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Aging Labor, ICT Capital, and Productivity in Japan and Korea

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Keywords

aging, ICT capital, productivity, Japan, Korea

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1. Introduction

Population aging, a consequence of increasing life expectancies and declining fertility rates, stands out as a significant challenge to many advanced and developing economies. Older workers are thought to be less productive and innovative than their younger counterparts due to the deterioration of physical and cognitive abilities with age. There are concerns among aging societies that an increase in the share of elderly and the aging workforce will hinder economic growth.

Japan is one of the world's most aged societies and has a rapidly aging population and shrinking labor force. The elderly aged over 65 years account for 28.0% of Japan's population in 2019, and this number is forecasted to increase to 30.9% by 2040 (Figure 1). Aging is also in progress within Japan's workforce. Figure 2 presents those aged 50–64 (defined as "older workers" or "old" in this text) as a share of the working-age population aged 15 to 64 years. As can be seen in Figure 2, the share of older workers will increase from 31.6% in 2019 to 36.8% by 2040 in Japan. Population aging is an urgent issue. The Japanese government has made several attempts to tackle Japan's low fertility rates and shrinking labor force, such as by improving workplace conditions for married couples and elderly people.

[FIGURE 1 HERE]

[FIGURE 2 HERE]

South Korea ("Korea" hereafter) is no exception to this global population aging trend. Following the path of Japan, it is one of the global economies that is experiencing a rapid demographic shift toward an aged society. By 2040, the elderly aged over 65 years will account for 33% of Korea's population, more than doubling from 15% in 2019 (Figure 1). Korea's working-age population aged 15–64 years will shrink by more than a quarter between 2019 and 2040. As in Japan, the shrinking labor force will have a significantly negative effect on the growth of the Korean economy, which is already losing economic vitality. More seriously, the pace of workforce aging is faster in Korea than in any other economy, as shown in Figure 2. The share of older workers has been rising rapidly since the 1990s, more than doubling from 16% in 1990 to 33% in 2019. It is expected to continue to rise until 2050, outpacing Japan and Germany.

Over the coming decades, an increase in the share of older workers may hinder human capital growth and technological progress in Japan and Korea if old workers are less productive than young workers. However, if they are better-educated, continuously develop their human capital after their formal education by adapting to new technologies, and have longer work experience, their productivity might not be lower than that of younger workers.

Japan and Korea are the two Asian economies that have invested heavily in new technologies, as measured by the number of patents and the use of information and communication technology (ICT) (Chomik and Piggot, 2019). As also documented in OECD (2019), Japan and Korea maintained relatively higher ICT investment share over the past two decades, but lower than the U.S. did.[1]As of 2015, the ICT sector accounted for about 10.4% of total value-added in the Korean economy due to strong ICT manufacturing (OECD, 2017), ranking first among OECD economies (Figure 3). Japan's ICT sector is smaller than Korea's, accounting for 6.0% of the total value-added of the Japanese economy. The Korean ICT sector has grown rapidly and has become a major industry.

[FIGURE 3 HERE]

Against this backdrop, investigating the Japanese and Korean experience of aging populations and adaptation to technology-dependent environments will provide useful insights and policy implications for other economies encountering the same demographic challenge.

[1] ICT investment share in total non-residential gross fixed capital formation rose rapidly in Korea from 7.2 in 1993 to 18.0 in 2000. Japan's ICT investment share rose gradually from 7.4 in 1985 to 15.0 in 2000. Investment has declined in both Korea and Japan since 2000.

This study empirically examines whether aging has had detrimental effects on labor productivity in Japan and Korea, and further examines how aging interacts with new technologies in the workplace. This study focuses on the role of ICT investment in improving elderly workers' productivity, by using industry-level data.

Many empirical studies investigate the relationship between productivity and (population) aging using both micro- and macro-level data. Some empirical studies show that workers' productivity declines with age due to a deterioration of physical and cognitive capacities (Truxillo et al., 2015). However, other studies show that aging is not necessarily accompanied by productivity decline, possibly due to the offsetting effects of human capital investment and technologies. For instance, using data drawn from a truck assembly plant in Germany, Borsch-Supan and Weiss (2016) report a constant increase in productivity among individuals up to the age 60, on average. Burtless (2013) also argues that there is little evidence for the negative link between aging and productivity in the US. Finally, firm-level studies conducted in many countries suggest that productivity tends to peak around age 30 to 45 but that this range varies across countries and industries, as summarized in Chomik and Piggott (2019). Some firms also exhibit relatively long peak-age periods while others have very short ones. The variation in the duration of productivity peak ages suggests that workers in some sectors may exhibit higher productivity even at later stages in their careers (ADB, 2018).

Empirical studies based on aggregate economy-level data show that aging, especially in advanced economies, has negative effects on the economy's output growth. Masestas, Mullen, and Powell (2016) reports that, in the US, a 10% increase in the elderly (aged 60 and above) share in total population reduced GDP per capita growth rates by 5.5% between 1998 and 2010. One-third of this decline can be explained by the shrinking workforce and the remaining two-thirds by the slower growth rate of labor productivity. Other studies, including Tang and MacLoed (2006) and Gordon (2017), also report that a higher share of older workers in the workforce lowers productivity, thereby hindering growth. Using data on EU 28 countries from 1950 to 2014, Aiyar et al. (2016) show that an aging workforce has a negative effect on labor productivity and total factor productivity (TFP) growth. Wasiluk (2014) considers a model in which firms with a higher share of older workers update their technology less often and are more reluctant to train them for new technologies and estimates a 0.17-percentage-point decrease in the annual productivity growth rate for Germany between 2010 and 201, due to the aging of the workforce. By contrast, Acemoglu and Restrepo (2017) report a significant positive link between aging and GDP per capita. They argue that population aging may have a positive effect on productivity growth, as a shortage of young and prime-age workers can facilitate the adoption of automation technologies, thereby resulting in a higher growth in output per capita.

The literature has also examined the impact of ICT capital stock on labor productivity and total factor productivity (TFP). Positive effects of ICT capital on TFP have been reported in Jorgenson et al. (2003) and O'Mahony et al. (2010). Basu et al. (2003) find that the TFP growth in the late 1990s was positively associated with the growth of ICT capital services in the US. They suggest that ICT capital reflects an unobserved accumulation of intangible organizational capital, spillovers of a general-purpose technology, or both,

Studies using firm-level microdata provide evidence for the link between firm-level ICT adoption and productivity growth (Bresnahan, Brynjolfsson, and Hitt, 2002; Brynjolfsson, Hitt, and Yang, 2002). Bresnahan et al. (2002) argue that investments in training and organization change must be made in order to obtain the relative productivity benefits of ICT adoption.

A number of studies have explored the impact of ICT capital on labor productivity in Japan and Korea using the growth accounting techniques based on industry-level data, especially those from the EU KLEMS (Timmer et al., 2007) and WORLD KLEMS (Jorgenson, 2012). Fukao et al. (2009) find that productivity growth was strong in ICT-producing manufacturing sectors (such as electrical machinery and electronics) but relatively weak in ICT-using service sectors (such as retail, wholesale, and transportation) in both Japan and Korea from 1995 to 2005. They argue that excessive regulations and a lack of competition in service sectors may have prevented the enhancement of ICT-usage effects. Fukao (2013) also points out that, in Japan, ICT capital accumulation was very slow in non-ICT manufacturing and service industries, especially among small and medium-sized enterprises, contributing to declining TFP growth during the "two lost decades." By contrast, Jung et al. (2013) and Hwang and Shin (2017) confirm the significant positive spillover effects of ICT investment on TFP growth across ICT-producing and ICT-using industries in Korea. Jung et al. (2013) argue that these positive spillovers were due to the construction of a quality nationwide network that allows connections across all households and industries. Using a multifactor general equilibrium model, Kim et al. (2019) find that ICT investment has greater positive effects on productivity in Korea than in Japan.

Despite the rapidly changing labor market and the significance of new technologies such as ICT and artificial intelligence (AI) in workplaces in Japan and Korea, few studies have analyzed the interplay of ICT and older workers in these two countries and its consequence on productivity. Using Japanese industry-level data, Kawaguchi and Muroga (2019) find no empirical evidence supporting that population aging encourages the adoption of robots or ICT and that technological progress has a mitigating effect on the decline in older workers' productivity in Japan. Using Korean data, Park et al. (2019) also find no evidence that robots are more heavily adopted in the industries with aging workers. They find some evidence that adopting robot technology mitigates the negative effects of aging on TFP growth particularly in labor-intensive industries. Ilmakunnas and Miyakoshi (2013) use aggregate manufacturing data from 13 OECD countries, including Japan and Korea, to investigate the effect of aging and ICT capital on labor productivity from 1970 to 2005. Although their discussion on each economy is limited, they confirm that investment in ICT capital has positive effects on labor productivity for high-skilled older workers across the economies.

This study builds on that line of research and contributes to it by investigating the effects of ICT capital on the productivity of older workers in Japan and Korea using industry panel data. To the best of our knowledge, this study is the first to explore the interactions between ICT capital and workers in different age groups using comparative industry-level data from Japan and Korea.

The remainder of this paper is organized as follows. Section 2 provides our empirical specification. Section 3 describes the study's data. Section 4 examines how aging affects labor productivity in Japan and Korea using industry-level data. Section 5 discusses whether the effects differ according to the sector (manufacturing vs. services). Finally, Section 6 concludes the paper.

2. Empirical Specifications

We suppose that an industry *i* produces output using workers with different skills and of different ages and different types of capital that are ICT and non-ICT capital. To elaborate, we first suppose that industrial output at time *t* has a production function with capital (K) and labor (L) inputs. There are two types of labor inputs—high-educated (L_h) and low-educated labor inputs (L_l)—which are imperfect substitutes. Likewise, capital is an aggregate of ICT (K_{ICT}) and non-ICT capital $(K_{non-ICT})$, and these two capital inputs are imperfect substitutes. We can thus express the production function as follows:

$$\mathrm{Y_{it}} = A_{it}\ F(K_{it}, L_{it}) = \mathrm{A_{it}} F(K(K_{ICT,it}, K_{non-ICT,it}), L(L_{h,it}\ , L_{l,it}\ )) \tag{1}$$

We further assume that labor (L) input, as well as each of high-educated (L_h) and low-educated labor inputs (L_l), is subdivided into three age groups: young, middle, and old. These labor inputs of different age groups are imperfect substitutes. Workers' age structure is important for labor productivity.

$$\mathrm{L_{it}} = \left(\sum_a \alpha_\alpha L_{a,it}^{\varepsilon}\right)^{\frac{1}{\varepsilon}}, \quad \varepsilon < 1, \quad \mathrm{a = young, mid\ \ and\ \ old} \tag{2}$$

$$\mathrm{L_{lit}} = \left(\sum_a \beta_\alpha L_{la,it}^{\eta}\right)^{\frac{1}{\eta}}, \quad \eta < 1, \quad \mathrm{a = young, mid\ \ and\ \ old} \tag{3}$$

$$\mathrm{L_{hit}} = \left(\sum_a \gamma_\alpha L_{ha,it}^{\mu}\right)^{\frac{1}{\mu}}, \ \mu < 1, \quad \mathrm{a = young, mid\ \ and\ \ old} \tag{4}$$

where ε, η, and μ are parameters for the substitution elasticities among age groups for labor input, low-educated, and high-educated, respectively.

We consider the production function with different substitution elasticity between ICT capital and each of the labor inputs for different age groups. For example, there may be complementarity between ICT capital and older labor. This means that the substitution elasticity between ICT capital and older workers in the production function is lower than that between ICT capital and young workers. Hence, complementarity between ICT capital and older workers implies that an increase in ICT capital stock for production will help increase the marginal product of older workers relative to that of younger workers, thereby raising the relative demand for older workers. Under this assumption, ICT capital can augment the productivity of older workers. We can express this complementarity in the production function as follows:[2]

$$\mathrm{Y_{it}} = A_{it}F\big(K_{it}, L_{it}, G(K_{ICT,it}, L_{old,it})\big) \tag{5}$$

[2] Appendix 1 presents a specific form of the production function of Equation (5) based on Krusell et al. (2000). It shows mathematically that, under the production function allowing the complementarity between ICT capital and older workers, the increase in ICT capital to the older ratio increases the marginal product of older workers relative to that of younger workers.

$$\mathrm{Y_{it}} = A_{it}F\big(K_{it}, L_{hit}, L_{lit}, G_1\big(K_{ICT,it}, L_{hold,it}\big), G_2(K_{ICT,it}, L_{lold,it})\big) \quad (6)$$

where $K_{ICT,it}$ is the share of ICT capital in the total capital input. Equation (6) expresses that output depends on capital and labor inputs, under the assumption of the complementarity between ICT capital and high-educated older workers or between ICT capital and low-educated older workers, relative to their young counterparts.

The production function can also allow for different substitution elasticity between ICT capital and each of the labor inputs at different education levels. For instance, as discussed in the literature (Krusell et al., 2000), capital–skill complementarity may exist. This means that the substitution elasticity between ICT capital and high-educated workers in the production function is lower than that between ICT capital and the low-educated. Under this assumption, the production function can be specified as follows:

$$\mathrm{Y_{it}} = A_{it}F\big(K_{it}, L_{it}, G(K_{ICT,it}, L_{h,it})\big) \quad (7)$$

We can also express Equation (1) in terms of output per unit of labor (i.e., labor productivity). Using the empirical models below, we examine how aging affects labor productivity and whether ICT capital improves the effects of an aging workforce on labor productivity at the industry level.

The following estimates a logarithmic form of the production function of firms in industry *i* at time t in Equation (5):

$$\ln(Y/L)_{it} = \theta + \alpha_k \ln(K/L)_{it-k} + \beta_l \ln(L_l/L)_{it-k} + \beta_h \ln(L_h/L)_{it-k} + \phi_{mid}^{*} Sh_{mid,it-k} + \phi_{old}^{*} Sh_{old,it-k} + \psi_{ICT}^{*} K_{ICT,it-k} + \phi_{midICT}^{*} K_{ICT,it-k} Sh_{mid,it-k} + \phi_{oldICT}^{*} K_{ICT,it-k}\ Sh_{old,it-k} + \mu_i + \mathrm{f}_t + \epsilon_{it} \quad (8)$$

where the subscripts i, t, and k stand for industry, year, and number of lags, respectively. Y/L indicates labor productivity, which is the output per unit of labor; and K/L is the capital-to-labor ratio (capital per unit of labor). L_l/L denotes the share of low-educated labor in total labor input, and L_h/L the share of high-educated labor in total labor input. $Sh_{mid,it}$ denotes the share of labor inputs aged 30–49 and $Sh_{old,it}$ the share of labor inputs aged 50 or above. $K_{ICT,it}$ is the share of ICT capital in the total capital input.

We account for aggregate-level time shock and industry-specific unobserved factors using year and industry fixed effects, f_t and μ_i. By including μ_i, we effectively use only over-time variation within the industry, which means that we compare outcomes in the same industry at different time periods rather than comparing outcomes in different industries using variation between industries. The use of industry fixed effects can eliminate the bias arising from time-invariant industry-specific confounding factors. In our main specification, we also use lagged explanatory variables with $k = 1$ rather than contemporaneous explanatory variables to remove potential bias arising from simultaneity.[3] We are mainly interested in the parameters ϕ^*_{old}, ϕ^*_{oldICT} and ψ^*_{ICT}, to examine how aging and ICT capital affect labor productivity by interacting with each other. In this model, the group of labor inputs 16–29 is the reference.

We extend Equation (8) to examine the interactions between aging, education, and ICT capital by subdividing each of the low- and high-educated labor inputs by age group (young, middle, and old). Within the low-educated group, the shares of young, middle, and old are $Sh_{lyoung} = \frac{L_{lyoung}}{L_l}$, $Sh_{lmid} = \frac{L_{lmid}}{L_l}$ and $Sh_{lold} = \frac{L_{lold}}{L_l}$, respectively. Within the high-educated group, the shares of young, middle, and old are $Sh_{hyoung} = \frac{L_{hyoung}}{L_h}$, $Sh_{hmid} = \frac{L_{hmid}}{L_h}$ and $Sh_{hold} = \frac{L_{hold}}{L_h}$, respectively. Then, Equation (8) can be rewritten as follows:

[3] We also examined the robustness of our results using different lags for explanatory variables such as k=2 and k=3 in the estimation of Equations (8) and (9). We found that the results and marginal effects were robust with different time lags for the explanatory variables in both Japanese and Korean industries.

$$\ln(Y/L)_{it} = \theta + \alpha \ln(K/L)_{it-k} + \beta_l \ln(L_l/L)_{it-k} + \beta_h \ln(L_h/L)_{it-k} + \phi^*_{lmid} Sh_{lmid,it-k} + \phi^*_{lold} Sh_{lold,it-k} + \phi^*_{hmid} Sh_{hmid,it-k} + \phi^*_{hold} Sh_{hold,it-k} + \psi^*_{ICT} K_{ICT,it-k} + \phi^*_{lmidICT} K_{ICT,it-k} Sh_{lmid,it-k} + \phi^*_{loldICT} K_{ICT,it-k} Sh_{lold,it-k} + \phi^*_{hmidICT} K_{ICT,it-k} Sh_{hmid,it-k} + \phi^*_{holdICT} K_{ICT,it-k} Sh_{hold,it-k} + \mu_i + f_t + \epsilon_{it} \quad (9)$$

where the reference is the group of labor inputs aged 16–29, and k indicates number of lags. The parameters of interest are ϕ^*_{lold}, ϕ^*_{hold}, $\phi^*_{loldICT}$, $\phi^*_{holdICT}$ and ψ^*_{ICT}.

3. Data

We use a Japanese dataset drawn from the EU KLEMS published in 2008 and Korean datasets from the WORLD KLEMS published in 2015 (Timmer et al., 2007; Jorgenson, 2012).[4,5] Both are in a panel structure consisting of information on industries covering a long period: 1973 to 2005 for Japan and 1980 to 2012 for Korea. The datasets provide detailed information on outputs, labor inputs, and capital inputs for every industry.

The KLEMS datasets include different categories of labor inputs divided by educational attainment and age group, as well as various capital input categories, which allows us to examine the interplay between aging, education, and ICT capital. Data on 18 types of labor input (i.e., 2 gender × 3 educational attainments × 3 age groups) are available for both

[4] The World KLEMS (Jorgenson, 2012) also provides the latest version of a Japanese dataset published in 2015. This dataset contains a larger number of industries and sub-categorizes some industries (i.e., manufacturing) over a period of time longer than the period covered by the data we used. However, since this dataset does not include different categories of labor inputs divided by educational attainment, age group, and gender, we decided to use the dataset from the EU KLEMS published in 2008, which includes detailed information on both labor and capital inputs.

[5] The Japanese dataset can be downloaded from the EU KLEMS website: http://www.euklems.net/. The Korean dataset can be downloaded from http://www.worldklems.net/data.htm.

countries. There are eight types of capital inputs for Japan and 11 types of capital assets for Korea. Table 1 describes how we construct the variables for the analyses for Japan and Korea.

[TABLE 1 HERE]

To construct our Japanese sample, we use data covering 1973 to 2005. Some industries, such as recycling, private households with employed persons, and extra-territorial organizations and bodies, are excluded from our sample due to data non-availability. The final Japanese sample consists of data for 30 industries covering 1973 to 2005 (Appendix Table 1).

For the Japanese sample, we measure output per unit of labor using gross value added per hour worked, labor input using total hours worked, and capital input using real fixed capital stock. The labor inputs can be classified according to two educational attainment levels—low-educated (high school graduates and below) and high-educated (college graduates and above); and three age-groups—young (15–29 years), middle-aged (30–49 years), and old (50 years and above). For the capital inputs, we use information on the real fixed capital stock of ICT assets as ICT capital and the real fixed capital stock of all assets as total capital stock to calculate the ICT capital share. The ICT assets includes computing equipment, communications equipment, and software.

Descriptive statistics of the 30 industries in our Japanese sample for 1973–2005 are presented in Table 2.[6] Over the sample period, on average, most of the labor inputs are low-educated (about 83.4%). Middle-aged labor accounts for the largest proportion (48.5%), followed by the young (27.3%) and the old (24.2%). Among the low-educated, the middle-aged account for the largest proportion (46.7%), and the young and the old account for 26.3% and 37.0%, respectively. For the high-educated, the middle-aged account for the largest

[6] In contrast to Korean sample, Japanese sample includes 1970s when ICT Investment can be considered to be less active. We confirmed the robustness of the main results using the different sample period, 1980–2005, as shown in Appendix Table 4.

proportion (56.5%) followed by the young (30.9%) and the old (12.7%). The share of ICT capital in total capital stock is around 3.3% over the sample period.

[TABLE 2 HERE]

Data covering 1980 to 2012 were used to construct the Korean sample. We exclude industries from our sample if they either lack a full time series or have missing information on labor and/or capital inputs.[7] After this exclusion, our Korean sample shrinks to 65 industries (from 72) for 1980 to 2012 (Appendix Table 1).

In the Korean sample, output is measured as real gross value added, labor input as total hours worked, and capital input as real net capital stock. As in the Japanese sample, the labor inputs in the Korean sample are divided into two educational attainments and three age-groups. For the capital inputs, we construct ICT capital by combining three types of capital assets—equipment, communications equipment, and software—and calculate the share of ICT capital in total capital stock.

Table 3 presents descriptive statistics of the 65 Korean industries in our sample for 1980 to 2012. Over the sample period, about 86.7% of the labor inputs are low-educated.[8] The middle-aged labor group accounts for the largest proportion (45.8%), followed by the old (30.5%) and young (23.8%).[9] Among the low-educated, the middle-aged and the old make up

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[7] The following industries are excluded from the Korean sample: extraction of crude petroleum and natural gas and services, mining of uranium and thorium ores, other instruments, recycling, imputation of owner-occupied rents, extraterritorial organizations and bodies, and activities related to financial intermediation.

[8] Compared with Japan, Korea always has a smaller share of high-educated workers. From 1970 to 2009, Japan's share of high-educated workers in total workers went from 13.8% to 34.8%, whereas Korea's increase was from 7% in 1980 to 20% in 2009, for an annual growth rate of 3.6%.

[9] Korea showed a rapid increase in its share of older workers aged 50 and above, from 18% in 1980 to 64% in 2010, with its rate exceeding Japan's in 1996. The share of older workers in Japan rose gradually from 20% to 37% from 1970 to 2009. Note that the figures for Korea are somewhat higher than those reported by Statistics of Korea. According to Statistics of Korea's Economically Active Population Survey, the share of workers aged 50 and above has continuously increased from 18.1%

47.1% and 33.0%, respectively, whereas the young accounts for the smallest proportion (19.9%). This pattern is reversed for the high-educated. The young accounts for the largest proportion (48.3%) followed by the middle-aged (32.9%) and the old (18.8%).The share of ICT capital in total capital stock is around 14.5% over the sample period.

[TABLE 3 HERE]

Figure 4 depicts how the share of older workers is associated with a log of the ICT capital share across industries in the starting and ending years of the sample period—1973 and 2005 for Japan and 1980 and 2012 for Korea. Both Figures 4(a) and 4(b) show a positive association between the two variables over time for all industries. We first observe an increase in the share of workers aged 50 and above across most of the industries in both countries.

[FIGURE 4 HERE]

In Japan, many ICT-unrelated industries—including real estate, woods, mining, and basic and fabricated metals—show significant increases in the share of older workers over the two periods. By contrast, the increase in the share of older workers was small in industries with a higher share of ICT capital in 1975 as well as in 2005, some of which are ICT-related (e.g., telecommunication, finance, electrical, optical equipment).

In Korea, however, the industries with a higher share of ICT capital in 1980 and 2012, some of which are ICT-related (e.g., telecommunication, computing and computers) show significant increases in the share of older workers. By contrast, the increase in the share of

in 1980 to 34.0% in 2012. Note that the employment figures from the WKLEMS do not include all industries and are measured in total hours worked by people engaged, whereas the number of workers is used to construct the employment share in the Statistics of Korea data. We also observe an unusual peak in 2010 across Korean industries. We checked the robustness of the main results using the sample up to 2005 (like the Japan sample). The main results and marginal effects (reported in Appendix Table 5) are consistent with those shown in Section 4. We consider that the inclusion of industry and year fixed effects to control for industry characteristics and macroeconomic shocks in the estimation can also control for any systematic bias or mismeasurement in the estimates to the certain extent..

older workers is small in industries with relatively small ICT shares, such as mining and textiles. Service industries such as public administration and education had a higher share of old workers and a smaller share of ICT capital in 1980, but they increased their ICT capital share in 2012.

Figure 5 depicts how the share of old workers aged 50 and above among high-educated workers is associated with the share of old workers aged 50 and above among low-educated workers across the industries in Japan and Korea in the two selected years. Figures 5(a) and 5(b) show a positive association between the two variables in both countries, implying increases in the share of old workers for both educational levels. They also suggest that the increases in the share of low-educated older workers are greater than those in the share of high-educated older workers across the industries over time in both countries.

[FIGURE 5 HERE]

4. Aging and Labor Productivity in Japan and Korea

Table 4 shows the estimation results using Japanese industry-level data for the production function [i.e., Equations (8) and (9)]. Column (1) reports the estimates without the interactions of worker shares or the log value of the ICT capital share. Labor inputs are subdivided by educational attainment (low and high) and age [middle (30–49 years) and old (50 years and above)]. The estimates with the interactions between ln(ICT capital share) and age are shown in Column (2). The reference age group is the young (15–29 years) in Columns (1) and (2). Column (3) adds the interaction term of ln(ICT share) with the share of high-educated labor to examine ICT capital–skill complementarity. The reference group is the low-educated. Colum (4) includes both the interactions between ln(ICT capital share) and age and the interaction term of ln(ICT share) and the share of high-educated labor. Column (5) shows the estimates when labor inputs divided by educational attainment are further subdivided by age group. Column (6) presents the estimates with the interactions between the high- and low-educated worker shares by age group and ICT capital share.

[TABLE 4 HERE]

Column (1) presents the estimation results of the production function without any interactions between capital and labor inputs. The estimated coefficient for share of labor aged 50 and above is positive but statistically insignificant. This result implies that there is no significant difference depending on age, which conflicts with the argument made by previous studies that aging lowers productivity. The estimates for the share of labor aged 30–49 also appear statistically insignificant. Column (1) shows that ln(ICT share) has a negative but statistically insignificant effect on labor productivity in Japanese industries.

Column (2) reports the estimates with the interaction of age group shares with a log value of the ICT capital share (i.e., ln(ICT share)). Among the interaction terms, the coefficient of $K_{ICT,it}Sh_{old,it}$ (i.e., ln(ICT share) $\times$ share of labor aged 50 and above) is positive and statistically significant. Relative to the reference age group (i.e., young), the increase in the share of labor aged 50 and above has a positive effect on labor productivity at the mean of the ln(ICT share) ($\phi^*_{old} + \phi^*_{ICTold} \times \overline{K_{ICT}} = 8.954 + 1.085 \times (-4.269) = 4.322$). Hence, a one-standard-deviation (1SD) increase in the share of labor aged 50 and above of 0.080 would lead to an increase in labor productivity of 0.346 (relative to the labor productivity of those aged 15–29) at the mean value of the ln(ICT share), which amounts to 34.6% of the labor productivity. Figure 6(a) illustrates this quantitative effect of an increase in the share of labor aged 50 and above on labor productivity. As Figure 6(a) shows, the share of ICT capital or ln(ICT share) is important for determining the magnitude of the productivity effect of population aging: If an industry possesses a higher value of ln(ICT share) by 1SD above, this marginal effect of population aging on productivity increases to 5.855. Hence, a 1SD increase in the share of labor aged 50 and above of 0.080 would lead to increase in labor productivity of $0.468\ (= 5.855 \times 0.080)$. This result may imply that an increase in ICT capital share (ICT investment) can improve the productivity of older workers (as measured by valued-added per workhour) relative to that of young workers in Japan on the one hand. On the other hand, this result may reflect the productivity of those older workers who were able to adapt to ICT development and remained in the labor market. In addition, it also implies that relatively high substitutivity between ICT capital and young workers, which may contribute to youth unemployment. These employment-related issues are important, but we cannot test whether these two phenomena actually happened in Japan using our data.

[FIGURE 6 HERE]

Column (3) reports the estimates when we add an interaction term between ln(ICT share) and share of high-educated workers to Column (1). The coefficient of ln(ICT share) is negative and statistically significant, whereas its interaction term with share of high-educated workers has a positive and statistically significant estimate (1.593). This implies that an industry with a high share of high-educated labor can enhance productivity by investing in more ICT capital. Hence, this confirms the complementarity between ICT capital and high-educated labor in Japanese industries.

Column (4) adds an interaction term between ln(ICT share) and share of high-educated workers to Column (2). The estimation results in Column (4) are consistent with those in Column (2), supporting the complementarity effect between ICT capital and older workers. By contrast, the interaction term between ICT capital and high-educated workers is positive but statistically insignificant [unlike that in Column (3)], indicating that the complementarity effect between ICT capital and high-educated workers is not robust after the complementarity effect between ICT capital and older workers is controlled for.

Column (5) reports the estimates when we include the high- or low-educated worker shares subdivided by age group but without interactions. The estimated coefficient for the share of the low-educated aged 50 and above is 4.589, positive, and statistically significant, while the estimate for the share of high-educated aged 50 and above is -0.864 but statistically insignificant. These results show that an increase in the share of older workers relative to young among the low-educated tends to have significantly positive effects on labor productivity. This implies that low-educated older workers may have been utilized more efficiently across industries than their younger counterparts were and contributed more to labor productivity. By contrast, there is no significant difference in labor productivity between the younger and older among high-educated workers.

Column (6) adds interaction terms between workers shares and ln(ICT share) to Column (5).[10] The coefficients of the interaction terms, $K_{ICT,it}\ Sh_{lold,it}$ and $K_{ICT,it}\ Sh_{hold,it}$, are statistically insignificant. Relative to the share of labor aged 15–29 (reference group), an increase in the share of low-educated aged 50 and above has a positive effect on productivity at the mean value of the ln(ICT share) ($\phi^*_{lold} + \phi^*_{loldICT} \times \overline{K_{ICT}} = 7.239 + 0.621 \times (-4.269) = 4.58$). Thus, a 1SD (= 0.088) increase in the share of low-educated labor aged 50 and above at the mean value of the ln(ICT share) produces a 40.4% (4.588×0.088=0.404) increase in labor productivity. However, the productivity impact of an increase in the share of high-educated aged 50 and above is negative ($\phi^*_{ho} + \phi^*_{hoICT} \times \overline{K_{ICT}} = 1.103 + 0.383 \times (-4.269) = -0.532$, though statistically insignificant. Figure 6(b) illustrates this quantitative effect of an increase in the share of high-educated labor aged 50 and above and the effect of low-educated older workers on labor productivity. As mentioned, aging can have positive effects on labor productivity when the older workers are low-educated in Japan. This positive

[10] The estimation results are robust to the inclusion of an interaction term between ln(ICT capital) and share of high-educated workers. The coefficient for this interaction term appears statistically insignificant, implying that the productivity effect of an increase in the share of high-educated (or low-educated) older workers does not result from an increase in high-educated workers in the labor market.

effect can be augmented in industries with a higher ICT capital share, as shown in Figure 6(b); this effect is limited for high-educated older workers. This result implies that ICT capital is more of a complement for the old than the young among low-educated workers.[11] This finding is consistent with that of Nishimura and Shirai (2003), who find that low-educated older workers are less substitutable with ICT capital than are their younger counterparts.

The estimation results using the sample of Korean industries are presented in Table 5. Columns (1) to (6) in this table correspond to Columns (1) to (6) in Table 4. Column (1) reports the results of estimating the production function without interaction terms between capital and labor inputs. The estimate for the share of older workers aged 50 and above is negative but statistically insignificant, which indicates that there is no significant difference depending on the age group. As seen in Column (1) of Table 4 with the sample of Japanese industries, the result provides no evidence of a negative productivity effect of aging. Column (1) also reports that ln(ICT share) has a negative but statistically insignificant effect on labor productivity.

[TABLE 5 HERE]

Column (2) shows estimates with the interaction of age group shares with ln(ICT share). The estimate for ln(ICT share) remains negative but is statistically significant. Its interaction terms with age group shares, $K_{ICT,it}Sh_{mid,it}$ (i.e., ln(ICT share) $\times$ share of labor aged 30–49) and $K_{ICT,it}Sh_{old,it}$ (i.e., ln(ICT share) $\times$ share of labor aged 50 and above), have positive and statistically significant estimates, suggesting that the increase in the share of those aged 50 and above has a positive and greater effect on labor productivity than the reference group: Relative to the effect of the share of labor aged 15–29, an increase in the share of those aged 50 and above has a small negative effect on labor productivity at the mean of the ln(ICT share)

[11] This implies that increase in ICT capital causes low-educated young workers to be substituted with low-educated older workers in the production process, which may cause higher youth unemployment rates in Japan. Note that the complementary effect between ICT capital and older workers is not statistically significant.

$(\phi^{*}_{old} + \phi^{*}_{ICTold} \times \overline{K_{ICT}} = 2.827 + 1.230 \times (-2.38) = -0.100)$. Hence, a 1SD increase in the share of labor aged 50 and above of 0.175 would lead to a labor productivity decrease of 0.018 (relative to the labor productivity of labor aged 15–29) at the mean value of the ln(ICT share). Figure 7(a) illustrates this quantitative effect of an increase in the share of labor aged 50 and above on the labor productivity in Korean industries. The estimates in Figure 7(a) show that, if an industry possesses a higher value of ln(ICT share) by a 1SD (1.195), this marginal effect of population aging on productivity increases to 1.369. Hence, a 1SD increase in the share of labor aged 50 and above of 0.175 would lead to increase in labor productivity of 0.24 $(= 1.369 \times 0.175 = 0.240)$.

[FIGURE 7 HERE]

Column (3) reports the estimates when we add an interaction term between ln(ICT share) and share of high-educated workers to Column (1). The coefficient of ln(ICT share) is negative and statistically significant, and the estimated coefficient for its interaction term with share of high-educated workers is 1.593, positive, and statistically significant. This suggests that an industry with a high share of high-educated labor can enhance productivity by investing more in ICT capital, confirming the complementarity between ICT capital and high-educated labor in Korean industries.

Column (4) adds an interaction term between ln(ICT share) and share of high-educated workers to Column (2). The estimation results in Column (4) are consistent with those in Column (2): The coefficient for the interaction term is positive but statistically insignificant [unlike that in Column (3)]. This result shows that the complementarity effect between ICT capital and older workers remains strong.

Column (5) reports the estimates when we include the high- or low-educated worker shares subdivided by age group without interaction terms. The estimated coefficient for the share of low-educated workers aged 50 and above is -2.453, whereas the estimate for the share of the high-educated aged 50 and above is 2.307. Both estimates are statistically significant. These results indicate that an increase in the share of older workers relative to younger ones among the high-educated tends to have significantly positive effects on labor productivity. By contrast, an increase in the share of younger workers relative to older ones among the low-educated tends to have significantly positive effects on labor productivity. This implies that, in Korea, high-educated older workers and low-educated young workers may have been utilized more efficiently across industries than their counterparts. These results differ from those for Japan.

Column (6) adds interaction terms between worker shares and ln(ICT share) to Column (5).[12] The coefficients of the two interaction terms, $K_{ICTit}\ Sh_{loldit}$ and $K_{ICTit}\ Sh_{holdit}$, are statistically significant. Compared to the impact on labor productivity from the change in the share of labor aged 15–29 (reference group), the productivity impact of a 1SD change in the share of low-educated worker aged 50 and above at the mean value of the ln(ICT share) is negative ($\phi^*_{lold} + \phi^*_{loldICT} \times \overline{K_{ICT}} = -0.496 + 1.083 \times (-2.380) = -2.082$). However, the productivity impact of a 1SD change in the share of high-educated workers aged 50 and above is positive ($\phi^*_{ho} + \phi^*_{hoICT} \times \overline{K_{ICT}} = 0.261 + -0.872 \times (-2.380) = 2.336$). Thus, a 1SD (= 0.128) increase in the share of high-educated labor aged 50 and above at the mean value of the ln(ICT share) leads to a 29.9% ($2.336 \times 0.128 = 0.299$) increase in labor productivity. These results contrast with those for Japan, where the marginal effects of aging on labor productivity are negative, though statistically insignificant, for high-educated older workers but positive for low-educated older workers.

[12] As in the analysis using the Japanese sample, the estimation results for Korean industries also remain unchanged after the inclusion of an interaction term between ln(ICT capital) and share of high-educated workers. The coefficient for the interaction term appears statistically insignificant, implying that the productivity effect of an increase in the share of high-educated older workers does not result from an increase in high-educated workers in the labor market.

Figure 7(b) illustrates the quantitative effect on Korean labor productivity of an increase in the share of high-educated labor aged 50 and above and that of low-educated older workers. The estimates in this figure suggest that aging can have positive effects on labor productivity when older workers are high-educated. Figure 7(b) also shows that an increase in the share of ICT capital could mitigate the negative effect aging has on labor productivity among low-educated workers, but the marginal effect remains negative. However, it appears to have a negative effect on labor productivity for high-educated workers. Nonetheless, its marginal effect remains positive, and at a greater magnitude than that for low-educated workers. These results are similar to the finding of Ilmakunnas and Miyakoshi (2013) based on a sample of 13 OECD countries.[13]

Overall, the empirical results in Section 4 provide evidence of a complementary effect between ICT capital and older workers in both Japan and Korea, implying that ICT capital is more effective for older workers than young workers: As shown in Figures 6(a) and 7(a), both Japanese and Korean industries with a higher ln(ICT share) value can enjoy significant productivity gains from the aging process.

However, we also find that, in both countries, the complementary effect is observed only when the older workers are low-educated. As shown in Figures 6(b) and 7(b), the increased ln(ICT share) will have a positive impact on the productivity effect of low-educated older workers. This finding may occur because ICT capital is less substitutable for low-educated older workers than for low-educated young workers, whereas ICT capital is more

[13] The complementary effect between ICT capital share and low-educated older workers in Figure 7(b) indicates that an increase in ICT capital can improve the productivity of low-educated older workers relative to that of young workers on the one hand. On the other hand, this result may reflect the productivity of those older workers who remained in the labor market. In addition, it may imply that over the sample period, firms in Korea might substitute ICT capital for low-educated young workers, which may contribute to youth unemployment. Note that we cannot examine these statements using our data.

substitutable for high-educated older workers than for high-educated young workers. This implies that industries with a high ICT capital share in both countries utilize high-educated younger workers (or low-educated older workers) more efficiently than high-educated older workers (or low-educated younger workers) for the production.

5. Aging and Labor Productivity by Sector in Japan and Korea

This section examines the effects of aging on labor productivity by sector (i.e., manufacturing and services) in Japan and Korea using industry-level data. The manufacturing sector includes all of the manufacturing industries in our sample, and the service sector comprises the service industries in the sample. The estimation results are reported in Appendix Tables 2 and 3.

Appendix Table 2 reports the estimation results of the production function for Japanese industries by sector: manufacturing industries in Columns (1) to (3) and service industries in Columns (4) to (6). The results in Appendix Table 2 correspond to Columns (2), (5), and (6) of Table 4, where the estimation results for all Japanese industries are reported. The estimations for both the manufacturing and service industries are close to those in Table 4. The results provide evidence of the complementarity effect between ICT capital and older workers in both industries. A difference emerges in Column (6) of Appendix Table 2, where the interactions between the high- or low-educated worker shares by age group and the ICT capital share are included. The coefficient for the interaction term between ln(ICT share) and the share of high-educated older workers aged 50 and above in the service industries [Column (6) of Appendix Table 2] is negative and statistically insignificant whereas it is statistically positive in manufacturing industries [Column (3) of Appendix Table 2] and in all industries in Column (6) of Table 4. The estimation results for the Japanese service sector shows that the increase in the share of high-educated labor aged 50 and above would have a positive effect on labor productivity at the mean of ln(ICT share; $\phi_{old}^{*} + \phi_{ICThold}^{*} \times \overline{K_{ICT}} = 2.002 + -0.116 \times (-4.031) = 2.470$) in the service sector relative to the impact of high-educated young workers.

The marginal effect of a 1SD increase in the share of older workers aged 50 and above on output per worker in the manufacturing and service industries is shown in Figure 8. The marginal effects shown in Figure 8(a) also confirm that, for both industries, an increase in ln(ICT capital share) would augment the positive effect of aging on labor productivity, which is consistent with the results shown in Figure 6(a). Figure 8(b) shows that the aging process can have positive effects on labor productivity when older workers are low-educated and employed in either manufacturing or service industries, or when they are high-educated and employed in service industries. This shows that the negative effect that aging has on labor productivity in all industries in Japan [Figure 6(b)] comes mainly from the manufacturing sector. Figure 8(b) confirms the complementary effect of ICT capital for low-educated older workers in both sectors and the effect for high-educated older workers in the manufacturing sector in Japan.

[FIGURE 8 HERE]

Appendix Table 3 shows the results of estimating the production function for Korean industries by sector: manufacturing industries in Columns (1) to (3) and service industries in Columns (4) to (6). The results in Appendix Table 3 correspond to those in Columns (2), (5), and (6) of Table 5, where the estimation results for all Korean industries are reported. The estimation results of Appendix Table 3 are close to those of Table 5. The results provide evidence for the complementary effect between ICT capital and older workers in both Korean industries. They also confirm that the effect of aging on labor productivity is positive for high-educated older workers but negative for low-educated workers.

Figure 9 illustrates the marginal effect of a 1SD increase in the share of labor aged 50 and above on output per worker in Korean manufacturing and service industries using the estimates in Appendix Table 3. As shown in Figure 9(a), although the effect is slightly positive for manufacturing industries and negative for services, both industries would enjoy considerable labor productivity gains from aging with a greater ICT capital share. Figure 9(b) shows that aging can have positive effects on labor productivity when older workers are high-educated in both industries, which is consistent with the results in Figure 7(b). Figure 9(b) confirms the complementary effect between ICT capital and low-educated older workers in both sectors, like in Japan. It also shows complementarity between ICT capital and high-educated older workers in manufacturing industries but not in service industries. We conjecture that the limited complementary effect between ICT capital and high-educated older workers in the service sector occurs largely because public services include education, health, and public administration, where a high proportion of high-educated older workers have remained (due to high job security) without necessarily having adopted ICT technologies, as shown in Figures 4(b) and 5(b). On the other hand, in the manufacturing sector, ICT capital is well-combined with older workers with higher productivity, leading to productivity gains due to aging. In short, an inefficient use of ICT capital with high-educated older workers in the service sector may cause productivity loss in Korea [Figure 7(b)].

[FIGURE 9 HERE]

6. Conclusion

This study examined the effects of aging on labor productivity using industry-level data from Japan and Korea. Our analysis revealed a complementary effect between ICT capital and older workers. This demonstrates that the aging process has positive effects on labor productivity when the older workers work in industries with a large share of ICT in the capital stock. This finding is consistent across all industries in both Japan and Korea. We also found that, on average, aging has positive effects on labor productivity when older workers are low-educated in Japan and high-educated in Korea. Thus, an increase in low-educated older workers in Japan or in high-educated older workers in Korea relative to their respective young counterparts can enhance labor productivity.

We also found that the complementary effect between ICT capital and older workers is observed for both high- and low-educated workers in Japan but only for low-educated workers in Korea. We considered the interplay among educational attainment, industry characteristics, and production techniques to explain the differences in older worker productivity between the two countries. In Japan, aging has positive effects on labor productivity when the low-educated older workers are in either the manufacturing or service sector, or when the high-educated older workers are employed in service industries. In Korea, only the high-educated older workers have positive effects on labor productivity in both sectors. The complementary effect between ICT capital and older workers operates similarly in both sectors of the two countries. The complementary effect of ICT capital with low-educated older workers is observed in both the manufacturing and service sectors in Japan and Korea, while with high-educated older workers, the effect appears only in the manufacturing sector.

Our findings suggest that the rapid demographic shift toward aged societies is not necessarily an economic threat. We can mitigate productivity decline due to aging by increasing investments in ICT. Investing in ICT capital and technologies can help improve productivity and extend the working age of aging populations. Meanwhile, the complementary effect between ICT capital share and older workers (especially, low-educated ones) may imply that over the sample period, firms in both countries might substitute ICT capital for young workers, which may contribute to decreasing job opportunities for young workers (especially, low-educated ones). These cannot be examined using our data. We will leave this important issue for future research.

Our empirical investigations are subject to several limitations. We used ICT capital stock at the industry level as a measure of ICT capital services or technologies that are available to firms and workers in an industry. This variable may not be a perfect measure of ICT technologies.[14] In addition, our empirical techniques relied on fixed effects to account for unobserved confounding factors. Using fixed effects alone may not fully control for possible endogeneity issues in the estimations. The use of valid instrumental variables to control for endogeneity in the adoption of ICT and the employment of older workers would provide consistent estimates, but the ideal instruments—those closely correlated with ICT investment or older workers, but not with productivity—are hard to find. Furthermore, estimations of substitution elasticities and case studies at the firm level could deepen our understanding of the interplay among ICT capital, population aging, and labor productivity. A more in-depth investigation of how population aging affects productivity using firm- and individual worker-level data would assist in the design of policies for helping older workers stay productive in the labor market, thereby alleviating the negative economic consequences of population aging.

[14] Our subsequent research adopts individual-worker level data and shows that older workers who have a high level of ICT skills and/or who often use ICT skills at work tend to have higher productivities (measured in wages) (Lee, Kwak and Song, 2019).

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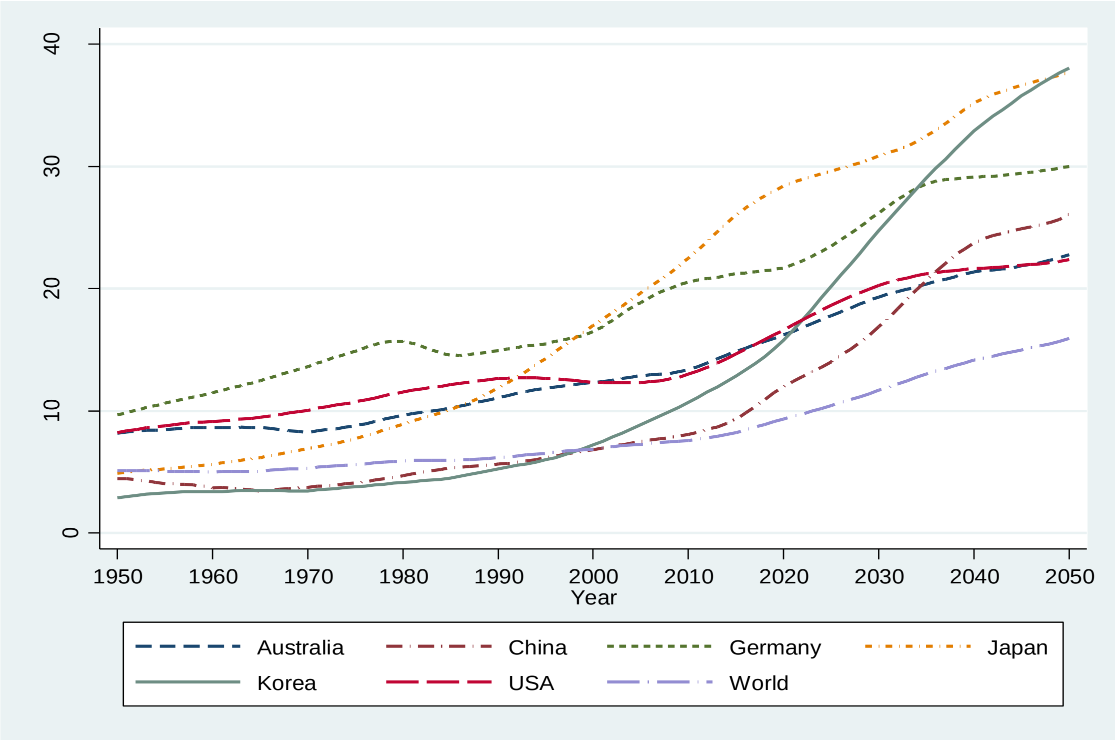


Figure 1 Share of Population Aged 65 and Above in Total Population

Source: Authors' construction from UN's (2019) *World Population Prospects*.

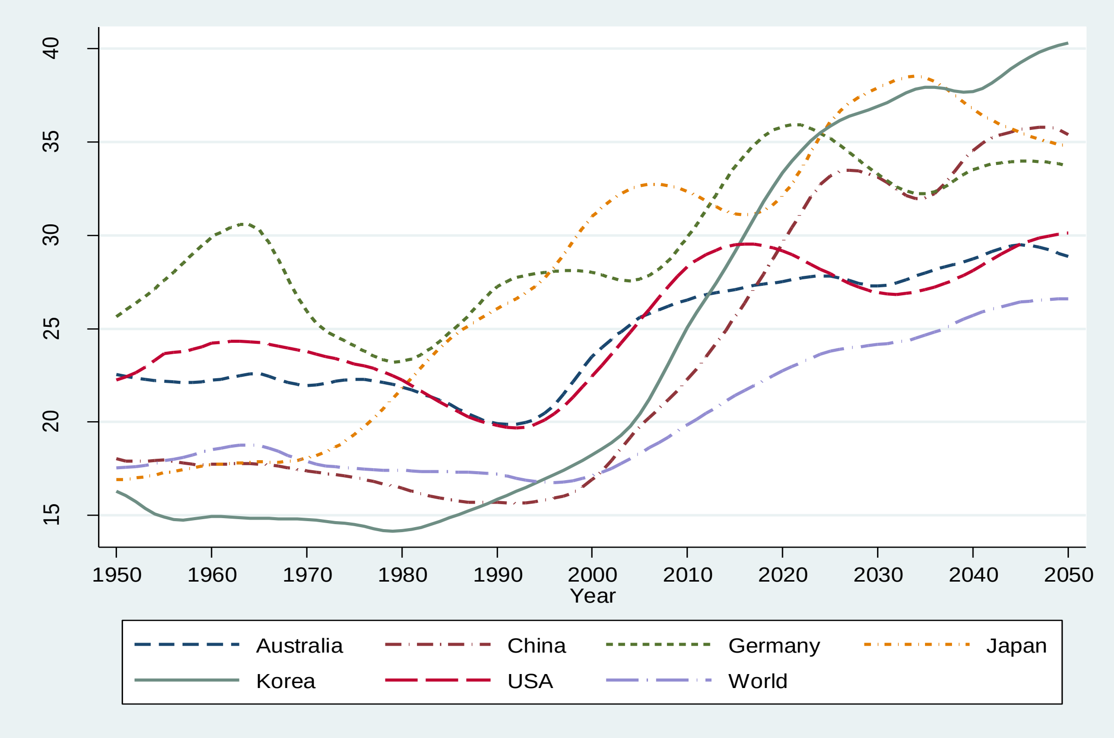


Figure 2 Share of Population Aged 50–64 in Working-age Population (16–64 years)

Source: Authors' construction from UN's (2019) *World Population Prospects*.

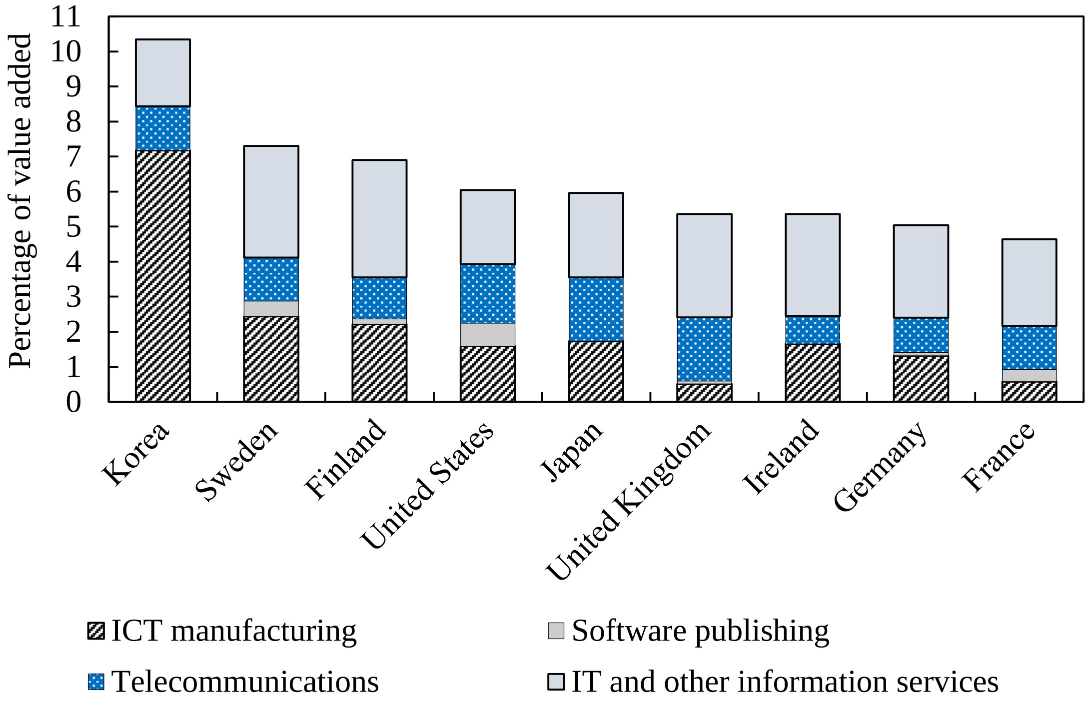
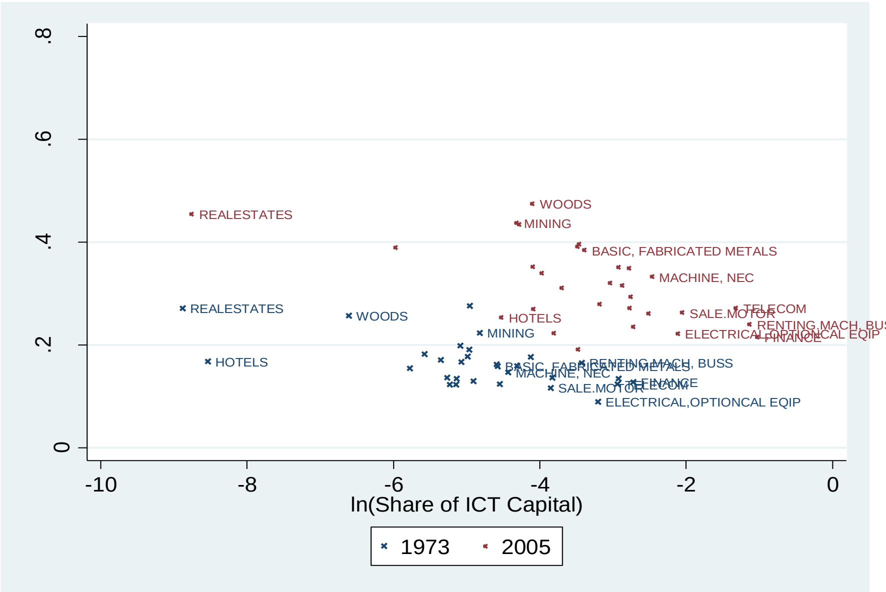


Figure 3 Value-added of the ICT Sector and Sub-sectors in Selected OECD Countries, 2015

Note. As a percentage of total value added at current prices. ICT manufacturing indicates computer, electronic and optical products (ISIC rev.4: 26). Data on software publishing were not available for Ireland, Japan, and Korea; therefore, their share could be underestimated. IT = information technology; ICT = information and communication technology. Source: OECD (2017).

a) Japan



b) Korea

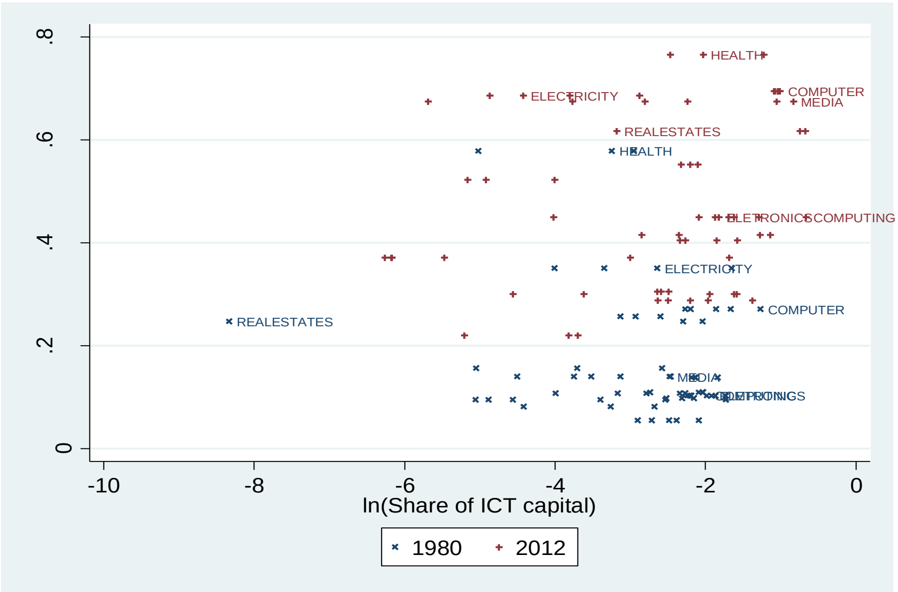
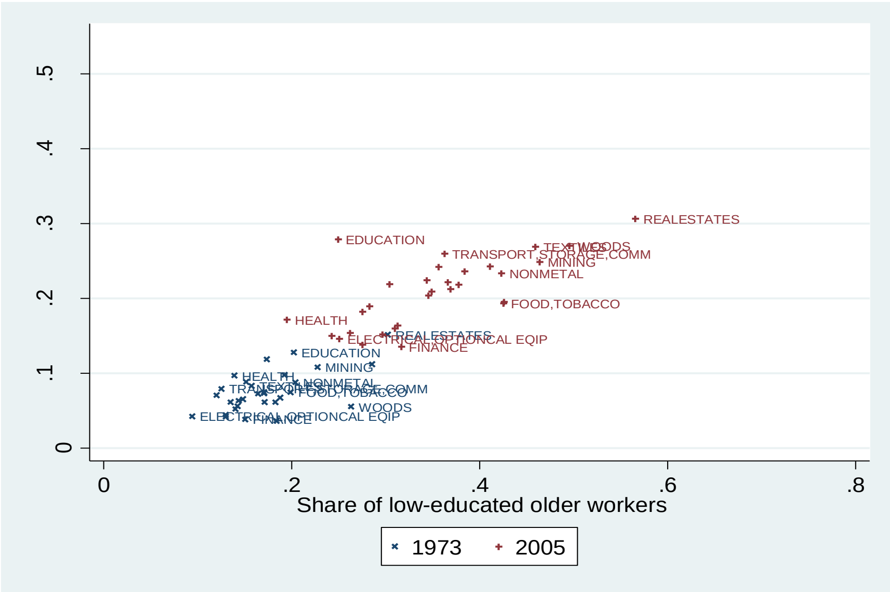


Figure 4 Share of Workers Aged 50 and Above and ICT Capital Share by Industry in Japan and Korea, Selected Years

Note: This figure depicts how the share of old workers aged 50 and above in total workers is associated with a log value of the share of ICT capital in the total capital stock across industries in Japan and Korea in two selected years. The Japanese sample includes 30 industries, whereas the Korean sample has 65 industries (see Appendix Table 1).

Source: Authors' construction using the Japanese and Korean samples in the EU KLEMS (Timmer et al., 2007) and WORLD KLEMS (Jorgenson, 2012), respectively.

a) Japan



b) Korea

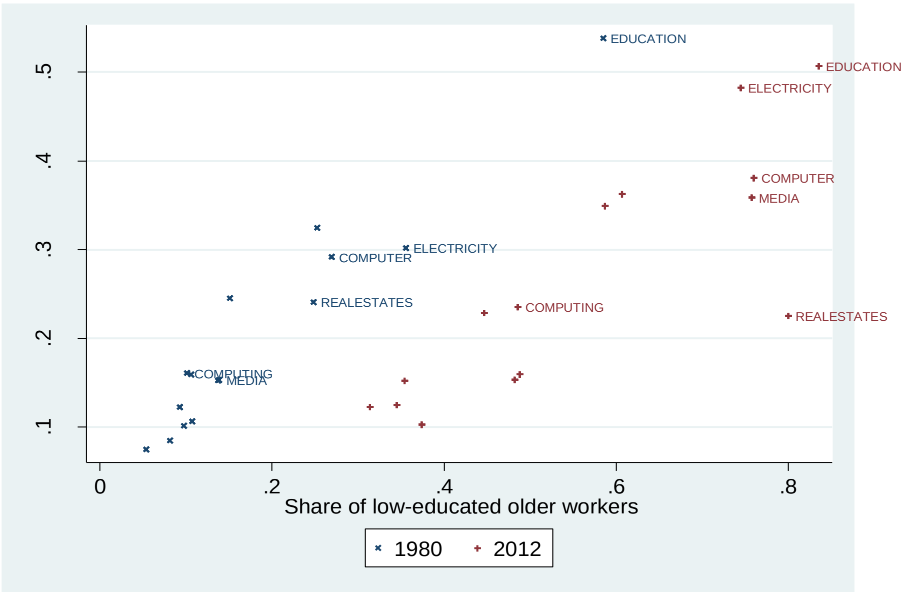
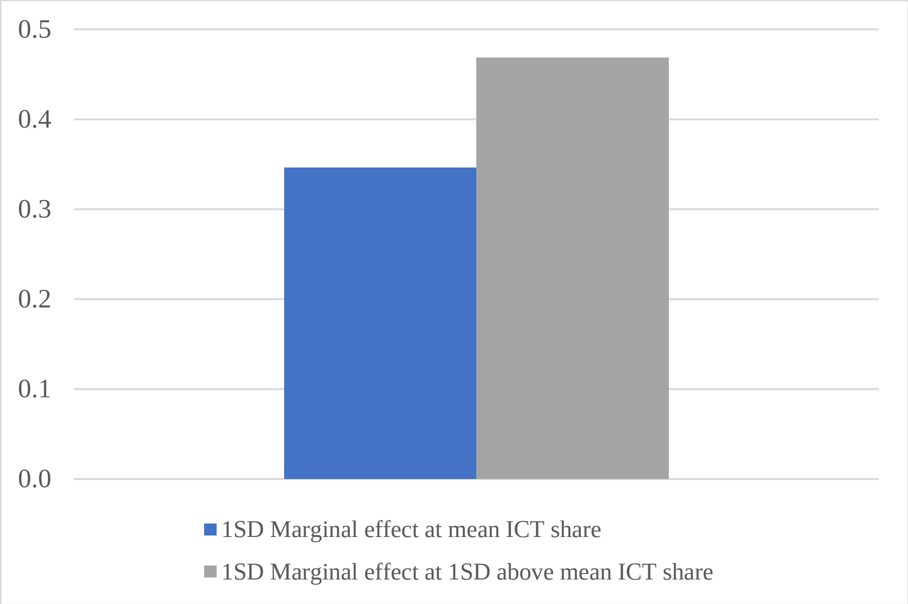


Figure 5 Share of Older Workers Aged 50 and Above by Educational Level across Industries in Japan and Korea, Selected Years

Note: This figure depicts how the share of older workers aged 50 and above among high-educated workers is associated with the share of older workers aged 50 and above among low-educated workers across industries in Japan and Korea in two selected years. The Japanese sample comprises 30 industries, whereas the Korean sample comprises 65 industries

Source: Authors’ construction using the Japanese and Korean samples in the EU KLEMS (Timmer et al., 2007) and WORLD KLEMS (Jorgenson, 2012), respectively.

a) Effect of 1SD Increase in Share of Labor Aged 50 and Above on Output per Worker



b) Effect of 1SD Increase in Share of Labor Aged 50 and Above on Output per Worker by Education Level

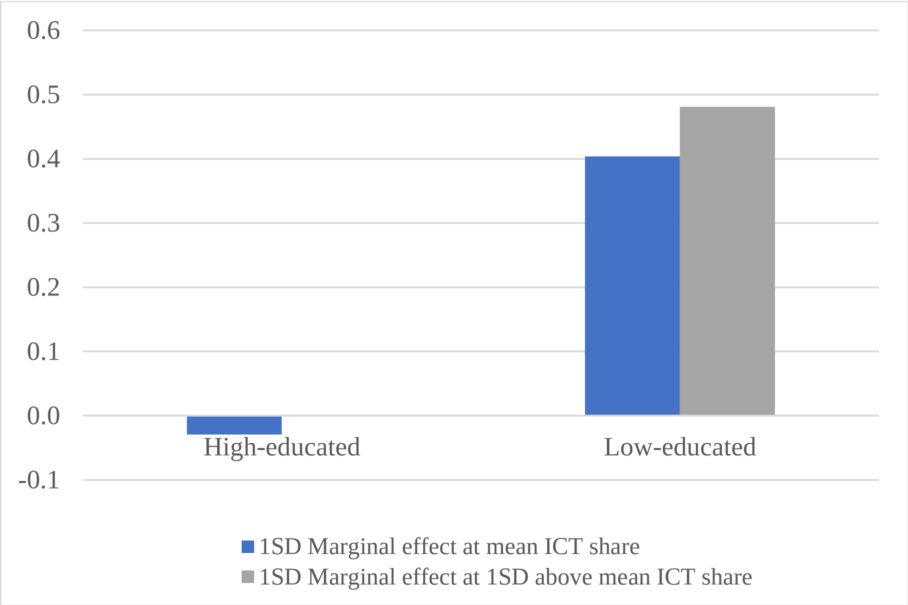
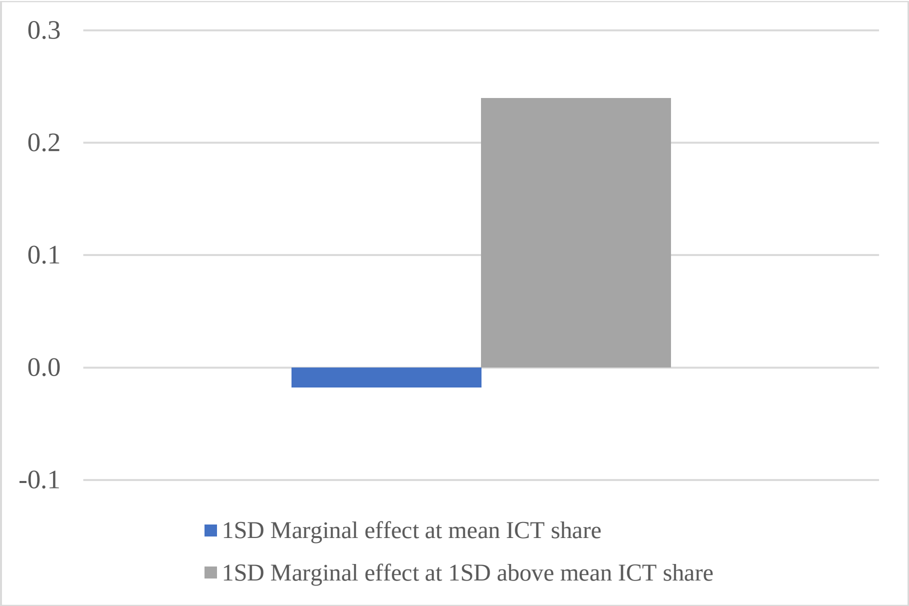


Figure 6 Impact of Older Worker Share on Output per Worker in Japan

Note: Marginal effects in a) and b) are drawn based on the estimates in Columns (2) and (6) of Table 4, respectively.

a) Effect of 1SD Increase in Share of Labor Aged 50 and Above on Output per Worker



b) Effect of 1SD Increase in Share of Labor Aged 50 and Above on Output per Worker by Education Level

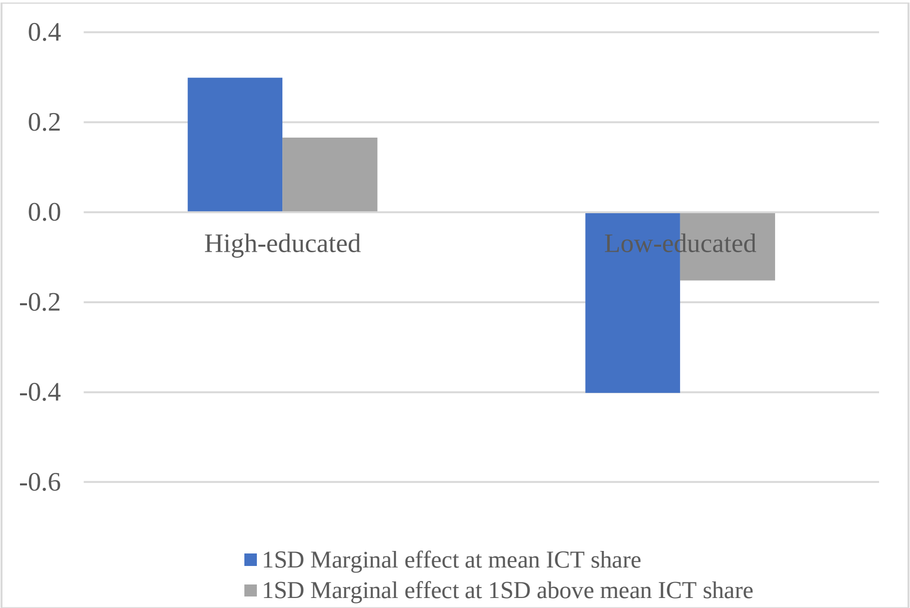
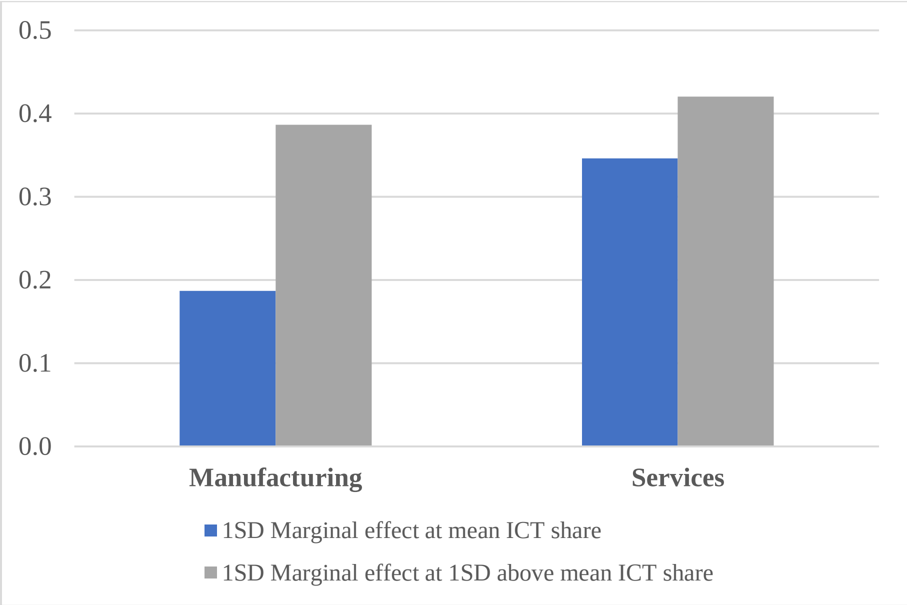


Figure 7 Impact of Older Worker Share on Output per Worker in Korea

Note: Marginal effects in a) and b) are drawn based on the estimates in Columns (2) and (6) of Table 5, respectively.

a) The Effect of 1SD Increase in Share of Labor Aged 50 and above on Output per Worker



b) The Effect of 1SD Increase in Share of Labor Aged 50 and above on Output per Worker by Levels of Education

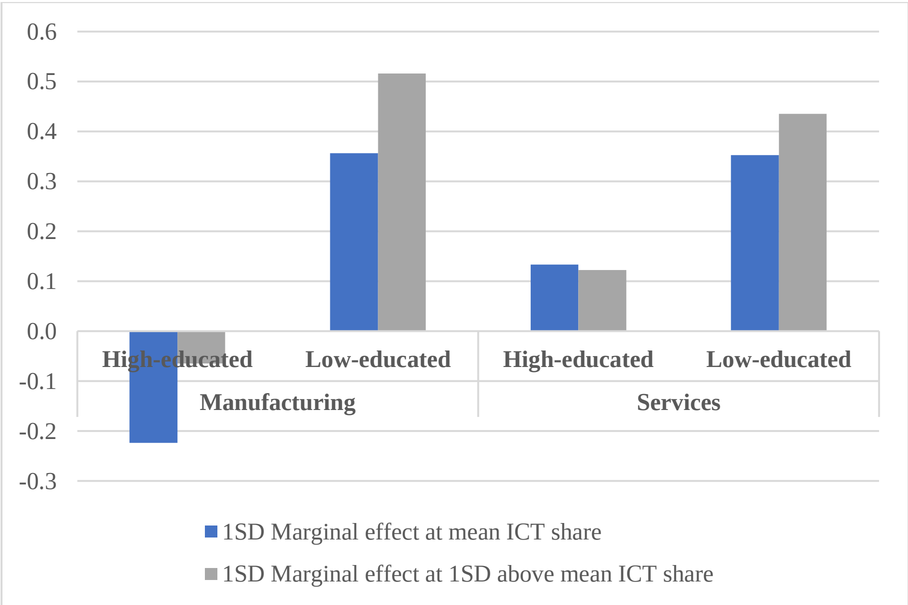
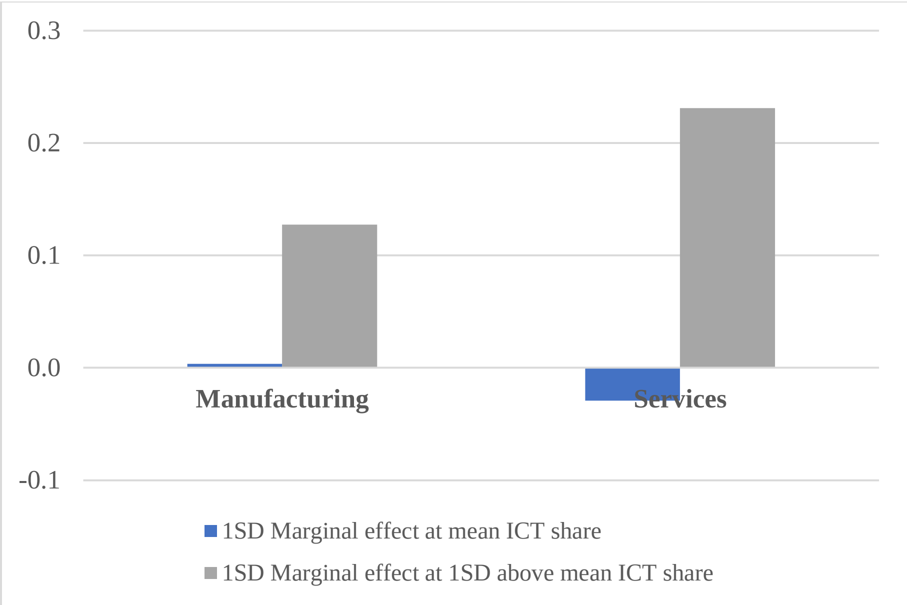


Figure 8 Impact of Older Worker Share on Output per Worker by Sector in Japan

Note: The marginal effects in a) and b) are drawn based on the estimates in Columns (2)–(3) and (5)–(6) of Appendix Table 2.

a) Effect of 1SD Increase in Share of Labor Aged 50 and Above on Output per Worker



b) Effect of 1SD Increase in Share of Labor Aged 50 and Above on Output per Worker by Education Level

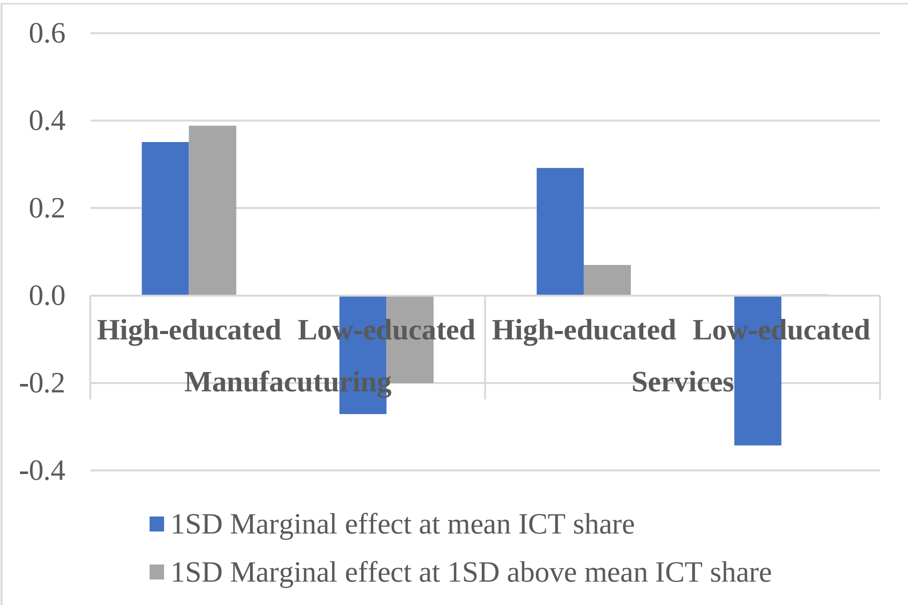


Figure 9 Impact of Older Worker Share on Output per Worker by Sector in Korea

Note: The marginal effects in a) and b) are drawn based on the estimates in Columns (2)–(3) and (5)–(6) of Appendix Table 3.

	Japan	Korea
Data source	EU KLEMS (Timmer et al., 2007)	WORLD KLEMS (Jorgenson, 2012)
Industry	30[a)]	65
Sample period	1973–2005	1980–2012
Variables		
Y/L	Gross value added per hour worked (real)	Real gross value added divided by total hours worked
K/L	Capital services divided by labor services (volume indices, 1995=100)	Real net capital stock divided by total hours worked
Labor inputs (L)		
Share of labor by educational attainment	High-educated labor with college graduates and above; Low-educated labor with high school graduates and below	
Share of labor by age group	Labor aged 15–29 (young); Labor aged 30–49 (middle); Labor aged 50 and above (old)	
Share of high-educated by age group	High-educated young labor aged 15–29; High-educated mid labor aged 30–49; High-educated older labor aged 50 and above	
Share of low-educated by age group	Low-educated young labor aged 15–29; Low-educated mid labor aged 30–49; Low-educated older labor aged 50 and above	
Capital inputs (K)		
ICT capital	Real fixed capital stock of ICT assets	Summation of 3 types of capital assets (real net capital stock) capital—computing equipment, communication equipment and software
Total capital stock	Real fixed capital stock of all assets	Real net capital stock

Table 1 Description of Japanese and Korean samples

Note: See Appendix Table 1 for industry classification.

	All		Manufacturing		Services	
	Mean	SD	Mean	SD	Mean	SD
ln(Y/L)	4.402	0.472	4.314	0.555	4.444	0.389
ln(K/L)	8.918	1.247	8.761	0.957	9.060	1.494
ln(high-educated)	-1.985	0.626	-2.143	0.539	-1.775	0.634
ln(low-educated)	-0.192	0.147	-0.148	0.083	-0.243	0.178
Share of high-educated	0.166	0.107	0.134	0.069	0.205	0.125
Share of low-educated	0.834	0.107	0.866	0.069	0.795	0.125
Share of labor aged 15–29	0.273	0.087	0.248	0.068	0.310	0.086
Share of labor aged 30–49	0.485	0.055	0.496	0.046	0.475	0.060
Share of labor aged 50 and above	0.242	0.080	0.256	0.083	0.215	0.063
Share of low-educated aged 15–29	0.270	0.091	0.245	0.070	0.308	0.090
Share of low-educated aged 30–49	0.467	0.060	0.482	0.051	0.452	0.064
Share of low-educated aged 50 and above	0.263	0.088	0.274	0.088	0.240	0.079
Share of high-educated aged 15–29	0.309	0.079	0.293	0.071	0.326	0.082
Share of high-educated aged 30–49	0.565	0.047	0.579	0.038	0.552	0.051
Share of high-educated aged 50 and above	0.127	0.055	0.128	0.058	0.122	0.054
ICT capital share in total capital stock	0.033	0.053	0.018	0.018	0.049	0.069
Ln(ICT capital share in total capital stock)	-4.269	1.413	-4.383	0.905	-4.031	1.743
Observations	990		429		495	

Table 2 Descriptive Statistics of Japan KLEMS Sample

Notes: This sample consists of 30 industries from 1973–2005. SD stands for standard deviation.
Source: Japanese industry data from EU KLEMS (Timmer et al., 2007).

	All		Manufacturing		Services	
	Mean	SD	Mean	SD	Mean	SD
ln(Y/L)	9.125	1.036	9.143	1.037	9.163	1.051
ln(K/L)	9.788	1.482	9.795	1.282	9.904	1.637
ln(high-educated)	-2.170	0.568	-2.369	0.611	-1.994	0.426
ln(low-educated)	-0.147	0.093	-0.124	0.097	-0.164	0.078
Share of high-educated	0.133	0.075	0.113	0.076	0.149	0.064
Share of low-educated	0.867	0.075	0.887	0.076	0.851	0.064
Share of labor aged 15-29	0.238	0.162	0.283	0.169	0.180	0.130
Share of labor aged 30-49	0.458	0.104	0.501	0.086	0.423	0.105
Share of labor aged 50 and above	0.305	0.175	0.216	0.109	0.397	0.187
Share of low-educated aged 15-29	0.199	0.169	0.249	0.176	0.138	0.133
Share of low-educated aged 30-49	0.471	0.114	0.520	0.088	0.431	0.117
Share of low-educated aged 50 and above	0.330	0.193	0.231	0.120	0.432	0.204
Share of high-educated aged 15-29	0.483	0.187	0.564	0.169	0.399	0.170
Share of high-educated aged 30-49	0.329	0.118	0.312	0.128	0.350	0.101
Share of high-educated aged 50 and above	0.188	0.128	0.124	0.055	0.251	0.154
ICT capital share in total capital stock	0.145	0.109	0.160	0.086	0.138	0.128
Ln(ICT capital share in total capital stock)	-2.380	1.195	-2.023	0.711	-2.642	1.455
Observations	2145		1056		990	

Table 3 Descriptive Statistics of Korea KLEMS Sample

Notes: This sample consists of 65 industries for 1980–2012. SD stands for standard deviation.
Source: Korean industry data from WORLD KLEMS (Jorgenson, 2012).

	(1)	(2)	(3)	(4)	(5)	(6)
ln(K/L)	0.434	0.374	0.389	0.382	0.542*	0.479*
	(0.265)	(0.252)	(0.262)	(0.254)	(0.283)	(0.269)
ln(high-educated)	0.475	0.383	0.532	0.339	0.317	0.256
	(0.400)	(0.374)	(0.379)	(0.398)	(0.354)	(0.346)
ln(low-educated)	-2.010*	-2.124*	-2.291**	-2.021*	-1.928**	-1.729**
	(1.054)	(1.125)	(1.070)	(1.123)	(0.833)	(0.820)
Share of labor aged 30–49	2.182	1.923	1.732	2.066		
	(1.726)	(2.096)	(1.714)	(2.143)		
Share of labor aged 50 and above	4.013	8.954**	3.687	10.029**		
	(3.007)	(3.388)	(2.966)	(4.827)		
ln(ICT Share)	-0.059	-0.317	-0.141	-0.328		
	(0.076)	(0.216)	(0.085)	(0.220)		
ln(ICT Share) X Share of labor aged 30–49		-0.072		-0.087		
		(0.400)		(0.412)		
ln(ICT Share) X Share of labor aged 50 and above		1.085***		1.289**		
		(0.338)		(0.629)		
ln(ICT Share) X High-educated			0.467**	-0.209		
			(0.211)	(0.392)		
Share of low-educated aged 30–49					2.689	1.871
					(1.692)	(1.829)
Share of low-educated aged 50 and above					4.589*	7.239**
					(2.278)	(2.743)
Share of high-educated aged 30–49					-1.341	-0.520
					(1.015)	(2.038)
Share of high-educated aged 50 and above					-0.864	1.103
					(1.780)	(3.337)
ln(ICT Share) X Share of low-educated aged 30–49						-0.138
						(0.402)
ln(ICT Share) X Share of low-educated aged 50 and above						0.621
						(0.455)
ln(ICT Share) X Share of high-educated aged 30–49						0.214
						(0.358)
ln(ICT Share) X Share of high-educated aged 50 and above						0.383
						(0.529)
Constant	-0.657	-1.612	-0.092	-2.042	-1.468	-2.266
	(3.162)	(3.194)	(3.133)	(3.562)	(3.331)	(3.289)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.608	0.633	0.617	0.634	0.622	0.653
No. of Observations.	960	960	960	960	960	960

Table 4 Regression for Value Added per Worker: All industries in Japan

Notes: The panel specification uses pooled data from 1973 to 2005 for 30 industries. Robust Standard errors clustered by industry are in parentheses. All explanatory variables are one-period lagged variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
ln(K/L)	0.221**	0.272***	0.251***	0.277***	0.194**	0.259***
	(0.091)	(0.091)	(0.087)	(0.090)	(0.091)	(0.089)
ln(high-educated)	1.149***	1.176***	0.937**	1.042***	1.166***	1.000***
	(0.360)	(0.319)	(0.361)	(0.365)	(0.331)	(0.302)
ln(low-educated)	3.794**	2.712**	-0.679	0.609	2.546	1.372
	(1.668)	(1.330)	(1.975)	(2.195)	(1.636)	(1.343)
Share of labor aged 30–49	0.003	2.177*	0.465	2.091*		
	(0.824)	(1.154)	(0.743)	(1.095)		
Share of labor aged 50 and above	-0.497	2.827**	-0.088	2.208*		
	(0.888)	(1.119)	(0.774)	(1.233)		
ln(ICT Share)	-0.140	-1.099***	-0.413***	-1.045***	-0.119	-0.671**
	(0.099)	(0.311)	(0.109)	(0.310)	(0.095)	(0.283)
ln(ICT Share) X Share of labor aged 30–49		0.890**		0.760*		
		(0.438)		(0.432)		
ln(ICT Share) X Share of labor aged 50 and above		1.230***		0.918**		
		(0.285)		(0.375)		
ln(ICT Share) X High-educated			1.593***	0.833		
			(0.372)	(0.543)		
Share of low-educated aged 30–49					-1.134	0.100
					(0.835)	(0.881)
Share of low-educated aged 50 and above					-2.453**	0.496
					(0.972)	(1.061)
Share of high-educated aged 30–49					1.397**	1.601
					(0.633)	(1.004)
Share of high-educated aged 50 and above					2.307***	0.261
					(0.806)	(0.859)
ln(ICT Share) X Share of low-educated aged 30–49						0.349
						(0.300)
ln(ICT Share) X Share of low-educated aged 50 and above						1.083***
						(0.237)
ln(ICT Share) X Share of high-educated aged 30–49						0.235
						(0.343)
ln(ICT Share) X Share of high-educated aged 50 and above						-0.872***
						(0.328)
Constant	9.612***	6.639***	7.736***	6.225***	9.853***	7.145***
	(1.190)	(1.122)	(1.176)	(1.178)	(1.130)	(1.110)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.597	0.639	0.628	0.645	0.609	0.666
No. of Observations.	2080	2080	2080	2080	2080	2080

Table 5 Regression for Value Added per Worker: All industries in Korea

Notes: The panel specification uses pooled data from 1980 to 2012 for 65 industries. Robust standard errors clustered by industry are in parentheses. All explanatory variables are one-period lagged variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix 1 Production Function with Complementarity between ICT Capital and Older Workers

Based on Krusell, et al. (2000), we can write the production function of Equation (5), with the complementary effect between ICT capital and older workers, as follows. To simplify, we assume that the young and middle-aged are perfect substitutes:

$$Y_{it} = A_{it}K^{\alpha}_{non-ICT,it}\left[\mu L^{\sigma}_{young,it} + (1-\mu)\left(\lambda K^{\rho}_{ICT,it} + (1-\lambda)L^{\rho}_{old,it}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}},\ 0<\delta<1,\ 0<\lambda<1,\ \rho<б<1. \tag{A1}$$

where μ and λ are parameters for the income shares of each factor. The elasticity of substitution between young workers (L_{young}) and ICT capital (K_{ICT}) as well as between young workers (L_{young}) and older workers (L_{old}) is 1/(1-σ); and the elasticity of substitution between ICT capital (K_{ICT}) and older worker (L_{old}) s is 1/(1-ρ). The assumption that ICT capital is more complementary with older workers allows σ> ρ.

The marginal product of young and older workers can be written as in Equations (A2) and (A3):

$$MPL_{young} = \frac{\partial Y_{it}}{\partial L_{young,it}}$$

$$= \frac{1-\alpha}{\sigma}A_{it}K^{\alpha}_{non-ICT,it}\left[\mu L^{\sigma}_{\mathrm{young},it} + (1-\mu)\left(\lambda K^{\rho}_{ICT,\mathrm{it}} + (1-\lambda)L^{\rho}_{\mathrm{old},it}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}-1} \times \sigma\mu L^{\sigma-1}_{young,it}. \tag{A2}$$

$$MPL_{old} = \frac{\partial Y_{it}}{\partial L_{old,it}}$$

$$= \frac{1-\alpha}{\sigma}A_{it}K^{\alpha}_{non-ICT,it}\left[\mu L^{\sigma}_{\mathrm{young},it}\ \ (1-\mu)\left(\lambda K^{\rho}_{ICT,\mathrm{it}} + (1-\lambda)L^{\rho}_{\mathrm{old},it}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}-1} \times \frac{\sigma}{\rho}(1-\mu)\left(\lambda K^{\rho}_{ICT,\mathrm{it}} + (1-\lambda)L^{\rho}_{\mathrm{old},it}\right)^{\frac{\sigma}{\rho}-1} \times \rho(1-\lambda)L^{\rho-1}_{\mathrm{old},it}$$

(A3)

Using Equations (A2) and (A3), we can derive the relative productivity between older and younger workers as in Equation (A4) and identify how an increase in the ICT capital share affects the relative productivity between older and younger workers. Equations (A4) shows mathematically that, under the production function that allows the complementarity between ICT capital and older workers, the ratio of the increase in ICT capital to the old (i.e., when the growth of ICT capital is larger than that of the old) will increase the marginal product of older workers relative to that of younger workers:

$$\frac{\mathrm{MPL_{old}}}{\mathrm{MPL}_{young}} = \frac{(1-\mu)(1-\lambda)}{\mu}\left(\lambda K_{ICT,it}^{\rho} + (1-\lambda)L_{old,it}^{\rho}\right)^{\frac{\sigma}{\rho}-1} L_{old,it}^{\rho-1}\ L_{young,it}^{1-\sigma}$$

$$= \frac{(1-\mu)(1-\lambda)}{\mu}\left[\lambda\left(\frac{\mathrm{K_{ict,it}}}{\mathrm{L_{old,it}}}\right)^{\rho} + (1-\lambda)\right]^{\frac{\sigma}{\rho}-1}\left(\frac{L_{young,it}}{L_{old,it}}\right)^{1-\sigma}$$

(A4)

Appendix Table 1 Industry Classification in Japan and Korea

KLMES CODE	DESCRIPTION	Japan	Korea
AtB	**AGRICULTURE, HUNTING, FORESTRY, AND FISHING**	O	
A	AGRICULTURE, HUNTING, AND FORESTRY		
1	Agriculture		O
2	Forestry		O
B	FISHING		O
C	MINING AND QUARRYING	O	
10t12	**MINING AND QUARRYING OF ENERGY-PRODUCING MATERIALS**		
10	Mining of coal and lignite; extraction of peat		O
11	Extraction of crude petroleum and natural gas and services		
12	Mining of uranium and thorium ores		
13t14	**MINING AND QUARRYING EXCEPT ENERGY-PRODUCING MATERIALS**		
13	Mining of metal ores		O
14	Other mining and quarrying		O
D	**TOTAL MANUFACTURING**		
15t16	**FOOD, BEVERAGES, AND TOBACCO**	O	
15	Food and beverages		O
16	Tobacco		O
17t19	**TEXTILES, TEXTILE, LEATHER, AND FOOTWEAR**	O	
17t18	Textiles and textile		
17	Textiles		O
18	Wearing Apparel, Dressing, And Dying Of Fur		O
19	Leather, leather, and footwear		O
20	**WOOD AND PRODUCTS OF WOOD AND CORK**	O	O
21t22	**PULP, PAPER, PAPER PRODUCTS, PRINTING, AND PUBLISHING**	O	
21	Pulp, paper and paper products		O
22	Printing, publishing, and reproduction		
221	Publishing		O
22x	Printing and reproduction		O
23t25	**CHEMICAL, RUBBER, PLASTICS, AND FUEL**		
23	Coke, refined petroleum, and nuclear fuel	O	O
24	Chemicals and chemical products	O	
244	Pharmaceuticals		O
24x	Chemicals excluding pharmaceuticals		O
25	Rubber and plastics	O	O
26	**OTHER NON-METALLIC MINERAL**	O	O
27t28	**BASIC METALS AND FABRICATED METAL**	O	
27	Basic metals		O
28	Fabricated metal		O
29	**MACHINERY, NEC**	O	O

30t33	**ELECTRICAL AND OPTICAL EQUIPMENT**	O	
30	Office, accounting, and computing machinery		O
31t32	Electrical engineering		
31	Electrical machinery and apparatus, NEC		
313	Insulated wire		O
31x	Other electrical machinery and apparatus NEC		O
32	Radio, television, and communication equipment		
321	Electronic valves and tubes		O
322	Telecommunication equipment		O
323	Radio and television receivers		O
33	Medical, precision, and optical instruments		
331t3	Scientific instruments		O
334t5	Other instruments		
34t35	**TRANSPORT EQUIPMENT**	O	
34	Motor vehicles, trailers, and semi-trailers		O
35	Other transport equipment		
351	Building and repairing of ships and boats		O
353	Aircraft and spacecraft		O
35x	Railroad equipment and transport equipment NEC		O
36t37	**MANUFACTURING NEC; RECYCLING**	O	
36	Manufacturing NEC		O
37	Recycling		
E	**ELECTRICITY, GAS, AND WATER SUPPLY**	O	
40	ELECTRICITY AND GAS		
40x	Electricity supply		O
402	Gas supply		O
41	WATER SUPPLY		O
F	**CONSTRUCTION**	O	O
G	**WHOLESALE AND RETAIL TRADE**		
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	O	O
51	Wholesale trade and commission trade, except of motor vehicles and motorcycles	O	O
52	Retail trade, except of motor vehicles and motorcycles; repair of household goods	O	O
H	**HOTELS AND RESTAURANTS**	O	O
I	**TRANSPORT AND STORAGE AND COMMUNICATION**		
60t63	TRANSPORT AND STORAGE	O	
60	Other Inland transport		O
61	Other Water transport		O
62	Other Air transport		O
63	Other Supporting and auxiliary transport activities; activities of travel agencies		O
64	POST AND TELECOMMUNICATIONS	O	O
JtK	**FINANCE, INSURANCE, REAL ESTATE, AND BUSINESS SERVICES**		
J	**FINANCIAL INTERMEDIATION**	O	

65	Financial intermediation, except insurance and pension funding		O
66	Insurance and pension funding, except compulsory social security		O
67	Activities related to financial intermediation		
K	**REAL ESTATE, RENTING, AND BUSINESS ACTIVITIES**		
70	Real estate activities	O	O
71t74	Renting of machinery and equipment, and other business activities	O	
71	Renting of machinery and equipment		O
72	Computer and related activities		O
73	Research and development		O
74	Other business activities		
741t4	Legal, technical, and advertising		O
745t8	Other business activities, NEC		O
LtQ	**COMMUNITY, SOCIAL, AND PERSONAL SERVICES**		
L	**PUBLIC ADMIN AND DEFENSE; COMPULSORY SOCIAL SECURITY**	O	O
M	**EDUCATION**	O	O
N	**HEALTH AND SOCIAL WORK**	O	O
O	**OTHER COMMUNITY, SOCIAL, AND PERSONAL SERVICES**	O	
90	Sewage and refuse disposal, sanitation and similar activities		O
91	Activities of membership organizations NEC		O
92	Recreational, cultural, and sporting activities		
921t2	Media activities		O
923t7	Other recreational activities		O
93	Other service activities		O
P	**PRIVATE HOUSEHOLDS WITH EMPLOYED PERSONS**		O
Q	**EXTRA-TERRITORIAL ORGANIZATIONS AND BODIES**		

Appendix Table 2 Regression for Value Added per Worker: Manufacturing vs. Service Industries in Japan

	Manufacturing Industries			Service Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(K/L)	0.407	0.301	0.116	0.234	0.243	0.250
	(0.382)	(0.314)	(0.274)	(0.277)	(0.293)	(0.285)
ln(high-educated)	0.383	0.980	0.999*	0.733*	0.797	0.623
	(0.399)	(0.710)	(0.556)	(0.385)	(0.462)	(0.434)
ln(low-educated)	-9.935**	-11.138***	-8.472**	-1.429	-1.335**	-1.171*
	(3.254)	(3.270)	(3.379)	(0.850)	(0.606)	(0.656)
Share of labor aged 30–49	12.988***			2.134*		
	(4.006)			(1.140)		
Share of labor aged 50 and above	13.900*			8.217*		
	(7.329)			(4.604)		
ln(ICT Share)	-1.929***	-0.052	-2.082***	-0.188	-0.082	-0.073
	(0.403)	(0.145)	(0.592)	(0.250)	(0.113)	(0.270)
ln(ICT Share) X Share of labor aged 30–49	2.317***			-0.165		
	(0.640)			(0.574)		
ln(ICT Share) X Share of labor aged 50 and above	2.657*			0.675**		
	(1.295)			(0.252)		
Share of low-educated aged 30–49		1.566	14.627**		2.659**	0.829
		(2.011)	(4.994)		(1.122)	(1.551)
Share of low-educated aged 50 and above		0.616	12.834		3.739	6.884**
		(2.967)	(8.156)		(2.512)	(3.025)
Share of high-educated aged 30–49		0.280	-0.331		0.693	0.465
		(1.239)	(3.023)		(0.887)	(1.335)
Share of high-educated aged 50 and above		-5.437	9.411		1.593	2.002
		(4.088)	(6.855)		(1.504)	(2.773)
ln(ICT Share) X Share of low-educated aged 30-49			2.535**			-0.518
			(0.923)			(0.584)
ln(ICT Share) X Share of low-educated aged 50 and above			2.004			0.601
			(1.159)			(0.394)
ln(ICT Share) X Share of high-educated aged 30-49			-0.080			0.086
			(0.662)			(0.199)
ln(ICT Share) X Share of high-educated aged 50 and above			3.027**			-0.116
			(1.376)			(0.423)
Constant	-9.659***	2.102	-6.557	0.611	1.002	0.552
	(3.107)	(4.486)	(3.974)	(3.177)	(3.447)	(2.980)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.781	0.770	0.810	0.714	0.701	0.735
No. of Observations.	416	416	416	480	480	480

Notes: The panel specification uses pooled data from 1973 to 2005 for 13 industries. Robust Standard errors clustered by industry are in parentheses. All explanatory variables are one-period lagged variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 3 Regression for Value Added per Worker: Manufacturing vs. Service Industries in Korea

	Manufacturing Industries			Service Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(K/L)	0.239*	0.236**	0.242**	0.232*	0.161	0.212
	(0.120)	(0.101)	(0.116)	(0.130)	(0.136)	(0.134)
ln(high-educated)	0.698	0.483	0.517	0.516	0.348	0.497
	(0.597)	(0.536)	(0.531)	(0.545)	(0.513)	(0.486)
ln(low-educated)	0.836	0.497	0.146	-0.390	-0.408	-0.720
	(1.618)	(1.841)	(1.655)	(1.928)	(2.260)	(1.987)
Share of labor aged 30–49	-3.595*			1.163		
	(2.073)			(3.221)		
Share of labor aged 50 and above	3.268			2.370		
	(2.782)			(2.012)		
ln(ICT Share)	-0.244	0.079	-0.370	-0.899	-0.195	-0.501
	(0.369)	(0.119)	(0.368)	(0.669)	(0.126)	(0.640)
ln(ICT Share) X Share of labor aged 30–49	-0.390			0.588		
	(0.798)			(0.855)		
ln(ICT Share) X Share of labor aged 50 and above	1.599			0.956		
	(1.020)			(0.607)		
Share of low-educated aged 30–49		-2.631**	-2.113		-0.874	0.896
		(1.116)	(1.878)		(1.367)	(2.950)
Share of low-educated aged 50 and above		-1.928	-0.566		-0.622	1.394
		(1.626)	(2.882)		(1.217)	(1.882)
Share of high-educated aged 30–49		0.336	-0.041		-0.153	-0.028
		(0.845)	(1.515)		(0.681)	(1.044)
Share of high-educated aged 50 and above		6.611***	8.317**		0.621	-0.718
		(1.873)	(3.740)		(0.843)	(0.745)
ln(ICT Share) X Share of low-educated aged 30-49			0.113			0.300
			(0.820)			(0.689)
ln(ICT Share) X Share of low-educated aged 50 and above			0.838			1.164**
			(1.012)			(0.497)
ln(ICT Share) X Share of high-educated aged 30-49			-0.106			-0.174
			(0.607)			(0.356)
ln(ICT Share) X Share of high-educated aged 50 and above			0.955			-0.988**
			(1.574)			(0.367)
Constant	8.722***	8.070***	7.086***	5.381**	7.810***	6.112**
	(1.806)	(1.325)	(1.531)	(2.529)	(1.533)	(2.636)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.748	0.751	0.756	0.448	0.401	0.511
No. of Observations.	1024	1024	1024	960	960	960

Notes: The panel specification uses pooled data from 1980 to 2012 for 32 industries. Robust Standard errors clustered by industry are in parentheses. All explanatory variables are one-period lagged variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 4 Regression for Value Added per Worker : All industries in Japan, 1980-2005

	(1)	(2)	(3)	(4)	(5)	(6)
ln(K/L)	0.415	0.361	0.352	0.355	0.427	0.311
	(0.276)	(0.268)	(0.272)	(0.271)	(0.260)	(0.224)
ln(high-educated)	0.211	0.126	0.346	0.178	0.109	0.041
	(0.362)	(0.315)	(0.350)	(0.344)	(0.336)	(0.293)
ln(low-educated)	-1.728*	-1.888*	-1.943**	-1.929**	-1.726**	-1.323*
	(0.923)	(0.940)	(0.915)	(0.928)	(0.777)	(0.703)
Share of labor aged 30-49	0.749	-0.638	0.303	-0.722		
	(1.635)	(2.140)	(1.624)	(2.157)		
Share of labor aged 50 and above	1.963	6.701**	1.937	5.762		
	(2.462)	(2.896)	(2.381)	(3.456)		
ln(ICT Share)	-0.055	-0.158	-0.223**	-0.162	-0.060	-0.553
	(0.081)	(0.226)	(0.108)	(0.218)	(0.079)	(0.335)
ln(ICT Share) X Share of labor aged 30-49		-0.454		-0.419		
		(0.423)		(0.403)		
ln(ICT Share) X Share of labor aged 50 and above		0.880**		0.698		
		(0.320)		(0.471)		
ln(ICT Share) X High-educated			0.602**	0.180		
			(0.231)	(0.292)		
Share of low-educated aged 30-49					0.754	-2.384
					(1.161)	(1.917)
Share of low-educated aged 50 and above					2.782	6.332***
					(1.673)	(1.888)
Share of high-educated aged 30-49					-0.360	3.543
					(0.843)	(3.104)
Share of high-educated aged 50 and above					-1.735	-0.545
					(1.185)	(2.533)
ln(ICT Share) X Share of low-educated aged 30-49						-0.823
						(0.489)
ln(ICT Share) X Share of low-educated aged 50 and above						0.667
						(0.414)
ln(ICT Share) X Share of high-educated aged 30-49						0.949
						(0.652)
ln(ICT Share) X Share of high-educated aged 50 and above						0.247
						(0.557)
Constant	-0.218	-0.980	0.356	-0.589	-0.428	-2.003
	(3.282)	(3.198)	(3.212)	(3.437)	(3.012)	(3.041)
Industry Fes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.594	0.624	0.614	0.625	0.607	0.655
Observations no.	750	750	750	750	750	750

Appendix Table 5 Regression for Value Added per Worker: All industries in Korea, 1980–2005

	(1)	(2)	(3)	(4)	(5)	(6)
ln(K/L)	0.173**	0.222**	0.209**	0.236***	0.140*	0.222***
	(0.082)	(0.084)	(0.081)	(0.083)	(0.082)	(0.080)
ln(high-educated)	1.038**	0.894**	0.999**	0.820*	1.081**	0.738*
	(0.437)	(0.404)	(0.440)	(0.415)	(0.417)	(0.383)
ln(low-educated)	5.102**	3.346	1.290	0.341	3.818	1.723
	(2.448)	(2.133)	(2.527)	(2.417)	(2.514)	(2.156)
Share of labor aged 30–49	-0.206	2.405*	0.298	2.620**		
	(0.924)	(1.287)	(0.867)	(1.079)		
Share of labor aged 50 and above	-1.422*	1.336	-1.197*	0.022		
	(0.756)	(1.071)	(0.645)	(1.075)		
ln(ICT Share)	-0.269***	-1.063***	-0.472***	-1.106***	-0.248***	-0.729***
	(0.090)	(0.337)	(0.090)	(0.296)	(0.087)	(0.261)
ln(ICT Share) X Share of labor aged 30-49		0.886		0.952**		
		(0.572)		(0.434)		
ln(ICT Share) X Share of labor aged 50 and above		0.957***		0.401		
		(0.322)		(0.360)		
ln(ICT Share) X High-educated			1.732***	1.559***		
			(0.348)	(0.519)		
Share of low-educated aged 30–49					-0.949	0.389
					(0.775)	(0.797)
Share of low-educated aged 50 and above					-2.707***	-0.972
					(0.898)	(0.985)
Share of high-educated aged 30–49					0.132	1.402
					(0.804)	(1.194)
Share of high-educated aged 50 and above					2.195**	-0.351
					(0.965)	(1.062)
ln(ICT Share) X Share of low-educated aged 30-49						0.517
						(0.330)
ln(ICT Share) X Share of low-educated aged 50 and above						0.921***
						(0.235)
ln(ICT Share) X Share of high-educated aged 30-49						0.471
						(0.411)
ln(ICT Share) X Share of high-educated aged 50 and above						-1.345***
						(0.326)
Constant	9.667***	6.433***	8.509***	6.011***	10.103***	6.897***
	(1.552)	(1.444)	(1.497)	(1.437)	(1.420)	(1.283)
Industry Fes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.598	0.621	0.624	0.635	0.607	0.665
Observations no.	1625	1625	1625	1625	1625	1625