Improving effects of industrial robot adoption on employment, TFP, and real wage in 52 world economies and OECD members

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Abstract
This paper investigates the effects of industrial robot adoption in production process on unemployment rate, employment ratio in manufacturing, and TFP growth of 52 countries for 2007–2017 and real wage growth of 30/20 OECD member countries for 2005–2017. The operating stock of robots per employee significantly impacts these variables; the robot adoption effectively lowers the unemployment rate and raises the TFP and real wage growth; on the other hand, it reduces the employment ratio in manufacturing. In addition, the positive contribution of the robot adoption is slightly larger on the 10- and 90-percentiles (bottom and top 10 percentiles) of the real wage distribution than on its mean. Interestingly, workers in both percentiles of wage distribution equivalently benefit from robotization. Either the industry ratio of value added or ICT development contributes to improving the labor market, e.g., repressing the unemployment rate and raising the employment ratio in Asian manufacturing industries and TFP and real wage growth.

JEL classification:
C12; C32; C33

Keywords:
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1. Introduction

Since Brynjolfsson and McAfee (2014) warned the threads of accelerating digitization including greatly improved computer power and rapid progress of machinization, to labor markets, a number of studies on the economic impacts of developed technologies replacing human labor by computers and machines have been vastly conducted. Some pioneering studies such as Autor (2015), Bessen (2016), Graetz and Michaels (2018), and Acemoglu and Restrepo (2020) provided noticeable insights on this issue. Autor (2015) pointed out that robots complement human labor in production, and this complementarity leads to the increase in productivity, wage bills, and employment. Bessen (2016)'s striking findings revealed that computer use may contribute to employment growth in the same occupation, but a part of this positive effect is offset by the inter-occupation substitution. Graetz and Michaels (2018) analyzed how much impacts an industrial robot adoption has on labor market and the whole economy. They showed that increased robot use has positive macroeconomic effects on annual labor productivity growth and TFP, while it lowers output prices and does not impact total employment. Acemoglu and Restrepo (2020) focused on the interplay between the robot usage and employment in US local labor markets. They estimated negative effects of robots on employment and wages across commuting zones.

Previous studies have presented various empirical evidence on how positively or negatively a robot adoption in production affects the macroeconomy. Optimistic views such as Autor (2015), Bessen (2016), and Autor and Salomons (2018) emphasize the productivity improvement in production process, wage rises, and increasing demand in labor in the whole labor market. On the other hand, pessimistic discussions such as DeCanio (2016), Acemoglu and Restrepo (2018, 2019), and Leduc and Liu (2019) pay more attention to the replacement of workers by automation, meaning that it eliminates routine-based tasks and requires some workers to learn new skills and shifts to other (non-routine or cognitive) tasks. From a different perspective, Caselli and Manning's (2019) simple model derived a theoretical conclusion that a new type of technology such as robots leads to real wage hikes in at least one occupation but does not rule out widening the income gap among occupations.

There also exist some studies on the prospects in developing countries. Maloney and Molina (2016) investigated why developing countries have different dynamics in their transforming labor markets from those of developed countries and showed no evidence of polarization in Census data. Das and Hilgenstock (2018) presented that some developing countries are less exposed to routinization, the tasks of which are replaceable by computers and machines and do not display any trend toward the polarization in labor share with increasing routine-intensive tasks.

As shown in Figures 1-3, the variables being investigated such as the unemployment rate, employment ratio in manufacturing, and TFP growth are expressed as a quadratic or cubic function of the operating stock of robots per 1,000 employees. Therefore, we need to capture these relationships in some nonlinear functional forms. To deal with this, as our first step, we add quadratic or cubic terms of a robot adoption variable in a model.

Moreover, some Asian countries have been rapidly increasing their robot usage (Figure 4); in particular, Korea, Singapore, and Taiwan are the top 3 users of industrial robots in 2018. Except Germany, the top 5 users are all Asian countries. As for China and India, their robot usage per employee is relatively small due to a huge amount of population; however, the speed of growth is high. In light of this fact, we also focus on possible different contributions of automation to macroeconomic variables in Asian countries.

The purpose of this paper is to investigate the effects of industrial robot adoption in production process on some important macroeconomic variables such as unemployment rate, employment ratio in manufacturing, and TFP growth of 52 countries for 2007–2017 and real wage growth of 30/20 OECD member countries for 2005–2017.

Our paper contributes to the literature in three ways. First, we cover more extended sample period compared to those of the previous studies. This may show current drastic changes in automation in industries. As shown in Acemoglu and Restrepo (2020), the empirical evidence obtained in more recent sample periods suggests some possible changes of impacts on employment shares and wage rates, meaning recent drastic shifts of tasks or some adjustments of labor supply. Second, we include Asian countries such as China, India, Japan, Korea, Taiwan, and Singapore, some of which are major robot users. As discussed above, these Asian countries take much advantage of industrial robots and have experienced structural changes in industries. Therefore, we also discuss features in these robot-intensive Asian economies. Third, Figures 1-3 illustrate the nonlinearity of the unemployment rate, employment ratio in manufacturing, and TFP growth as a function of the operating stock of robots per 1,000 employees. This paper explicitly treats this issue by expressing a quadratic or cubic function of robots per employees.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 discusses the empirical results. Section 4 concludes the study.

2. Literature review

A vast amount of literature has devoted to finding the best way to coexist with industrial robots or automation by machines in the society. Autor (2015) pointed out the complementarity of robots to workers, which is contributable to productivity increase, wage rise, and employment growth. Bessen (2016) supported this positive side of increasing labor demand although the substitution effect within occupation partially offsets it. Using the EU KLEMS dataset, Autor and Salomons (2018) analyzed the effects of automation from the upstream industries to the downstream industries and vice versa. They found out that the TFP growth (as a proxy of automation) in one industry decreases an employment, working hours, and labor shares, but increases wages per hour, wage bills, and nominal/real value added in the same industry. In addition, the upstream industry's TFP growth positively affects the employment and real value added in the downstream industries. The empirical evidence obtained in Graetz and Michaels (2018) showed that increased robot use has positive macroeconomic effects on annual labor productivity growth and TFP, while it lowers output prices and does not impact total employment.

There are also pessimistic or mixed views on more adoption of robot technologies in labor markets. Based on a two-level nested CES production function, DeCanio (2016) derived the threshold value of the elasticity of substitution where increases in robot labor lower wage rates. One of his estimates shows that when the elasticity of substitution is more than 1.9, wage rates decrease with increases in robot usage. This wage rate drop occurs with even lower estimate values in the manufacturing industry. Leduc and Liu's (2019) DSGE model with search frictions in labor market confirmed that automation removes some jobs and simultaneously creates new ones. Moreover, it raises labor productivity and amplifies unemployment variations. Caselli and Manning (2019) derived a theoretical conclusion that a new type of technology such as robots leads to real wage hikes in at least one occupation but does not rule out widening the income gap among occupations.

In the work of Acemoglu and Restrepo (2018), based on a task-based model that endogenizes both the direction of research toward automation and the creation of new tasks, they showed that automation technologies develop rapidly if capital is much cheaper than labor in the long run; on the other hand, if not, both effects coexist on a balanced growth path. They also pointed out one possible concern that the inequality among workers occurs due to the skill heterogeneity. In such a situation, the labor market benefits high-skill labor and squeezes out tasks previously performed by low-skill labor. Acemoglu and Restrepo (2019) investigated the balance of the displacement effect of automation on labor and reinstatement effect of created new tasks for 1947–1987 and 1987–2017. In the former sample period, the labor shares in industrial sectors were not decreasing except for transportation and mining. In the latter sample period, however, the labor shares were decreasing particularly in construction and manufacturing. In total, the displacement effect exceeds the reinstatement effect by 10%, leading to a 10% decrease in task contents in recent years. Acemoglu and Restrepo (2020) showed that the adoption of automation technology leads to declines in employment-to-population share and hourly wages in the US labor market, though it raises value added. However, their results imply that extending the sample span from 1990–2007 to 1990–2014 may reflect some changes of its impacts on the labor market because compared to the results obtained in 1990–2007, the negative impacts of automation on labor share and hourly wages become 40 % smaller in the former and 40 % larger in the latter in 1990–2014. This change may suggest recent drastic changes or some adjustments of labor supply.

In the demographical aspects in the society, Battisti and Gravina (2021) highlighted heterogenous effects of robots on the workforce by using age cohorts in the EU KLEMS. They obtained consistent evidence of a higher complementarity between robots and older workers, and a greater substitutability among robots and younger cohorts of the labor market. Acemoglu and Restrepo (2021) discussed the increasing demand in automation driven by the aging workforce. Blanas et al. (2019), Basso and Jimeno (2021), and Irmen (2021) are along the same line.

Compared to the studies on developed countries, there are fewer but meaningful studies on developing countries. Maloney and Molina (2016, 2019) displayed distinct differences of robot adoption impacts between advanced and developing countries. Controlling for Chinese import penetration, they observed that more robot-intensive strategies resulted in 25-50 percent job loss in manufacturing in advanced countries, while developing countries faced increasing number of operators and assemblers due to outsourcing leading to the introduction of robots with new operators in FDI recipient countries. Das and Hilgenstock (2018) revealed less exposure of developing countries to routinization, and the absence of job polarization even when routine-intensive tasks are increasing. The calibration of Shapiro and Mandelman (2021)'s firm-level model displays a strong negative link between firm digital adoption and self-employment rates in developing countries. Egana-delSol et al. (2022) studied Chile's ongoing change in automation during the COVID-19 pandemic. They showed that occupations with a higher risk of automation face the most significant employment contraction.

As for Asian countries, Cheng et al. (2019) explained why China has become the largest user of industrial robots (not in per employee but in total). Fan et al. (2021) examined that higher labor costs raise the adoption probability of robots in Chinese firms. Cali and Presidente (2021) measured the plant-level impacts of automation on the Indonesian economy. In the Japanese economy, Dekle (2020) analyzed the introduction of robots on labor markets at industry-levels, and Adachi et al. (2020) investigated the impacts of more robot installation in production facilities on wage rates.

3. Empirical analysis

3.1. Data

The robot data are sourced from International Federation of Robotics. The operating stock of robots per 1,000 employees is used as robot adoption measure. Other data sources are ILO database, OECD database, Penn World Table 9.0, World Development Indicators, National Statistics website of the government of the Republic of China, and World Telecommunication/ICT Indicators database. The sample period is 2007–2017 for 52 countries and 2005–2017 for OECD 30/20 countries (see Table A1 for the list of countries and Table A2 for the data sources). We use unemployment rate (%), employment ratio in manufacturing (%), real wage (2018 constant price in US dollars PPPs), and Total Factor Productivity (TFP) index as explained variables, respectively. Except the robot adoption, other explanatory variables are the industry ratio (value added in industry/value added in total) (%) and ICT (internet users) (%) (see also Table A2 for more details). These variables are expected to affect employment, real wage, and TFP. As for employment, the industry ratio shows the degree of industrialization progress in the economy. There are at least two effects to the labor market. One is that the more industrialized the economy becomes the more robots are likely to be introduced to replace human workers. The other is that in general, as the secondary industry relatively expands in terms of production in the whole economy, workers can find more job opportunities in this industry. These two effects may offset each other. The ICT variable is a proxy to show advances in ICT technologies to improve economic activities more efficiently, e.g., by getting faster and cheaper data access and handling a vast amount of information about production, management, HR, etc. and assisting more labor-saving factory staffing, which may lead to promoting the replacement of labor by automation. On the other hand, the ICT development raises labor productivity, which is a labor-augmenting technology progress; therefore, this may help to increase labor demand. This variable also has positive and negative effects on the labor demand. In terms of real wages, if the industrialization of the economy promotes to using more labor, the increased demand in labor will raise real wage rates (under ceteris paribus condition). The ICT progress is likely to pull up wage rates due to the productivity hike of already-employed workers. Focusing on effects on TFP, we consider the industrialization to be positively influential to it as the structure of manufacturing industries becomes more advanced; namely, advanced industrial technologies may lead to not only capital- and labor-augmenting progresses but also TFPaugmenting one. The ICT also raises favorable TFP contribution to the economy. In the analysis, the robot adoption, real wage, and TFP index are taken in natural logarithms and first-differenced.

3.2 Model

To examine the impacts of robot adoption growth on the unemployment rate, TFP growth, and employment ratio in manufacturing, we estimate the following model:

$$Y_{it} = const + \alpha Robot_{it} + \beta Robot_{it}^2 + \gamma Robot_{it}^3 + \delta Industry\ Ratio_{it} + \zeta ICT_{it}$$

$$+\theta Dummy\ (GFC,\ Asia)_t + \mu_i + u_{it},$$

where Y_{it} takes unemployment rate, TFP growth, and employment ratio in manufacturing for each estimation, respectively. μ_i represents country effects and u_{it} is an error term. This model includes the quadratic term of robot adoption growth for the unemployment rate and TFP growth and both quadratic and cubic terms of robot adoption growth for the employment ratio in manufacturing. We also consider two dummy variables such as the GFC (Global Financial Crisis) dummy and Asian country dummy. The GFC dummy takes one for 2008–2009 and zero otherwise, and the Asian country dummy takes one for Asian countries and zero otherwise.

For the real wage change for 30/20 OECD member countries, we do not use the quadratic and cubic term of robot use because any nonlinear feature is not observed. The model is as follows:

$$Y_{it} = const + \alpha Robot_{it} + \delta Industry\ Ratio_{it} + \zeta ICT_{it} + \theta GFC\ Dummy_t + \mu_i + u_{it},$$

where Y_{it} takes the real wage change and 10-/90-perceltiles real wage changes. This model includes only the GFC dummy.

3.3. Empirical results of 52 world economies

Tables 1 to 3 show the panel estimation results of 52 countries for 2007–2017. Table 1 displays the results of the unemployment rate. From the visual inspection shown in Figures 1 (a), (b), and (c), the data show a quadratic function of robot adoption; therefore, we include a quadratic term of robots per employee in the estimation model. Eq. (1) shows both variables of robot adoption are statistically significant at the 5 % significance level. From this estimated model, as long as the robot adoption growth is less than 66.7%, it consistently lowers the unemployment rate.[1] This improvement in the labor market always holds when robots are introduced at least at the annual average growth rate of operating stock of robots in all sample countries, e.g., 6.26% (2007–2017).[2] Both terms of robot adoption are also significant in all the equations. Moreover, except Eq. (5), their coefficient values are mostly stable even when other explanatory variables are included. To find out whether changes in the industry ratio and ICT factors reinforce or offset impacts of robot adoption on the unemployment rate, these are included in the regression model. The industry ratio is negatively significant in all the cases. This factor also contributes to improving the unemployment rate when it increases. The increased value added in the secondary industry, compared to the ones in the agriculture and service industries, reflects the expansion of this industry sector, which may result in raising the possibility of hiring more workers, e.g., to operate newly installed production facilities, to engage in management of growing organizations, etc. The interaction term with the GFC dummy is also supportive to this perspective even during the global financial crisis periods. Surprisingly, the interaction term with the Asian dummy takes an opposite sign, which may imply that highly automated production processes in some Asian countries could lead to unemployment rate hikes. The ICT variable is not significant alone, but it's interaction terms with the Asia dummy and the GFC dummy are negatively significant in Eq. (4), which means that the ICT development in Asian countries or during the global financial crisis periods enhances labor productivity, which may motivate companies to hire more workers to meet increasing demand of products. These channels could reduce unemployment. In Eq. (5), both interaction terms of the quadratic robot adoption and industry ratio/ICT are supported. However, these terms partially offset the improvement effects of robot adoption on the labor market when the industry ratio or ICT variable takes positive values.

Table 2 shows the results of the employment ratio in manufacturing. In this case, the model is specified as a cubic function of robot adoption based on the preliminary data plots shown in Figures 2 (a), (b), and (c). In Eq. (1), although some of the estimated coefficients of the quadratic and cubic terms of robot adoption are very small in their absolute values, all three variables of robot adoption are statistically significant less than at the 5% significance level. This implies that when the robot adoption growth is smaller

[1] The quadratic function of the unemployment rate is Unemployment rate = 8.118 – 0.040Robot per employee + 0.0003Robot per employee ^{2}. Thus, the inflection point of this equation is Robot per employee = 66.6667.

[2] The total operating stock of robots per 1,000 employees in 52 countries in 2007 and 2017 are 36.440 and 71.096, respectively. Thus, the annual average growth is 6.26%.

than 14.4% or greater than 85.6%, it decreases the employment ratio in manufacturing, but when it lies between 14.4% and 85.6%, it increases the employment ratio in manufacturing.[3] Realistically speaking, as long as the current increasing global trend of robot purchase continues around the average annual growth rate, 6.26%, adopting more robots means hiring less workers in the manufacturing industry. In all the equations, we also obtain the similar impacts of robot adoption on the employment ratio in manufacturing. The estimated magnitudes of their coefficients are relatively stable. Moreover, in Eq. (2), the industry ratio and ICT are all significant. Interestingly, the industry ratio increases the ratio of workers in the manufacturing industry against the total workers. That may suggest that more industrialization leading to the expansion of manufacturing industry in the whole economy needs more labor in production. On the other hand, the ICT development promotes less employment in the manufacturing industry because the digitalization brought by the ICT helps to reduce labor costs in the workplace. In Eq. (3), in Asia, the secondary industry expansion may simultaneously introduce more capital-intensive production process, reducing employment rates. However, this effect is rather weak or negligible because it shows insignificance in Eq. (5). In Eq. (4), the ICT improvement raises the possibility of hiring more workers in manufacturers in Asia and even during the crisis periods. In Eq. (5), the interaction term of the industry ratio and the GFC dummy is significant, which may partially offset the positive impact of the industry ratio, but it is not significant in Eq. (3). Therefore, the interaction effects of the industry ratio and the Asia/GFC dummies are still mixed.

Table 3 shows the results of the TFP growth. We also specify the quadratic form of robot adoption and TFP growth, which is suggested in Figures 3 (a), (b), and (c). Eq. (1) shows the significant impact of the robot adoption variables, which means that the robot adoption growth raises the TFP growth unless it annually exceeds 53.3%.[4] The similar magnitudes of its coefficients are observed in Eq. (2). The industry ratio and ICT are also significantly positive, which implies that the industrialization progress and ICT development may raise the possibilities of TFP growth of the economy.

As Graetz and Michaels (2018) have pointed out, however, the reverse causality of

[3] The levels of robots per employees at the local minimum and local maximum of the following equation, Employment ratio in manufacturing = 15.060 – 0.037 Robots per employee + 0.0015 Robots per employee^2 – 0.00001 Robots per employee^3, are 14.4097 and 85.5903. Therefore, as long as the robot adoption growth lies between 14.4097 and 85.5903, its marginal effect is positive. In other cases, it is negative.

[4] The quadratic function of the TFP growth is TFP = –0.126 + 0.032 Robot per employee – 0.0003 Robot per employee ^{2}. Thus, the inflection point of this equation is Robot per employee = 53.3333.

the robot adoption growth and the TFP growth may arise in this analysis. For instance, the TFP improvement in a certain industry may help to expand its scale of the industry in the economy. This leads to the expansion of production facilities, which provides more opportunities of the use of industrial robots in updated and new facilities.

To address this issue, we use the annual growth rate of total R&D investment for robots by three global Japanese robot makers, Kawasaki Heavy Industries, Fanuc Corporation, and Yasukawa Electric Corporation, as an instrument for the robot adoption growth.[5] We assume that higher R&D investment expenditures for robots create more versatile robots that can work for more difficult tasks traditionally done by humans. The possible replacement of more tasks by new robots encourages companies to adopt them in their workplaces or factories. On the other hand, the TFP improvement in the economy not always promotes this job replacement by newly invented robots. Therefore, this idea suggests that the annual growth rate of total R&D investment for robots works as an instrument.[6]

Eq. (3) reports 2SLS estimates using the annual growth rate of total R&D investment for robots as an instrument for the robot adoption growth.[7] Both variables of robots per employees and quadratic one are strongly significant with expected signs. Compared to Eq. (1), the magnitudes of obtained coefficients are different.[8] In this case, as long as the robot adoption grows by less than 60.8% annually, the introduction of new robots positively contributes to the TFP growth. Its marginal effect of robot adoption growth is up to 0.649 (0.681–0.032) greater than that obtained in Eq. (1). Therefore, the reverse causality may underestimate OLS estimates. In Eq. (4), the ICT's contribution to the TFP growth is much higher, but the industry ratio becomes insignificant. The size of the coefficient of robots per employees is slightly smaller but remains large enough. We only apply dummy variables in the OLS case, but we can observe their strongly significant coefficients. This implies that Asian countries have higher TFP growth, and all the sample

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[5] We collected the R&D investment data obtained from each company's IR web site, and basically estimated the R&D investments for robots based on the robot sector share of the total sales. The data of the remaining two major makers, ABB and KUKA, are not enough long for estimation. Therefore, they are excluded.

[6] Figure A1 shows a better capture of the fluctuations of operating stock of robots per 1000 employees by log of total R&D investment for robots for 2002–2018.

[7] The first stage regression of 2SLS is as follows:

$$TFP\ growth_{it} = const + a_1 R\&D_t + a_2 R\&D_{t-1} + \boldsymbol{b_i X_{it}} + u_{it},$$

where $\boldsymbol{X_{it}}$ is are exogenous variables.

[8] The quadratic function of the TFP growth is TFP = –6.854 + 0.681 Robot per employee – 0.0056 Robot per employee ^{2}. Thus, the inflection point of this equation is Robot per employee = 60.8036.

countries receive huge negative impacts on their TFP from the global financial crisis. Additionally, the results of the fixed effect model are shown for comparison. They are quite similar to those in Eq. (4).

3.4. Empirical results of 30/20 OECD member countries

Tables 4 and 5 display the estimation results obtained based on the OECD member countries' real wage growth. Table 4 shows the results of the annual real wage change of 30 OECD countries for 2005–2017. The robot adoption is statistically supported in Eqs. (1) – (3). All the estimated coefficients, which are positive and similar values, mean that 10 percent point increase in robot adoption growth leads to around 0.4 percent point rise in real wage growth. This positive effect of robot adoption on real wages is consistent with the implications of Autor (2015) and Autor and Salomons (2018). In addition, the industry ratio shows the significance of positive coefficients in Eq. (2). Thus, the further progress of the industrialization of the economy boosts the real wage growth in the labor market. The ICT variable is not significant in Eqs. (2) and (4). No significant interaction effect of robot adoption and industry/ICT is observed in Eq. (4). The interaction term of the robot adoption and GFC dummy, which is significant, overrides the positive effects of the robot adoption.

Eqs. (1) – (5) in Table 5 show the results of the 10- and 90-percentiles (bottom and top 10 percentiles) of annual real wage change of 20 OECD countries. In both percentiles of wage growth, the robot adoption is positively significant in all the equations. The magnitudes of its impacts on the 10-percentile wage growth in the selected random effect models of Eqs. (1) and (2) may be slightly susceptible to sets of control variables, but the robot adoption growth raises the annual real wage growth in 10-percentile point of wage distribution by 0.07–0.08 points. The magnitude of robot adoption of the fixed effect model as a reference shows the similar value (0.087). Those on the 90-percentile wage growth are quite similar to those on the 10-percentile wage growth. The striking feature of this finding is that robotization equally benefits workers in both tails of wage distribution. In other words, our results do not show any skilled wage premium for high-skilled workers in the upper tail of wage distribution (Acemoglu and Autor, 2011; Feenstra, 2007). Compared to the results of 50-percentile (mean) annual wage growth shown in Eqs. (6) and (7), the impacts of robot adoption growth in 10- and 90-perceltiles wage growth are slightly larger. However, we should cautiously interpret this fact by considering whether task contents can be not only replaceable by robots but also collaborative with them to increase labor productivity. If installed robots do not compete with existing workers; rather, help them to work, the robot adoption more effectively raises their wage growth, particularly in both tails of wage distribution rather than around its mean. While the industry ratio variable significantly positively affects both percentiles wage growth, the ICT variable does not have any effect on the wage growth in both tails of wage distribution except one case. Therefore, industrialization is beneficial to both lowest and highest wage earners, but the ICT development is limited or not effective in this sense. No significant interaction effect of robot adoption and industry/ICT is observed; therefore, they are omitted in this table.

3.5. Impacts on major robot user countries

As shown in Figure 4, five major robot user countries such as Korea, Taiwan, Germany, Japan, and US have become more robot-intensive in their production processes.[9] Therefore, we investigate whether such tendency makes some differences in their macroeconomic reactions with rapid increasing robotization to other countries. To this end, we use the robot-intensive dummy variable, which takes one for Korea, Taiwan, Germany, Japan, and US and zero otherwise. Table 6 shows the results. In Eq. (1), the significance of the interaction terms of Robot per employee and Robot per employee^2 implies that the increase in robot adoption growth makes further improvement for the unemployment rate in the major robot user countries. In Eq. (2), the significant interaction terms of Industry ratio and ICT show some deterioration and improvement of unemployment rate, respectively. As for the employment ratio in manufacturing, only the interaction of ICT is negatively significant in Eq. (4), which means more labor-saving tendencies in manufacturing industries in the major robot user countries. In Eq. (6), the negative contribution of ICT development to the TFP growth is opposite to our expectation, which seems difficult to understand. Looking at much larger coefficient value of the constant term dummy compared to that in Eq. (5), we should cautiously interpret this result because some estimated coefficients may be unstable possibly due to the insufficient sample size in both dimensions of country and time. To resolve this issue, we need to extend our sample span.

4. Concluding remarks

This paper investigates how significantly recent growing trends of industrial robot

[9] We exclude Singapore here because its population size is much smaller than the other five countries and its state-led development is quite unique; therefore, it may have some peculiarities in the industry structure from the others. Table A3 shows the results including Singapore, which differs from those of Table 6. The robot-intensive dummy variable is significant in less cases.

adoption in production process affect the unemployment rate in the whole economy, employment ratio in manufacturing, and TFP growth of 52 world economies for 2007–2017 and the real wage growth of 30/20 OECD members for 2005–2017.

Although people are more concerned about task displacements led by losing the competition to robots (e.g., Acemoglu and Restrepo, 2018, 2019) and some skepticism on increasing new job creation opportunities with expanding labor market, we have obtained some optimistic findings by including more countries in the analysis, some of which are growing Asian countries as major robot users. The increasing operating stocks of robots per 1000 employees consistently lower the unemployment rates in the world. The robot adoption growth raises the TFP growth in the economy, which may provide more possibilities of expansion of production facilities, probably helping to hire more workers. The automation by robots also contributes to the improvement of annual change of real wage rate. The benefits from this wage hike prevail more to workers in 10- and 90-percentiles of wage distribution. However, in manufacturing industries, the employment ratio of workers against total employment in the economy decreases with increasing trends of robot use. Expanding the scale of manufacturing itself may mitigate this shrinkage of job opportunities.

New innovative technologies (e.g., higher-level autonomous driving system, quantum computing, generative artificial intelligence, etc.) are waiting to be more practical. Our economies must keep up with possible transformations brought by them. We also should not be afraid of coming future changes because as long as the world economies grow, we can share our “pie” with even robots.

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Figure 1(a). Scatter diagram of robots per employee and unemployment rate (2007)

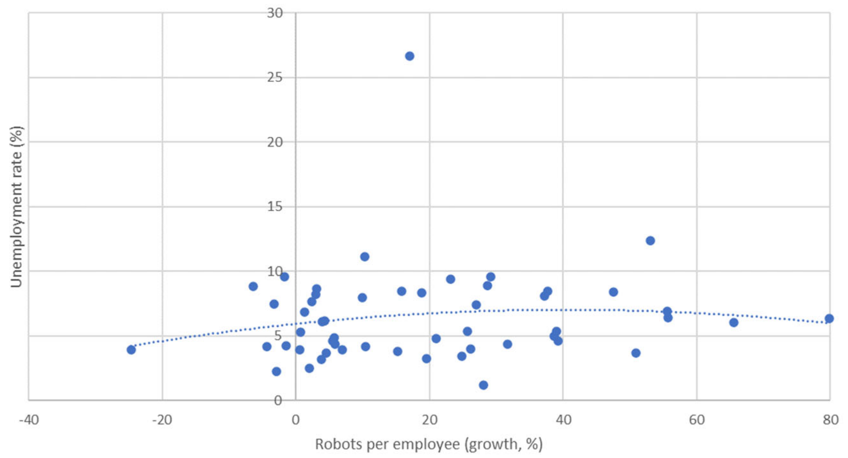

Figure 1 (b). Scatter diagram of robots per employee and unemployment rate (2013)

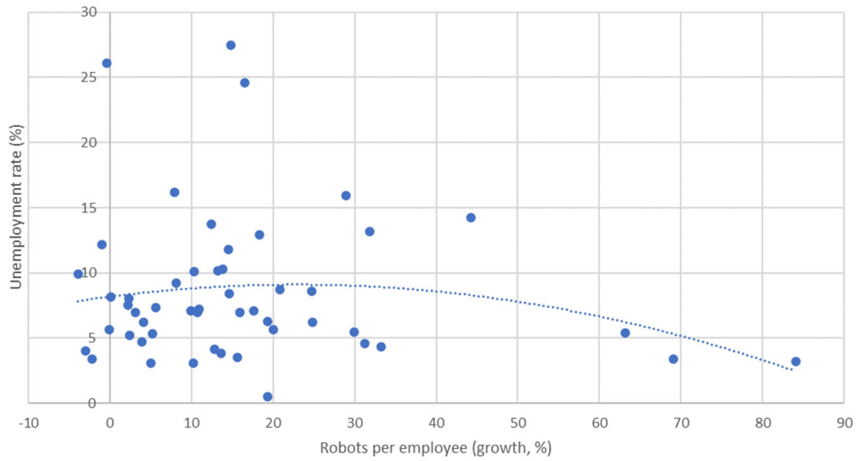

Figure 1 (c). Scatter diagram of robots per employee and unemployment rate (2017)

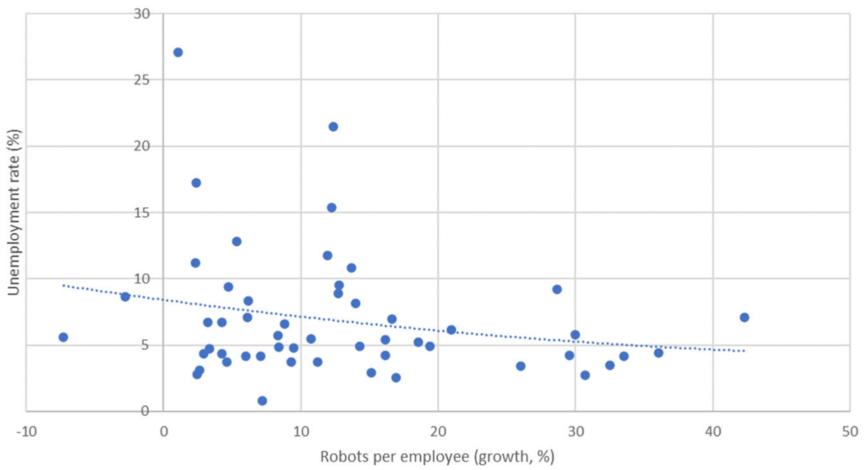

Figure 2 (a). Scatter diagram of robots per employee and employment ratio in manufacturing (2007)

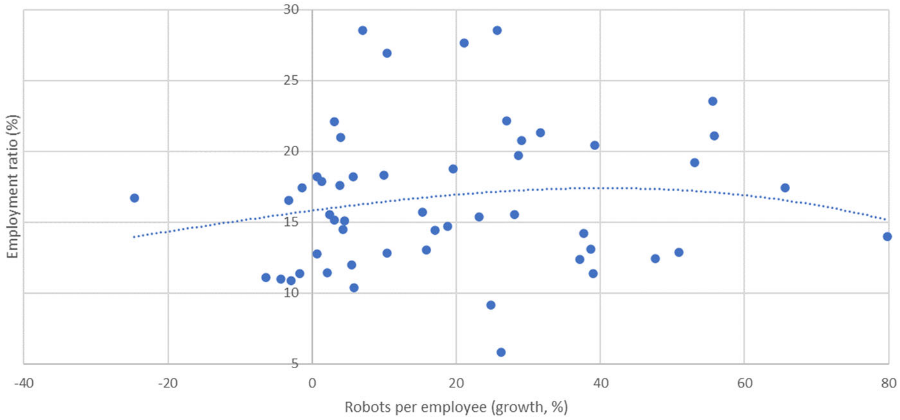

Figure 2 (b). Scatter diagram of robots per employee and employment ratio in manufacturing (2013)

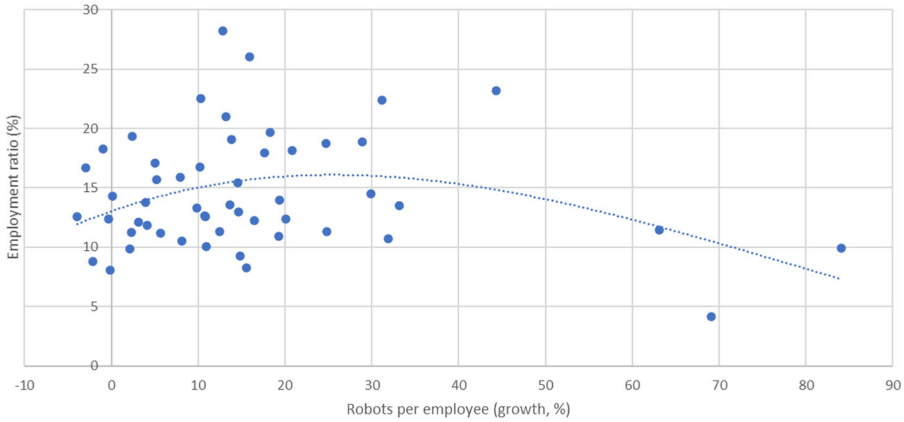

Figure 2 (c). Scatter diagram of robots per employee and employment ratio in manufacturing (2017)

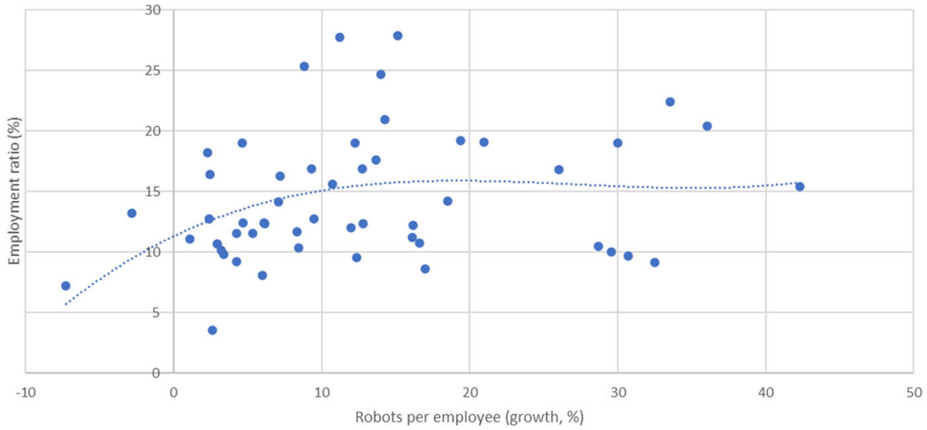

Figure 3 (a). Scatter diagram of robots per employee and TFP (2007)

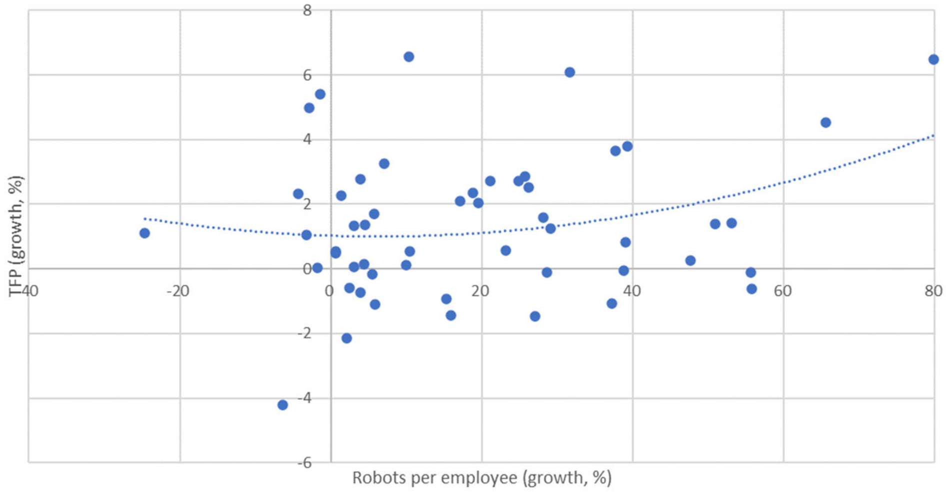

Figure 3 (b). Scatter diagram of robots per employee and TFP (2013)

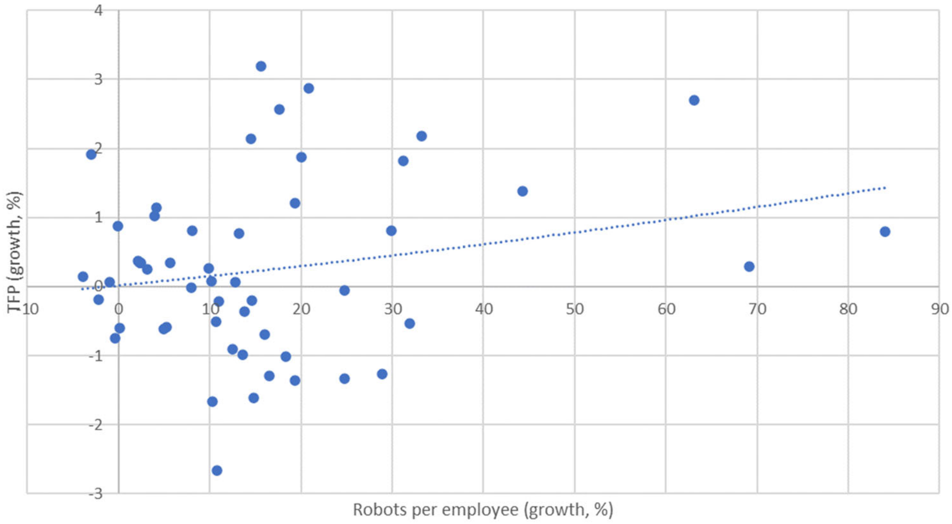

Figure 3 (c). Scatter diagram of robots per employee and TFP (2017)

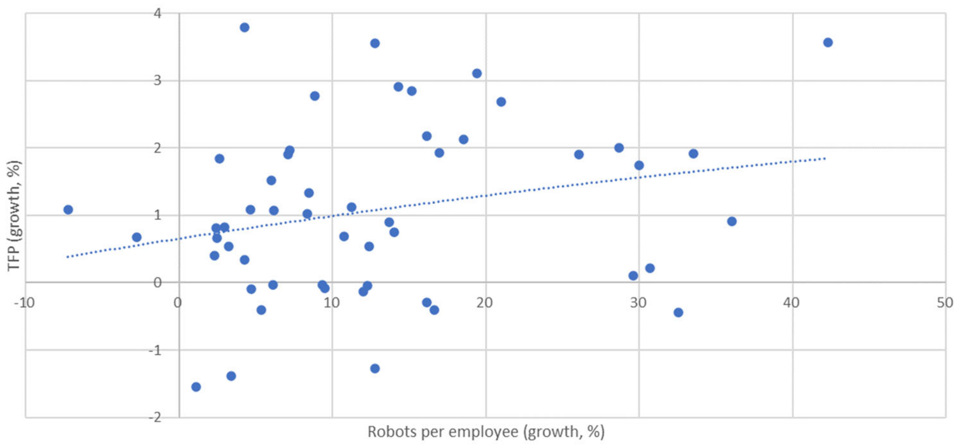

Figure 4. The operating stock of robots per employee (per 1000 employees)

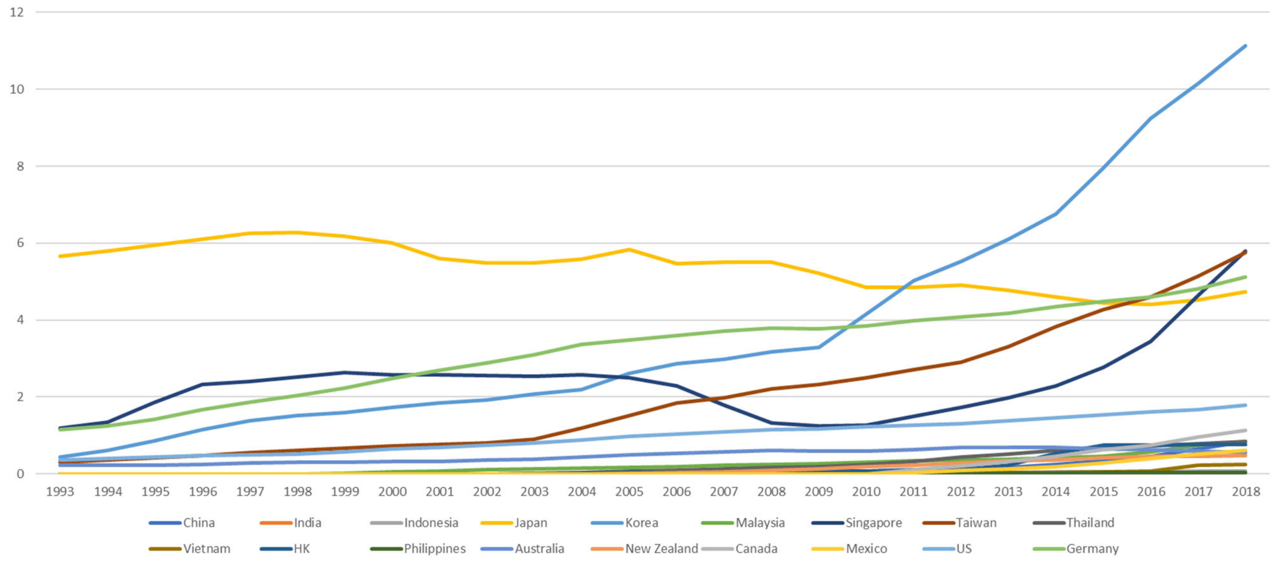

Table 1. Estimation of 52 countries (Explained variable: Unemployment rate)

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Constant	**8.118**	**13.514**	**13.478**	**6.621**	**13.968**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Robots per employee	**-0.040**	**-0.035**	**-0.036**	**-0.036**	**-0.034**
	(0.031)	(0.021)	(0.039)	(0.019)	(0.019)
Robots per employee ^{2}	**0.0003**	**0.0003**	**0.0003**	**0.0003**	**-0.0008**
	(0.030)	(0.025)	(0.030)	(0.019)	(0.057)
Industry ratio		**-0.220**	**-0.303**		**-0.229**
		(0.018)	(0.004)		(0.012)
ICT		0.007		0.034	0.003
		(0.739)		(0.174)	(0.883)
Robots per employee ^{2}×Industry ratio					**0.00003**
					(0.071)
Robots per employee ^{2}×ICT					**7.85×10^{-6}**
					(0.003)
Industry ratio ×Asia dummy			**0.405**		
			(0.008)		
Industry ratio ×GFC dummy			**-0.015**		
			(0.085)		
ICT ×Asia dummy				**-0.058**	
				(0.036)	
ICT×GFC dummy				**-0.007**	
				(0.014)	
Cross section effect	Fixed	Fixed	Fixed	Fixed	Fixed
F-statistic (p-value)	0.086	0.039	0.037	0.035	0.000
Observations	572	572	572	572	572

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level. The p-value of Hausman test statistic obtained from Eq. (2) is 0.053, which means the rejection of the null hypothesis.

Table 2. Estimation of 52 countries (Explained variable: Employment ratio in manufacturing)

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Constant	**15.060**	**15.158**	**15.474**	**15.068**	**15.311**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Robots per employee	**-0.037**	**-0.032**	**-0.034**	**-0.032**	**-0.032**
	(0.050)	(0.055)	(0.082)	(0.080)	(0.068)
Robots per employee ^{2}	**0.0015**	**0.0010**	**0.0010**	**0.0009**	**0.0010**
	(0.002)	(0.012)	(0.024)	(0.030)	(0.021)
Robots per employee ^{3}	**-0.00001**	**-8.24×10^{-6}**	**-8.70×10^{-6}**	**-7.53×10^{-6}**	**-8.14×10^{-6}**
	(0.000)	(0.003)	(0.006)	(0.010)	(0.005)
Industry ratio		**0.095**	**0.143**	**0.096**	**0.118**
		(0.020)	(0.005)	(0.011)	(0.005)
ICT		**-0.040**	**-0.040**	**-0.049**	**-0.053**
		(0.000)	(0.000)	(0.000)	(0.000)
Industry ratio ×Asia dummy			**-0.233**		-0.068
			(0.039)		(0.453)
Industry ratio ×GFC dummy			0.001		**-0.025**
			(0.742)		(0.000)
ICT ×Asia dummy				**0.053**	**0.042**
				(0.005)	(0.006)
ICT×GFC dummy				**0.005**	**0.014**
				(0.000)	(0.000)
Robots per employee ^{3}×GFC dummy	**4.61×10^{-6}**	**3.09×10^{-6}**	**3.31×10^{-6}**	**2.69×10^{-6}**	**3.14×10^{-6}**
	(0.000)	(0.001)	(0.002)	(0.005)	(0.001)
Cross section effect	Fixed	Fixed	Fixed	Fixed	Fixed
F-statistic (p-value)	0.006	0.000	0.000	0.000	0.000
Observations	572	572	572	572	572

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level. The p-value of Hausman test statistic obtained from Eq. (2) is 0.009, which means the rejection of the null hypothesis.

Table 3. Estimation of 52 countries (Explained variable: TFP growth)

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	2SLS	2SLS	OLS	2SLS
Constant	-0.126	**-2.901**	**-6.854**	**-9.304**	0.272	**-14.571**
	(0.351)	(0.001)	(0.004)	(0.000)	(0.109)	(0.003)
Robots per employee	**0.032**	**0.037**	**0.681**	**0.432**	**0.020**	**0.370**
	(0.005)	(0.001)	(0.004)	(0.000)	(0.069)	(0.000)
Robots per employee ^{2}	**-0.0003**	**-0.0003**	**-0.0056**	**-0.0034**	-0.0001	**-0.0027**
	(0.011)	(0.008)	(0.019)	(0.001)	(0.300)	(0.000)
Industry ratio		**0.058**		-0.013		0.132
		(0.017)		(0.777)		(0.389)
ICT		**0.018**		**0.081**		**0.110**
		(0.004)		(0.000)		(0.000)
Asia dummy					**0.917**	
					(0.000)	
GFC dummy					**-2.758**	
					(0.000)	
Cross section effect	Random	Random	Random	Random	Random	Fixed
Wald-statistic (p-value)	0.017	0.000	0.004	0.000	0.000	0.000
Observations	572	572	572	572	572	572

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level. The p-value of Hausman test statistic obtained from Eq. (2) is 0.1221, which means the non-rejection of the null hypothesis.

Table 4. Estimation of 30 OECD countries (Explained variable: Annual wage change)

Explanatory variables	(1)	(2)	(3)	(4)
Constant	**0.661**	-3.354	**-5.131**	-3.975
	(0.000)	(0.367)	(0.065)	(0.288)
Robots per employee	**0.041**	**0.036**	**0.038**	0.106
	(0.005)	(0.024)	(0.009)	(0.241)
Industry ratio		**0.200**	**0.232**	**0.229**
		(0.094)	(0.035)	(0.029)
ICT		-0.013		-0.015
		(0.355)		(0.398)
Robots per employee×Industry ratio				-0.0027
				(0.384)
Robots per employee×ICT				3.87×10^{-5}
				(0.916)
Robots per employee ×GFC dummy	**-0.060**	**-0.057**	**-0.057**	**-0.063**
	(0.014)	(0.015)	(0.016)	(0.004)
Cross section effect	Fixed	Fixed	Fixed	Fixed
F-statistic (p-value)	0.017	0.010	0.044	0.000
Observations	390	390	390	390

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level. The p-value of Hausman test statistic obtained from Eq. (2) is 0.0003, which means the rejection of the null hypothesis.

Table 5. Estimation of 20 OECD countries (Explained variable: 10/90-percentiles of annual wage change)

Explanatory variables	Explained variable:						
	10-percentile wage			90-percentile wage		50-percentile (Mean) wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	**0.361**	**-3.410**	**-8.202**	0.137	**-9.950**	**0.269**	**-8.031**
	(0.040)	(0.026)	(0.052)	(0.219)	(0.051)	(0.021)	(0.007)
Robots per employee	**0.071**	**0.080**	**0.087**	**0.085**	**0.083**	**0.063**	**0.063**
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Industry ratio		**0.070**	**0.292**		**0.382**		**0.297**
		(0.051)	(0.032)		(0.013)		(0.006)
ICT		**0.026**	0.017		0.010		0.013
		(0.026)	(0.307)		(0.661)		(0.234)
Cross section effect	Random	Random	Fixed	Fixed	Fixed	Fixed	Fixed
F-statistic (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	260	260	260	260	260	260	260

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level. The p-values of Hausman test statistic obtained from Eqs. (2), (5), and (7) are 0.115, 0.001, and 0.014, respectively. Eq. (2) does not reject the null hypothesis, but Eqs. (5) an (7) reject the null hypothesis.

Table 6. Robot-intensive country dummy (52 countries, three explained variables)

Explanatory variables	Unemployment rate		Employment ratio		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	**13.452**	**13.363**	**15.213**	**15.088**	**-2.814**	**-2.994**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Robots per employee	**-0.035**	**-0.035**	**-0.033**	**-0.032**	**0.039**	**0.039**
	(0.024)	(0.021)	(0.052)	(0.058)	(0.000)	(0.000)
Robots per employee ^{2}	**0.0003**	**0.0003**	**0.0010**	**0.0010**	**-0.0003**	**-0.0003**
	(0.027)	(0.024)	(0.011)	(0.013)	(0.007)	(0.006)
Robots per employee ^{3}			**-8.32×10^{-6}**	**-8.30×10^{-6}**		
			(0.003)	(0.003)		
Industry ratio	**-0.218**	**-0.218**	**0.093**	**0.098**	**0.055**	**0.059**
	(0.021)	(0.034)	(0.024)	(0.028)	(0.032)	(0.033)
ICT	0.007	0.009	**-0.040**	**-0.039**	**0.017**	**0.018**
	(0.725)	(0.686)	(0.000)	(0.000)	(0.010)	(0.008)
Robots per employee × dummy_robot_intensive	**-0.128**		0.040		-0.020	
	(0.086)		(0.143)		(0.725)	
Robots per employee ^{2} × dummy_robot_intensive	**0.006**		-0.001		0.001	
	(0.009)		(0.549)		(0.815)	
Robots per employee 3 × dummy_robot_intensive			3.11×10^{-6}			
			(0.974)			
Industry ratio ×dummy_robot_intensive		**0.262**		0.078		-0.017
		(0.064)		(0.272)		(0.554)
ICT ×dummy_robot_intensive		**-0.098**		**-0.040**		**-0.045**
		(0.076)		(0.083)		(0.097)
dummy_robot_intensive					**0.418**	**4.408**
					(0.065)	(0.039)
Robots per employee ^{3}×GFC dummy			**3.10×10^{-6}**	**3.12×10^{-6}**		
			(0.001)	(0.001)		
Cross section effect	Fixed	Fixed	Fixed	Fixed	Random	Random
F-statistic (p-value)	0.004	0.000	0.000	0.000	0.000	0.000
Observations	572	572	572	572	572	572

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level.

Figure A1. Scatter diagram of operating stock of robots per 1000 employees and log of total R & D investment for robots by three global Japanese makers for 2002–2018

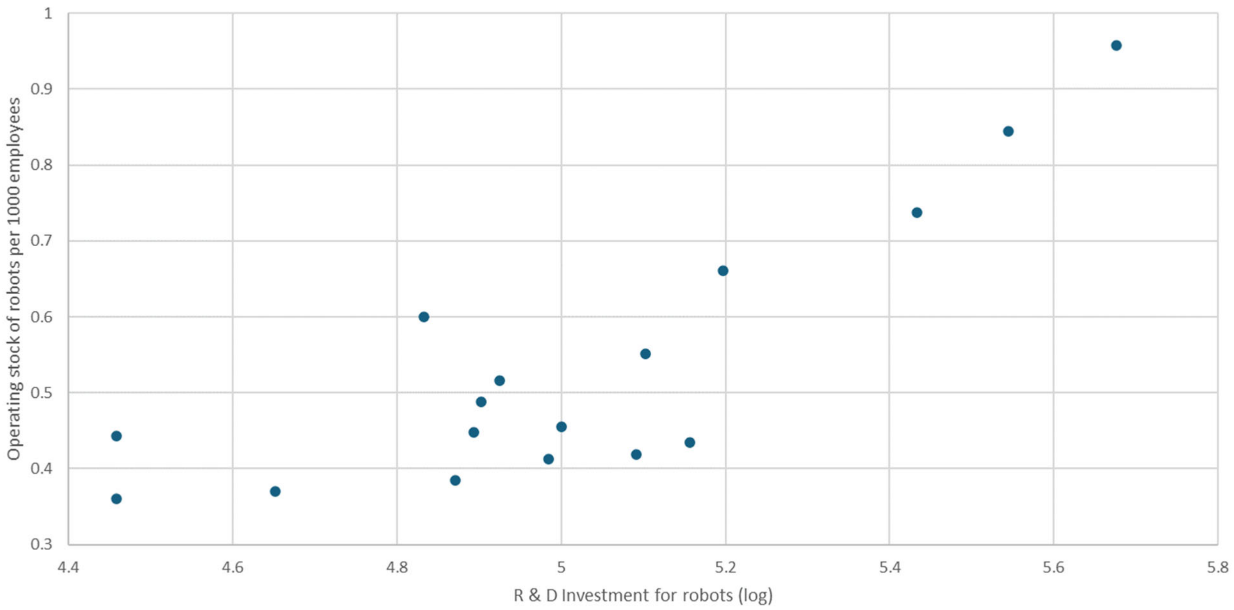

Table A1. Sample countries

Sample countries					
52 world countries				30 OECD countries	20 OECD countries
Asia & Pacific (13)	China	Europe (17)	Austria	Australia	Australia
	Hong Kong		Belgen	Austria	Austria
	India		Germany	Belgen	Belgen
	Indonesia		Spain	Chile	Czech
	Japan		France	Czech	Denmark
	Korea		Italy	Denmark	Finland
	Malaysia		Netherland	Estonia	France
	Philippines		Portgal	Finland	Germany
	Singapore		Switzland	France	Greece
	Taiwan		UK	Germany	Hungary
	Thailand		Denmark	Greece	Iceland
	Australia		Finland	Hungary	Israel
	New Zealand		Norway	Iceland	Japan
America (5)	US		Sweden	Ireland	Korea
	Argentina		Ireland	Israel	Norway
	Brazil		Iceland	Italy	Potugal
	Chile		Greece	Japan	Slovakia
	Peru	Eastern Europe, Russia & central Asia (11)	Hungary	Korea	Sweden
Africa (4)	South Africa		Czech	Lithuania	UK
	Egypt		Poland	Netherland	US
	Morroco		Romania	Norway	
	Tunigia		Russia	Poland	
Middle east (2)	Turkiye		Slovakia	Potugal	
	Israel		Slovenia	Slovakia	
			Bulgaria	Slovenia	
			Estonia	Spain	
			Lithuania	Sweden	
			Ukrane	Switzland	
				UK	
				US	

Table A2. Data descriptions

Variable	Description	Source
Robot adoption	Operating stock of robots per 1,000 employees	International Federation of Robotics, ILO database
Unemployment	Unemployment rate by sex and age ILO modelled estimates: Total, Youth adults 15+	ILO database
Employment ratio in manufacturing	Employment in manufacturing/ total employment ratio, based on ILO modelled estimates, Nov. 2019 (thousands).	ILO database
TFP index	TFP at constant national prices (2011=1), growth of productivity over time	Penn World Table 9.0
Real wage	Average annual wage (in 2018 constant price at 2018 USD PPPs)	OECD Employment and Labor Market Statistics
10/90 percentiles real wage	10/90 percentiles real wage are calculated based on 9/5 and 5/1 decile ratios of gross earnings, where the median (5 decile) is assumed to be equivalent to average annual real	OECD Employment and Labor Market Statistics
Industry ratio	Value added in industry/total value added ratio	World Development Indicators, National Statistics website (the government of the Republic of China)
ICT	Internet users (%)	World Telecommunication/ICT Indicators Database

Table A3. Estimation of 52 countries (Three explained variable, including Singapore)

Explanatory variables	Unemployment rate		Employment ratio		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	**13.513**	**13.476**	**14.917**	**15.015**	**-2.885**	**-3.019**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)
Robots per employee	**-0.037**	**-0.032**	-0.006	**-0.019**	**0.037**	**0.039**
	(0.032)	(0.040)	(0.622)	(0.031)	(0.003)	(0.000)
Robots per employee ^{2}	**0.0003**	**0.0003**	0.0004	**0.0007**	**-0.0003**	**-0.0003**
	(0.033)	(0.044)	(0.213)	(0.003)	(0.020)	(0.007)
Robots per employee ^{3}			**-4.37×10^{-6}**	**-6.40×10^{-6}**		
			(0.044)	(0.001)		
Industry ratio	**-0.218**	**-0.219**	**0.095**	**0.090**	**0.058**	**0.059**
	(0.019)	(0.035)	(0.018)	(0.036)	(0.023)	(0.035)
ICT	0.006	0.009	**-0.039**	**-0.038**	**0.018**	**0.019**
	(0.748)	(0.673)	(0.000)	(0.000)	(0.007)	(0.007)
Robots per employee × dummy_robot_intensive	0.012		-0.040		0.004	
	(0.498)		(0.280)		(0.813)	
Robots per employee ^{2} × dummy_robot_intensive	-0.001		-0.001		**-0.003**	
	(0.425)		(0.490)		(0.000)	
Robots per employee 3 × dummy_robot_intensive			**-0.00006**			
			(0.096)			
Industry ratio ×dummy_robot_intensive		0.110		**0.277**		0.014
		(0.428)		(0.017)		(0.763)
ICT ×dummy_robot_intensive		-0.059		**-0.097**		-0.043
		(0.178)		(0.010)		(0.116)
dummy_robot_intensive					0.397	3.084
					(0.111)	(0.211)
Robots per employee ^{3}×GFC dummy			**2.17×10^{-6}**	**2.66×10^{-6}**		
			(0.004)	(0.001)		
Cross section effect	Fixed	Fixed	Fixed	Fixed	Random	Random
F-statistic (p-value)	0.043	0.056	0.000	0.000	0.000	0.000
Observations	572	572	572	572	572	572

Notes: The values in the parentheses under the estimated coefficients are p-values, which are calculated under robust standard errors. The values in bold letters show the statistical significance at least 10% significance level.