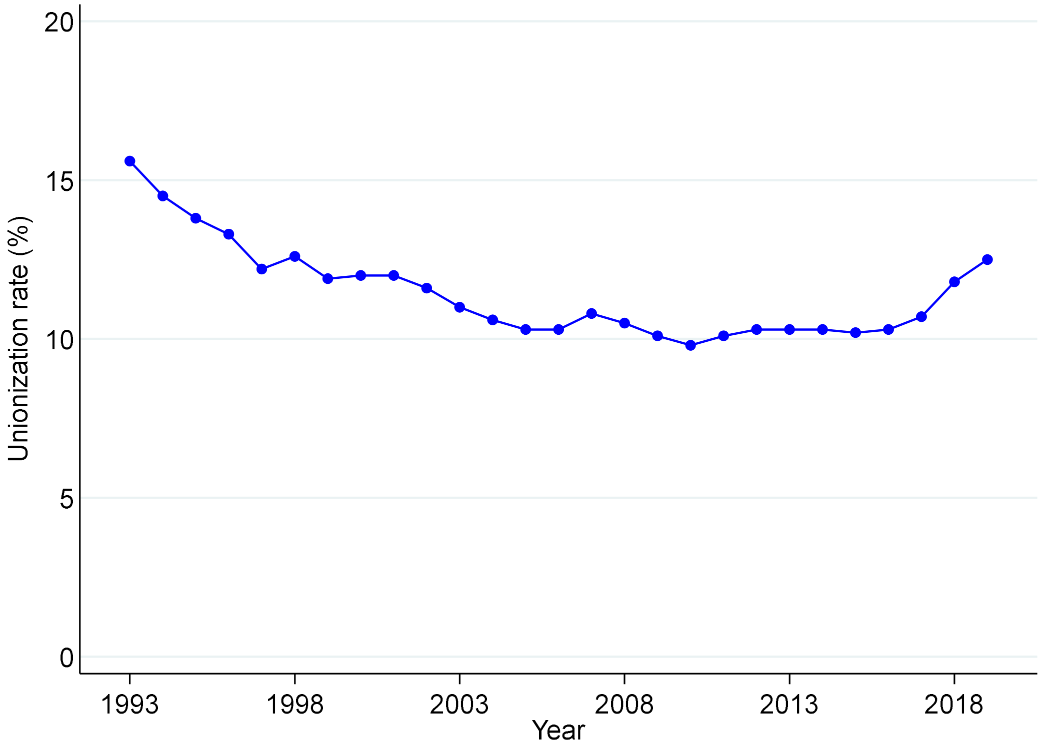
Fig A5. Initial Unionization Rate and Changes in Routine Employment



Source: Survey on Labor Conditions by Employment Type (SLCET) and Productivity Account of the Korea Information Society Development Institute (KISDI PA).

Note: This figure shows the initial unionization rate and the growth rate of routine employment in each industry for different time periods (1993-2003 and 2003-2019). The circle's size denotes the initial employment level of routine occupations in each industry.

Fig A6. Trends of Unionization Rate



Source: The National Labor Union Organizational Status from the Korea Ministry of Employment and Labor.

Note: This figure shows the share of union members in the total number of employees in each year between 1993 and 2019.

Table A1. Estimation Results of the Wage Regression, 2000

Variable	Coefficient	Variable	Coefficient
Male	0.208***	Routine	0.207***
	(0.003)		(0.004)
Age_2	0.072***	Cognitive	0.375***
	(0.004)		(0.005)
Age_3	0.143***	Teny	0.044***
	(0.004)		(0.001)
Age_4	0.132***	Teny^2	−0.001***
	(0.005)		(0.000)
Age_5	0.014**	Exp_2	0.111***
	(0.007)		(0.005)
Age_6	−0.062***	Exp_3	0.185***
	(0.016)		(0.005)
Edu_2	0.166***	Exp_4	0.226***
	(0.003)		(0.005)
Edu_3	0.236***	Exp_5	0.251***
	(0.005)		(0.005)
Edu_4	0.477***	Exp_6	0.271***
	(0.004)		(0.005)
Constant	0.494***	Exp_7	0.327***
	(0.010)		(0.005)
R^2	0.640	Observations	483,641

Note: Age1 to Age6 correspond to 18–24, 25–34, 35–44, 45–54, 55–64, and 65 years or older, respectively. Meanwhile, Edu1 to Edu4 correspond to workers with less than high school graduates, high school graduates, 2-year college graduates, and 4-year college graduates, respectively. All respondents who dropped out of school were classified in the lower educational group in the original survey. Teny is the total number of years that an employee has been working for the current establishment. Exp_1 to Exp_7 correspond to employees who have worked in their current job for less than 1 year, 1–2, 2–3, 3–4, 4–5, 5–10, and 10 years or more, respectively. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A2. Sources of Wage Variations (**R^2**)

	1993	2000	2010	2019
Total	0.681	0.640	0.573	0.548
(a) Industry only	0.181	0.172	0.141	0.132
(b) Covariates only	0.654	0.595	0.538	0.518
Observations	437,384	483,641	640,222	794,583

Note: We run the wage regression for different periods (1993, 2000, 2010, and 2019) and compute the explanatory power with and without industry dummies following Dickens and Katz (1987). The first row is the explanatory power (R^2) of the wage regression when individual characteristics and all industries are controlled for. The second row is the explanatory power of the wage regression when industry dummies are the only independent variables, and the third row is that of the wage regression when only covariates (i.e., individual characteristics) are considered as independent variables. The sum of the explanatory power reported in the second and third row is not equal to the value reported in the first row, since industries and covariates are not exactly orthogonal (Dickens and Katz, 1987). Robust standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A3. First-Stage Results

Panel A.	2000 Routine share	2000 Industry wage premium	2000 Unionization rate
1993 Routine share	0.971***	0.033	0.057
	(0.042)	(0.090)	(0.064)
1993 Industry wage premium	0.089	1.110***	0.184
	(0.093)	(0.154)	(0.170)
1993 Unionization rate	0.084	0.064	0.909***
	(0.071)	(0.093)	(0.140)
R^2	0.966	0.668	0.844
F- statistic	548.1	29.0	75.6
Panel B.	**2010 Routine share**	**2010 Industry wage premium**	**2010 Unionization rate**
1993 Routine share	0.866***	0.081	0.083
	(0.118)	(0.123)	(0.079)
1993 Industry wage premium	−0.001	0.844**	−0.063
	(0.247)	(0.364)	(0.362)
1993 Unionization rate	−0.021	−0.130	0.556***
	(0.102)	(0.149)	(0.179)
R^2	0.843	0.224	0.578
F-statistics	21.4	1.8	6.0

Note: Panels A and B present the first-stage results of the IV estimation, where we instrument the industrial factors in 2000 and in 2010, treated as endogenous regressors in the main regression model, with their corresponding values in 1993, respectively. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A4. Estimates of Employment Growth by Occupational Group: Robustness Check (subsamples: full-time worker, 2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	−0.123**	−0.230*	−0.078	−0.146**	−0.244*	−0.100
	(0.057)	(0.134)	(0.128)	(0.065)	(0.140)	(0.122)
$Industry\ wage\ premium_{t0}$	0.110	0.010	0.199	−0.065	−0.112	0.231
	(0.071)	(0.098)	(0.201)	(0.090)	(0.163)	(0.267)
$Unionization\ rate_{t0}$	−0.029	−0.041	−0.020	0.051	0.010	−0.023
	(0.031)	(0.046)	(0.161)	(0.052)	(0.043)	(0.175)
R^2	0.413	0.347	0.106	0.235	0.320	0.102

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A5. Estimates of Employment Growth by Occupational Group: Robustness check (applying different measure for employment: employment share, 2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	0.111**	−0.196*	0.085	0.081	−0.156	0.076
	(0.049)	(0.107)	(0.108)	(0.053)	(0.115)	(0.109)
$Industry\ wage\ premium_{t0}$	0.059	−0.185	0.126	−0.192*	0.021	0.170
	(0.132)	(0.134)	(0.107)	(0.112)	(0.156)	(0.179)
$Unionization\ rate_{t0}$	−0.024	0.013	0.011	0.104	−0.099	−0.005
	(0.056)	(0.066)	(0.071)	(0.103)	(0.108)	(0.080)
R^2	0.129	0.271	0.134	0.000	0.190	0.126

Note: The models are estimated for the period from 2000 to 2019. The dependent variable is the change in each occupation's employment share. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A6. Estimates of Employment Growth by Occupational Group -Robustness check (applying different measure for employment: number of employees, 2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	−0.157**	−0.293*	−0.184	−0.188**	−0.312*	−0.219
	(0.068)	(0.168)	(0.190)	(0.078)	(0.176)	(0.188)
$Industry\ wage\ premium_{t0}$	0.131	−0.000	0.222	−0.081	−0.163	0.230
	(0.085)	(0.122)	(0.252)	(0.110)	(0.208)	(0.337)
$Unionization\ rate_{t0}$	−0.032	−0.042	0.038	0.068	0.026	0.051
	(0.036)	(0.061)	(0.200)	(0.064)	(0.055)	(0.226)
R^2	0.440	0.350	0.150	0.268	0.322	0.147

Note: The models are estimated for the period from 2000 to 2019. The dependent variable is the annualized growth rate of the number of employees by occupation. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A7. Estimates of Employment Growth by Occupational Group: Robustness Check (applying different occupation classification system of Kim (2015), 2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	−0.102*	−0.227*	−0.157	−0.125*	−0.235*	−0.171
	(0.059)	(0.121)	(0.128)	(0.068)	(0.123)	(0.131)
$Industry\ wage\ premium_{t0}$	0.123	−0.011	−0.011	−0.063	−0.141	0.217
	(0.081)	(0.108)	(0.213)	(0.105)	(0.172)	(0.278)
$Unionization\ rate_{t0}$	−0.063*	−0.033	0.037	0.015	0.019	0.018
	(0.034)	(0.048)	(0.170)	(0.060)	(0.042)	(0.198)
R^2	0.394	0.368	0.192	0.221	0.338	0.187

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A8. Estimates of Employment Growth by Occupational Group: Robustness Check (using routine-specific industry wage premium, 2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$Routine\ share_{t0}$	-0.112*	-0.224*	-0.114	-0.176**	-0.259*	-0.169
	(0.064)	(0.130)	(0.173)	(0.066)	(0.137)	(0.186)
$Industry\ wage\ premium_{t0}$	0.106	0.039	0.090	-0.132	-0.100	-0.015
	(0.079)	(0.081)	(0.208)	(0.090)	(0.115)	(0.272)
$Unionization\ rate_{t0}$	-0.027	-0.050	0.043	0.075	0.007	0.088
	(0.036)	(0.055)	(0.177)	(0.063)	(0.049)	(0.211)
R^2	0.403	0.357	0.090	0.128	0.328	0.074

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A9. Estimates of Capital Intensity Growth by Capital Type: Robustness Check (using routine-specific industry wage premium, 2000–2019)

	Panel A. OLS			Panel B. IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	ICT	Non-ICT	Productivity	ICT	Non-ICT	Productivity
$Routine\ share_{t0}$	0.271***	0.138**	0.162***	0.263***	0.144***	0.154***
	(0.092)	(0.061)	(0.058)	(0.088)	(0.046)	(0.045)
$Industry\ wage\ premium_{t0}$	-0.043	0.070	0.171**	-0.095	0.001	0.052
	(0.129)	(0.080)	(0.074)	(0.189)	(0.135)	(0.146)
$Unionization\ rate_{t0}$	-0.284***	-0.057	-0.090	-0.248**	-0.043	-0.071
	(0.100)	(0.072)	(0.064)	(0.103)	(0.071)	(0.057)
R^2	0.461	0.112	0.137	0.456	0.098	0.108

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A10. Estimates of Employment Growth by Broad Occupational Group (applying two occupation groups: routine/non-routine, 2000–2019)

	Panel A. OLS		Panel B. IV	
	(1)	(2)	(3)	(4)
	Routine	Non-Routine	Routine	Non-Routine
$Routine\ share_{t0}$	−0.232*	−0.108*	−0.248*	−0.138**
	(0.133)	(0.055)	(0.140)	(0.065)
$Industry\ wage\ premium_{t0}$	0.013	0.124	−0.115	−0.048
	(0.099)	(0.083)	(0.165)	(0.101)
$Unionization\ rate_{t0}$	−0.042	−0.018	0.013	0.065
	(0.048)	(0.037)	(0.044)	(0.063)
R^2	0.355	0.402	0.328	0.211

Note: The models are estimated for the period from 2000 to 2019. Panel A presents OLS estimates. Panel B presents IV estimates when we instrument the industrial factors with their corresponding values in 1993. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A11. First-Stage Results for Additional Analyses

Panel A.	2000	2000	2000
	Routine share	Industry wage premium	Unionization rate
1993 Routine share	0.969***	0.042	0.055
	(0.041)	(0.091)	(0.064)
1993 Industry wage premium	0.089	1.132***	0.170
	(0.090)	(0.158)	(0.164)
1993 Unionization rate	0.083	0.062	0.920***
	(0.069)	(0.094)	(0.134)
R^2	0.967	0.669	0.850
F- statistic	600.4	28.7	84.3
Panel B.	2000	2000	2000
	Routine share	Industry wage premium	Unionization rate
1993 Routine share	1.019***	0.024	0.058
	(0.039)	(0.088)	(0.065)
1993 Industry wage premium	−0.003	1.107***	0.187
	(0.070)	(0.149)	(0.170)
1993 Unionization rate	0.067	0.074	0.908***
	(0.056)	(0.094)	(0.140)
R^2	0.976	0.676	0.844
F-statistics	819.8	33.5	76.0
Panel C.	2000	2000	2000
	Routine share	Routine wage premium	Unionization rate
1993 Routine share	0.976***	-0.067	0.075
	(0.041)	(0.081)	(0.081)
1993 Routine wage premium	0.092	0.928***	0.224
	(0.073)	(0.100)	(0.176)
1993 Unionization rate	0.086	0.112	0.905***
	(0.065)	(0.091)	(0.139)
R^2	0.966	0.647	0.847
F-statistics	587.4	41.5	63.8

Note: Panel A presents the first-stage results of the IV estimation, where we instrument the industrial factors in 2000 with their 1993 values, when the sample is restricted to full-time workers. Panel B presents the corresponding results when we use occupation classification system of Kim (2015). Panel C presents the corresponding results when we use routine-specific industry wage premium. The regressions are weighted by each industry's initial employment. All models include an intercept. N = 29. Robust standard errors are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

노동시장의 초기 조건이 일자리 양극화에 미친 영향*

권 영 순** · 심 명 규*** · 양 희 승****

초 록 본 논문은 노동시장의 초기 조건이 한국의 일자리 양극화(job polarization)에 어떠한 영향을 미쳤는지 분석하였다. 구체적으로, 두 경쟁 가설 – 전문화 가설(specialization hypothesis) 및 산업 간 임금 격차 가설(inter-industry wage differentials hypothesis) – 의 실증적 유효성을 비교하였다. 2000년부터 2019년까지의 기간을 대상으로 분석한 결과, 전통적으로 정형적 직무(routine task) 의존도가 높았던 산업일수록 정보통신기술 자본 집약도의 증가와 함께 일자리 양극화가 더욱 심화된 것으로 나타났다. 반면, 같은 기간 초기 시점의 산업 간 임금 격차는 일자리 양극화와 관련이 없었다.

핵심 주제어: 일자리 양극화, 초기 조건, 정형 직무 근로자, 산업별 임금 프리미엄, 정보통신기술 자본

경제학문헌목록 주제분류: J20, J23, J31

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