Diffusion of Industrial Robotics and Inclusive Growth: Labour Market Evidence from Cross Country Data

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Abstract

This paper investigates the impact of industrial robot adoption on inclusive growth based on labour market evidence from a cross-country panel dataset of 74 economies between 2004 and 2016. It finds that the adoption of industrial robots is associated with significant gains in labour productivity and total employment in developed economies, while such effects are insignificant in developing countries. Increased robot adoption is related to a significantly lower labour share of GDP in developing economies but not in developed countries. Overall, in both developed and developing economies, increased robot adoption is linked with significantly higher income inequality, although there is no evidence of technological unemployment. Furthermore, the employment of both male and female workers is positively associated with the adoption of industrial robots in developed economies, although females benefit slightly more. In developing countries, however, only those with middle or advanced levels of education benefit from the diffusion of robots.

Key Words: Emerging technology, industrial robotics, inclusive growth, employment, income inequality, labour productivity

1. Introduction

The remarkable change in robot capabilities over the past two decades has the potential to change our lives and jobs (Brynjolfsson and McAfee, 2014; Autor, 2014; Acemoglu and Restrepo, 2017; McKinsey Global Institute, 2017; and International Federation of Robotics, 2018, among others). Unlike earlier robots, the new generation of robots is more flexible, versatile, and autonomous. They perform a range of routine physical work activities more efficiently than humans and are increasingly capable of undertaking activities that require cognitive capabilities (Edward et al., 2017; Sousa and Rocha, 2019). Therefore, along with some positive expectations, such as improvements to productivity and quality of life, there are deep concerns about the potential negative impacts of robot adoption. Large-scale job losses and increasing inequality may result from these innovations (Edwards et al., 2017; Graetz and Michaels, 2018). These interrelated challenges of robotic innovation highlight the need for inclusive economic growth, for better opportunities for all sectors of the population and for the benefits of increased prosperity to be distributed fairly across society.

The published literature indicates that robots may stimulate labour productivity when they are applied to tasks they perform more efficiently with a higher and more consistent level of quality than humans (Dauth et al., 2017; International Federation of Robotics, 2018). There are two different views in the literature about the effects of robot adoption. The first view favours the displacement effect, suggesting that increased robot use may affect employment and wages by directly displacing workers from tasks they used to perform. By contrast, the second view argues for the productivity effect, wherein there may be increases in the demand for labour in industries or tasks that arise as a result of technological advances associated with robot adoption. The ultimate impacts of robot adoption on employment, labour share of gross domestic product (GDP), and income equality depend on which of the two effects plays a dominant role in the economy (Autor and Dorn, 2013; Acemoglu and Restrepo, 2017).

However, there is little empirical evidence about the implications of robot adoption on inclusive growth. Jäger et al. (2016) employ a subset sample of the European Manufacturing Survey 2012 covering 2,848 manufacturing companies and find that while companies secure labour productivity gains from robot utilization, industrial robots have no direct effect on company-level employment. Similarly, Graetz and Michaels (2018) find that increased robot use significantly boosted labour productivity in 17 developed countries between 1993 and 2007. They find that robots did not significantly reduce total employment, although they did reduce the employment rate for low-skilled workers. Using data on individual manufacturing workers in Germany over the period 1994-2014, Dauth et al. (2017) find that robots changed the composition of employment without affecting aggregate employment because the decline in manufacturing employment was fully offset by an increase in the number of jobs in the service industry. They also find that robots raised labour productivity but not wages and led to a decline in the aggregate labour income share. In contrast, Acemoglu and Restrepo (2017) find that robots significantly reduced employment and wages in the United States between 1990 and 2007. Similarly, Chiacchio et al. (2018) study the impact of industrial robots on employment and wages in six European Union countries (Finland, France, Germany, Italy, Spain and Sweden) during the period 1995-2007 and find that robots significantly reduced the employment rate but no evidence of a significant impact on wages.

These studies focus predominantly on developed economies. However, technological innovations are often not neutral (Acemoglu, 2002), and hence, the impact of robot adoption on developed economies may be different from that on developing economies. Therefore, this paper investigates whether and how the impacts of robot adoption in developing countries differ from those in developed countries.

This work extends the existing literature in four respects. First, building upon existing theories, the paper develops a comprehensive theoretical framework addressing the relationship between robot adoption and inclusive growth in four dimensions: employment, labour share of GDP, income inequality, and labour productivity. Second, this study is the first to estimate the impacts of robot adoption on inclusive growth in developing economies and compare these impacts with those for developed economies along the four theoretical dimensions. This comparison enables exploration of the different patterns of influence and more accurately and effectively exposes policy implications. Third, we decompose the employment effect by gender and by education level and compare it between developed and developing economies to identify which groups are more sensitive to rapidly evolving technologies. Finally, employing a larger and more recent dataset than recently published papers, this study aims to capture the ongoing influences of robot adoption on inclusive growth and provides timely policy suggestions.

2. Theoretical Framework

This paper systematically evaluates the impact of industrial robot adoption on inclusive growth in four dimensions: labour productivity, labour share of GDP, employment, and income inequality.

2.1. Robot adoption and labour productivity

Typically, the literature documents a positive relationship between robot adoption and labour productivity because when robots are applied to tasks they perform more efficiently and at a higher and more consistent level of quality than humans, it may stimulate labour productivity

(Dauth et al., 2017). For example, Graetz and Michaels (2018) present a model for the adoption of robots in production, suggesting that a fall in robot price may increase robot density and lead to a fall in output prices and a rise in output and labour productivity.

2.2. Robot adoption and employment

With regard to the effects of robot adoption on employment, labour share of GDP, and income inequality, there are two streams of theories in the literature: one emphasizes the displacement effect, and the other focuses on the productivity effect. If the displacement effect dominates, increased robot use may lead to a decline in employment and wages because more existing jobs are substituted by robots than are created (or than additional demand for labour is created) by robot adoption. In contrast, if the productivity effect plays a dominant role, robot adoption does not necessarily result in a commensurate decline in the aggregate number of jobs. Under this effect, although some existing jobs are undertaken by robots, robot adoption may create new jobs and/or offer productivity gains, which in turn may stimulate additional demand for labour in other industries (Acemoglu and Restrepo, 2017).

There are two different hypotheses about the transmission mechanism of the displacement effect. Under the skill-biased technological change hypothesis, technological change is biased towards replacing labour in low-skill tasks. This hypothesis is used to explain the situation where demand for labour is shifting in favour of more educated workers (Katz and Autor, 1999; Goldin and Katz, 2008; Acemoglu and Autor, 2011). Under the routine-biased technological change (RBTC) hypothesis, technological change is biased towards replacing labour in routine tasks. Since these tasks are normally carried out by middle-skill workers, they are more likely to be affected by emerging technologies such as robotics. This hypothesis is usually used to explain job polarization (Goos, et al., 2014).

2.3. Robot adoption and labour share of GDP

Turning to the effect of capital-intensive robot adoption on the labour share of GDP, increased robot use may result in greater capital intensity in the production of goods and services. If the displacement effect prevails, this generally increases the total return on capital and the share of capital income in GDP. As a result, the labour share of GDP decreases. In contrast, robotics may be less capital embedded because increases in robot density are usually driven by a decline in robot price, which implies that robot adoption may not necessarily result in increased capital intensity (Graetz and Michaels, 2018). Therefore, if the productivity effect plays a dominant role in influencing employment, there will be a fall in the capital share of GDP and a simultaneous rise in the labour share of GDP.

2.4. Robot adoption and income inequality

Regardless of which technological change hypothesis holds, skill-biased or routine-biased robot adoption may exaggerate income inequalities if the displacement effect dominates (Autor and Dorn, 2013). However, increased robot usage may not necessarily lead to income inequalities if the productivity effect dominates. Specifically, Aghion et al. (2017) suggest that payoffs to low-skill workers may increase due to a higher degree of complementarity between low-skill and high-skill workers in companies that are more robot intensive. In addition, Holzer (2015) argues that the middle-skill bracket covers a very wide spectrum of jobs and related skillsets. There are areas in which demand is not being satisfied. Thus, although some middle-skill jobs are being carried out by robots, particularly in the manufacturing industry, the number of middle-skill jobs in some service sectors, such as healthcare, mechanical maintenance and repair, continues growing consistently.

Furthermore, in accord with the RBTC hypothesis, Aghion et al. (2017) argue that low-skill workers benefit more than high-skill workers from working in more robot-intensive companies, as these increase the pay of reliable low-skilled workers to keep them within the company. Aghion et al. (2017) offer two reasons. The first reason is that these robot-intensive companies display a higher degree of complementarity between low-skill and high-skill workers, with the former focusing on addressing various downstream problems to ensure that the latter can have more free time to concentrate on solving the most difficult tasks. The second reason is that highly skilled labour is less company-specific, and these workers' value is mainly determined by their education and accumulated reputation. The quality of reliable low-skill workers is usually more company-specific, and the potential economic loss from unreliable low-skill employees is larger in robot-intensive companies. Thus, reliable low-skill workers who are retained by companies have increased bargaining power because they can make a large difference in companies' performance. As a result, robot-intensive companies would be willing to invest more (e.g., offer higher pay) to keep those low-skill workers with outstanding ability and trustworthiness within their company. Furthermore, maintaining a higher degree of complementarity between reliable low-skill and high-skill workers may in turn help improve labour productivity and increase the incentive for robot deployment. Ultimately, this may help reduce any income inequality caused by robot adoption.

The rapid development of robotic adoption has substantially changed the pattern and organization of manufacturing production, yet the impact of robot adoption on developed economies may be quite different from that on their developing counterparts. According to the directed technical change theory developed by Acemoglu (2002), technological innovations are not neutral but are biased: some benefit capital, and some favour labour. Whether the new technology is biased towards labour or capital depends on the priorities and decisions of those who develop it. As with most new technologies, robotics are emerging in developed countries with sufficient capital and limited labour; these new technologies typically require more capital input and less labour input and often prioritize production conditions that are abundant in developed countries, such as capital and a workforce with digital competencies. By contrast, the pace of technological innovation in developing economies lags behind that of developed economies due to gaps in knowledge, infrastructure, and education between the two types of economies. As a result, developed countries often surpass developing countries in designing, adopting, and applying new technologies, and therefore, developed countries receive greater impacts from these emerging technologies than their developing counterparts.

In summary, the impacts of robot adoption on inclusive growth might be different in developed and developing economies. Whether a positive or a negative impact would be witnessed along the four theoretical dimensions mainly depends on the degree of robot intensity as well as which effect plays a dominant role: the productivity effect or the displacement effect. Given that robot adoption is more widespread in developed countries than in developing countries, it is expected that the labour productivity enhancement effect is more pronounced in developed economies than in their counterparts. However, the impacts of robot adoption on employment, labour share of GDP, and income inequality could be mixed if such adoption facilitates the displacement and productivity effects in both developed and developing economies. Therefore, this study sets out to investigate whether and how the impacts of robot adoption in developing economies differ from the impacts in developed economies within the context of inclusive growth. In particular, we test whether there are any productivity and/or displacement effects along the above four dimensions in the two types of economies, and if so, which one takes the dominant role?

3. Research Method

3.1. Methodology

The various effects of robot adoption on inclusive growth are estimated using country-level data from 74 economies. To address potential reverse causation issues associated with various measures of inclusive growth, we use lagged values of robot stocks as a robustness check. Our panel data model has the following general form:

$$Y_{i,t} = \alpha + \beta * LNROBOT_{i,t} + \delta * CV_{i,t} + \rho_i + \rho_t + \varepsilon_{i,t} \quad (1)$$

where Y denotes one of the four dimensions of inclusive growth, which are labour productivity (*LNLFP*), employment rate (*EMP*), labour share of GDP (*LIS*), and income inequality (*GINI*). *LNROBOT* measures the stock of robots, and we take logarithms of the robot stock to alleviate heteroscedasticity problems. CV denotes a vector of control variables and varies by dependent variable. To account for the time-invariant factors and economic trends during the sample period, we also control for the country and year fixed effects, which are separately denoted by ρ_i and ρ_t. i and t are country and time subscripts, respectively.

To investigate the relationship between labour productivity (*LNLFP*) and robot adoption, we use the logarithms of output per worker (GDP constant 2010 US$) to measure *LNLFP*. Following common practice, the control variables include country size (*LNSIZE*) measured by the logarithm of total population, human capital level (*HCL*) measured by the secondary school enrolment rate, and degree of economic openness (*EXPORT*) measured by the share of exports in GDP (Mankiw et al., 1992).

The declining share of labour income in GDP has received a great deal of attention in the published literature (e.g., Dorn et al., 2017), but the effect of robots on this metric remains unclear. The share of labour income in GDP (*LIS*) is used as the dependent variable to examine whether robot adoption has shifted income from labour to capital. The following control variables are included in the model: the share of imports in GDP (*IMPORT*); the share of exports in GDP (*EXPORT*); the price of capital (*PWT*) measured by the domestic price of investment; and the human capital level (*HCL*) measured by secondary school enrolment rate (Karabarbounis and Neiman, 2014; Dorn et al., 2017). To address the potential effects of intangible capital on the measurement of capital and labour shares, intangible capital (*LNPATN*) as measured by the number of patent applications filed by residents is also included.

To examine the effect of robot adoption on the employment rate, we use the aggregate employment rate (*EMP_TOTAL*) as the dependent variable. Following Graetz and Michaels (2018), the control variables include the annual GDP growth rate (*GDPGR*), country size (*LNSIZE*) measured by the logarithm of total population, the share of imports in GDP (*IMPORT*), and the share of exports in GDP (*EXPORT*). We also add the share of the population aged 15-64 over the total population (*POP15*) to control for the influence of demographic changes. To explore which group is more sensitive to emerging technology shock, we further decompose the employment rate by gender and by education level, including male (*EMP_MALE*) and female (*EMP_FEMALE*) employment rates, and the employment rate of advanced (*EMP_EDU_ADV*), intermediate (*EMP_EDU_INT*), basic (*EMP_EDU_BAS*), and less than basic (*EMP_EDU_LTB*) education levels.

Finally, we use the GINI coefficient as a measure of income inequality to capture the impacts of robot adoption on income distribution. Following Anand and Kanbur (1993) and Gustafsson and Johansson (1999), as the control variables in the model, we include the share of exports in GDP (*EXPORT*), the share of workers in agricultural sectors (*EMP_AGR*), the share of workers in manufacturing sectors (*EMP_IND*), the log value of government expenditure (*LNGOV*) and the annual GDP growth rate (*GDPGR*).

3.2. Data

Our study covers 74 economies for the period between 2004 and 2016, including 45 developed and 29 developing economies.[1] The main source of data on robots is the official website of the International Federation of Robotics (IFR), which produces yearly robot adoption data from national robot manufacturers. The IFR data have been utilized in previous studies, but to the best of our knowledge, this paper is the first to cover such a large number of countries and the first to include developing economies. The second major source of data is the official website of the International Labour Organization, which provides data on labour productivity, labour share in GDP, and the employment rate for countries worldwide. Other country-level data are extracted from the World Development Indicators data (World Bank, 2016) and the Penn World Table (PWT) 9.0 (Feenstra et al., 2015).

Table 1 presents descriptive statistics for the variables that are used in this study. Compared with developing economies, developed economies may benefit from holding approximately five times the amount of robot stock and achieving approximately six times the labour productivity on average over the sample period. Developed economies report a greater labour share of GDP, a higher total employment rate, and a lower GINI index. In addition, developed economies record lower male employment rates but higher female employment rates. It is also interesting to find that developed economies present a lower employment rate for low education level workers but a higher employment rate for high education level workers. Unsurprisingly, developed economies show a lower employment rate in agriculture but a similar employment

[1] We label the high-income economies classified by the World Bank as developed economies and the remainder as developing economies.

rate in industry. Finally, developed economies have a higher secondary school enrolment rate than their developing counterparts.[2]

(*Table 1 inserted here*)

Figure 1a presents the robot stocks of the sample economies over time. It shows an upward growing trend of robot stocks over the entire sample period from 2004 to 2016 and shows that aggregate robot stocks more than doubled. Compared with the pre-crisis period, robot stocks grew much faster after the recent global financial crisis. Figure 1b reveals an uneven distribution of robot stocks between developed and developing economies, with many more robot stocks being recorded in the developed world. Although an upward trend in robot stocks is witnessed for both developed and developing economies, robot adoption in developing economies demonstrates a steeper trend, particularly during the post-economic crisis period.

(*Figures 1a & 1b inserted here*)

To alleviate the concern that such high growth rates from low levels in one of the two country groups may bias the results, we exclude China, Japan and Korea from our sample and re-estimate all the models, as shown in Appendices C-H. The main results remain unchanged except that the relationship between robotic adoption and income inequality becomes positive and significant in developed economies.

There is substantial variation in robot adoption across economies. In 2016, records show China held the largest stock of robots (340,000), which accounts for 20 percent of the entire stock of robots in the sample. It is followed by Japan (290,000), the U.S. (250,000), South Korea (246,000), and Germany (190,000). The robot stocks in these five countries alone account for 75 percent of total robot stocks, suggesting an unequal distribution of robots globally. In

[2] Appendix B presents the correlation coefficients of the variables used in this paper. The figures show that the magnitude of the estimated coefficients is less than 50% in the majority of cases and suggests that our models do not suffer from multicollinearity problems.

addition, among the top 20 economies in terms of robot stocks, only six are from the developing world. The top five economies in terms of robot density (robots per thousand labourers) are South Korea (8.89), Germany (4.37), Japan (4.30), Singapore (3.57), and Slovenia (2.46).[3] There is no developing economy on the top 20 chart of robot density.

4. Empirical Results

4.1. Robot adoption and labour productivity

Table 2 displays estimates of the effect of robot adoption on labour productivity. Columns (1)-(3) present the results estimated using *LNROBOT* as a proxy for robot adoption. The results indicate that there is a significant and positive relationship between robot adoption and labour productivity in the full sample, and a significantly positive impact is observed for developed economies but not for developing economies. To address the potential reverse causality between robot adoption and labour productivity, *LNROBOT* is replaced with the lagged value of robot stocks (*L.LNROBOT*). The results are reported in Columns (4)-(6) and confirm a significantly positive relationship between robot adoption and labour productivity in the full sample and the developed subsample. Specifically, the coefficient of *LNROBOT* is 0.019 in column (2), which indicates that a one percent increase in the robot stock leads to a 0.019 percent increase in labour productivity in developed economies. This result is consistent with that obtained in Jäger et al. (2016), Dauth et al. (2017), and Graetz and Michaels (2018) and lends support to the productivity effect view by demonstrating that widespread adoption of industrial robots leads to significant gains in labour productivity in developed economies.

In developing economies, however, neither the productivity effect nor the displacement effect

[3] The usual approach to measuring robot density is to divide the stock of industrial robots by the number of employees in industry. However, data on the number of employees in industry are not available for most developing economies. Thus, this study employs the ratio of robot stock over the labour force to measure robot density.

dominates. The heterogeneous effects of robot adoption on labour productivity between developed and developing economies might be explained by the fact that, in general, robot density in developing economies was much lower than that in developed economies during the sample period. As shown in Table 1, the average robot stock in developed economies (22,147) is almost five times that in developing countries (4,982), indicating the more widespread adoption of industrial robots in developed than in developing countries in line with the directed technical change theory proposed by Acemoglu (2002), i.e., technological innovations are not neutral but are biased. Given that most robotics are invented and developed in developed countries, these new technologies often prioritize conditions in production that are abundant in developed countries. However, as demonstrated in the theoretical model developed by Graetz and Michaels (2018), widespread adoption of industrial robots is the key factor that leads to significant gains in labour productivity. Given their low robot density, it is not surprising to find that robot adoption does not lead to increased labour productivity in developing countries.[4]

(Table 2 inserted here)

4.2. Robot adoption and labour share of GDP

Table 3 reports the estimates of the effect of the robot stock on the share of labour income. Similarly, Columns (1)-(3) present the results estimated using *LNROBOT* as a proxy for robot adoption, whereas Columns (4)-(6) provide the results estimated using *L. LNROBOT* as an indicator of robot adoption to address potential reverse causality. Focusing on the developed subsample, the coefficients of *LNROBOT* and *L. LNROBOT* are significantly positive and insignificantly positive in Columns (2) and (5), respectively. The results suggest that as long as reverse causality is considered, increasing robot adoption would not have any significant

[4] To further illustrate this point, we re-estimate the model using China's data only because China is a developing economy with the largest robot stock. The results confirm that there is a significant and positive relationship between robot adoption and labour productivity in China. The results are available upon request.

impact on the labour income share in the developed world. In contrast, the coefficients of *LNROBOT* and *L. LNROBOT* are insignificantly negative and significantly negative in Columns (3) and (6), respectively. These results suggest that increased robot use is significantly associated with a lower share of labour income in developing economies. This finding implies that unlike their advanced counterparts, developing countries have to confront greater capital intensity in production if they increase robot adoption. This is not surprising because developing economies in general would not be able to achieve economies of scale in robot adoption at this stage and, in consequence, could not enjoy the benefits of a declining robot price. A key reason is that the majority of robotics are invented in developed countries, so they are biased towards capital, whereas the developing world in general is lacking in capital. This finding is therefore consistent with the directed technical change theory proposed by Acemoglu (2002).

(Table 3 inserted here)

4.3. Robot adoption and employment

The empirical results concerning the impact of robot stock on aggregate employment are presented in Table 4. Comparing the baseline results shown in Columns (1)–(3) with those estimated under the robustness checks as shown in Columns (4)–(6), it is found that the coefficients of *LNROBOT* and *L. LNROBOT* are significantly positive in both Columns (1) and (4) for the full sample and in both Columns (2) and (4) for the developed sample. Specifically, the coefficients of *LNROBOT* are 1.186 and 0.965 in Columns (1) and (3), which suggest that a one percent increase in robot stock is related to a 1.186 percent increase in aggregate employment in the full sample and to a 0.095 percent increase in aggregate employment in developed economies. However, no evidence of significant gains in aggregate employment is observed for developing countries. This finding implies that the scale of robot adoption in developed countries is large enough to create new jobs and/or generate productivity gains, which in turn stimulates additional demand for labour in other industries. Consequently, these new employment opportunities may exceed the number of jobs lost to robot adoption.

(Table 4 inserted here)

To deepen our understanding of the difference between developed and developing economies in this regard, we estimate the impact of robot stock on total employment according to educational background and present the results in Table 5[5]. For the subsample of developed economies, the coefficient of *LNROBOT* is significantly positive in both Columns (1) and (5), but the coefficient of *L. LNROBOT* is insignificant in both Columns (3) and (7). In contrast, the coefficients of both *LNROBOT* and *L. LNROBOT* are significant and positive in Columns (2), (4), (6), and (8). Specifically, the coefficient of *LNROBOT* in Column (2) is 1.234, indicating that a one percent increase in robot adoption leads to a 1.234 percent increase in the employment rate of workers with a basic education level. Similarly, the coefficient of *LNROBOT* in Column (6) is 1.647, suggesting a higher-level increase is recorded for the intermediate education level. The results demonstrate that there is a robust and significantly positive effect of robot adoption on the employment rate for workers with a middle level of education in developing economies but not for those in developed economies. Overall, the findings highlight that increased robot use may create new jobs in favour of workers with middle or high levels of education in the developing world.

This interesting finding is partially in line with that of the McKinsey Global Institute (2017) that middle-skill or wage jobs will experience the most net job growth in emerging economies

[5] Table 5 reports the impact of industrial robots on the employment of workers with basic and intermediate education levels. Due to space limitations, the estimated results of robots' impact on employment of workers with less than a basic education level and with an advanced education level are not reported here. They are available from the authors upon request.

such as China and India. There are two reasons for this finding. First, the declining robot prices documented in Graetz and Michaels (2018) have gradually made previously unaffordable robots affordable for developing economies. Given the relatively poorer social welfare system available in developing economies, workers with a middle or high level of education are more desperate to secure a job once robot adoption has improved working conditions and made previously challenging tasks performable. Second, Fu and Akter (2016) investigate the impact of a mobile phone-enhanced intervention in agricultural extension service delivery in India. They find that the quantity, quality, and speed of service delivery improved significantly due to the intervention. In addition, they also find additional benefits in terms of greater knowledge and awareness of new agricultural practices, farmers' ambition to try new technology in the future, and access to credit. Such benefits may spur self-employment by making it easier for individuals with a middle level of education to build up a reputation, which is consistent with the argument of Tirole (2017). Given that no significant impact is observed for workers in developed economies, one possible explanation is that the displacement and productivity effects offset each other.

(Table 5 inserted here)

We also estimate the impact of robot adoption on total employment by gender. The results reported in Table 6 indicate that there is a significant, robust, and positive relationship between robot adoption and employment rate for both males and females in developed countries but not in developing economies. Specifically, the coefficients of *LNROBOT* in Columns (1) and (5) are 1.478 and 1.547, respectively. The result suggests that in the developed world, a one percent increase in robot adoption leads to a 1.478 increase in the employment rate of male workers and a slightly higher-level (1.547 percent) increase in this rate for female workers. The finding implies that in developed economies, both males and females can enjoy the job creation benefits of increased robot use, while it seems that females might adapt slightly better to this dramatic change than males.

(Table 6 inserted here)

4.4. Robot adoption and income inequality

The results presented in Table 7 show that robot adoption has a significant and positive influence on income inequality in developing economies. This result is in line with the abovementioned finding concerning total employment, which suggests that only workers with middle or advanced levels of education can enjoy the job creation benefit of increased robot adoption in developing countries. This finding implies that those with less than a basic education level might be left out during this remarkable revolution, leading to greater income inequality in the developing world. By contrast, the influence of robot adoption on income inequality is insignificant in developed countries. This result is partially consistent with that of Dauth et al. (2017) and Chiacchio et al. (2018), which finds no evidence of a significant impact of robot adoption on wage growth in several developed economies. There are three possible explanations. First, as illustrated above, the productivity effect offsets the displacement effect under the majority of circumstances. Second, as argued by Holzer (2015), there is a wide spectrum of middle-skill jobs that can meet the demand caused by robot adoption either within an industry or between industries. Finally, the complementarity between low-skill workers and other production factors as proposed by Aghion et al. (2017) may contribute to the insignificant relationship between robot adoption and income inequality.

(Table 7 inserted here)

To consider the polarization effects of robot adoption, we divide the sample into five categories by income decile—(0, 20%], (20%, 40%], (40%, 60%], (60%, 80%], (80%, 100%]—and examine how robot adoption affects the labour income share for different income decile groups.

The estimated results for the lowest and highest income deciles are reported in Appendix I[6]. The regression results show that robot deployment leads to increasing income inequality in both developed and developing economies, highlighting the potential threat of large-scale robot deployment to income inequalities worldwide, a result that is consistent with the arguments of Autor and Dorn (2013) and the United Nations (2018).

5. Conclusions

5.1. Summary and policy implications

Using data from 74 countries from 2004 to 2016, this paper investigates how robotic process automation affects labour productivity, the labour income share, income inequality, and the employment rate in both developed and developing economies. First, for the full sample, the estimates show that robot adoption helps to improve labour productivity and total employment, lending support to the productivity effect view. Hence, robotic process automation can be used to complement labour activities in industrial production, improving the quality standards of the work and the production efficiency of the workers. It may provide the opportunity for workers to specialize in highly skilled tasks. In both developed and developing economies, however, there is evidence that robotic process automation has a significant effect on income inequality. It further appears that increased robot adoption makes the rich become richer, although no evidence of so-called technological unemployment is witnessed.

Second, robot adoption has heterogeneous effects between developed and developing economies. On the one hand, there is a significant positive effect of robotic process automation on labour productivity and aggregate employment in developed countries but no significant

[6] Due to space limitations, the estimated results of robot adoption's effects on the labour income share for other income decile groups are not reported here. They are available from the authors upon request.

evidence for such in developing economies. On the other hand, a significantly negative effect of robot adoption on the share of labour income is observed for developing economies but not for developed economies. Furthermore, the employment of both male and female workers is positively associated with the adoption of industrial robots in developed economies, with females appearing to adapt slightly better to increasing robot use in comparison with males. In developing countries, however, only those with middle or advanced levels of education benefit from the skills-biased labour demand increase.

The analysis indicates that a new era of robotics is emerging in which robots can accomplish a range of routine physical work activities more efficiently than humans and are becoming increasingly capable of performing activities that require cognitive capabilities. This new generation of robotics will potentially have favourable and unfavourable consequences for social inclusion. In conjunction with the rapid advances in AI, increased robot usage has the potential to deepen global inequality. By contrast, it also has the potential to transform our world by creating economic opportunities, fostering social inclusion, and manifesting shared prosperity worldwide. There are some differences between developed and developing economies in the relationship between robot adoption and different measures of inclusive growth. A collaborative approach is needed for policies concerning robot adoption that involve all stakeholders, including individuals, companies, and governments, both domestic and international, and it is necessary to avoid policies that benefit only a small elite group. Farsighted policymakers can guide this technological revolution towards creating an inclusive and prosperous world that will surely benefit us all.

Both developed and developing economies should redesign education policies because education plays a vital role in achieving inclusive growth. This approach should be combined with supportive macroeconomic, industrial and social policies (UNCTAD, 2016). As Philip Jennings, the General Secretary of the global UNI union, said, “We need some governance to ensure a democratic evolution and that requires public policy discussion. There is the opportunity to shape technology to improve people’s lives through connectivity, education, and health. We shouldn’t be fearful and fatalist about it” (Elliot, 2016).

Policy and regulatory guidance are needed to direct human efforts and financial investments to ensure that research and development activities are directed towards the wellbeing of the majority and not a select few. There is sufficient investment in technological innovations worldwide, but there is a lack of investment in research that addresses sustainable development. Policies are required to redistribute the benefits from technical progress. Redistributive policies provide compensation to groups who make sacrifices for the development of technologies, for example, laid-off workers and skilled labourers. Compensation can be provided in different ways, including vocational training, reemployment, and social welfare. The policy framework should support the improvement of digital competencies, including education in ICT skills, as well as targeted programmes that provide financial support, online platforms, community activities, and tax incentives to individuals and organizations undergoing this transition.

Finally, overseas aid and international policies are needed so that rather than falling further behind, developing countries instead realize the opportunities and benefits of technological progress. Specific examples of such policies include the international exchange of technologies and collaboration in technology and training. Multinational corporations (MNCs) can play an active role in such an exchange by, for example, building factories near the production sites of raw materials in Africa. Currently, market forces ensure that investors in MNCs will receive most of the profits unless governments implement systematic policies for the redistribution of income.

5.2. Limitations and future research

More research in this area is needed to better understand the effects of robotic process automation on labour productivity, wage growth and the employment rate. Our analysis employs data from 74 economies, including 45 developed and 29 developing economies. The findings reflect the variation in robot adoption between countries but fail to capture the variation in industries within countries. Future research should utilize country-industry pair data to investigate how robot adoption affects the labour market across different industries within countries. Further analysis is needed of the mechanisms through which robots affect the labour market. For example, aggregate estimates could mask the offsetting effects of job destruction and job creation across countries. Future research should utilize data at the occupational or even task level to investigate the impact of robotic process automation on different occupations.

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Table 1. Descriptive statistics

Variable	Definition	Obs.	Mean	S.D.	Obs.	Mean	S.D.	Obs.	Mean	S.D.	Source
			Full sample			**Developed economies**			**Developing economies**		
ROBOT	robot stocks	962	15420	50888	585	22147	60931	377	4982	25934	IFR
LNROBOT	log(ROBOT)	962	5.82	3.47	585	6.49	3.50	377	4.79	3.17	IFR
LFP	output per worker (constant 2010 US$)	947	47944	37906	585	69888	32032	362	12481	7997	WDI
LNLFP	log(output per worker, constant 2010 US$)	947	10.33	1.07	585	11.04	0.51	362	9.20	0.72	WDI
GINI	GINI index (%)	520	34.60	7.62	334	31.90	4.96	186	39.46	9.05	WDI
LIS	labour share in GDP (%)	630	49.34	9.71	512	51.18	9.12	118	41.38	8.07	ILO
EMP TOTAL	total employment rate (%)	756	55.56	9.67	514	56.72	8.41	242	53.11	11.55	ILO
EMP MALE	male employment rate (%)	753	64.70	9.55	511	64.14	8.01	242	65.87	12.12	ILO
EMP FEMAL	female employment rate (%)	754	46.48	12.35	512	49.18	10.01	242	40.76	14.69	ILO
EMP EDU LTB	employment rate of a less than basic education level (%)	465	85.54	16.32	255	81.11	18.03	210	90.91	11.97	ILO
EMP EDU BAS	employment rate of a basic education level (%)	689	87.27	8.74	461	86.25	8.45	228	89.31	8.97	ILO
EMP EDU INT	employment rate of an intermediate education level (%)	685	90.95	5.81	469	91.86	4.79	216	88.97	7.20	ILO
EMP EDU ADV	employment rate of an advanced education level (%)	698	94.28	4.20	473	95.40	2.76	225	91.91	5.52	ILO
EMP AGR	employment in agriculture (% of total employment)	962	13.03	14.32	585	4.53	3.62	377	26.22	14.74	ILO
EMP IND	employment in industry (% of total employment)	962	25.15	6.91	585	25.05	7.13	377	25.32	6.57	ILO
GDPGR	GDP annual growth (%)	947	3.41	4.32	585	2.75	4.51	362	4.47	3.79	WDI
IMPORT	gross import of GDP (%)	883	37.30	25.70	550	39.05	29.11	333	34.41	18.44	WDI
EXPORT	gross export of GDP (%)	947	50.08	35.24	585	58.41	39.96	362	36.62	19.42	WDI
POP15	population ages 15-64 (% of total)	962	67.99	4.32	585	68.49	4.73	377	67.20	3.46	WDI
LNGOV	log(government expenditures, constant 2010 US$)	910	24.44	1.58	577	24.65	1.67	333	24.09	1.35	WDI
LNSIZE	log(population)	962	16.67	1.67	585	16.02	1.47	377	17.68	1.43	WDI
LNPATN	log(number of patents filed by residents)	877	6.83	2.29	513	6.99	2.45	364	6.61	2.04	WDI
PWT	domestic price of investment	388	0.91	0.21	265	0.83	0.18	123	1.07	0.20	PWT
HCL	school enrolment, secondary (% of gross)	803	97.69	17.74	509	105.00	14.43	294	84.99	15.65	WDI
INL20	income share held by the lowest 20%	538	6.98	2.24	334	7.73	1.42	204	5.75	2.73	WDI
INSD20	income share held by the second 20%	538	11.70	2.94	334	12.87	1.35	204	9.79	3.74	WDI
INTD20	income share held by the third 20%	538	15.76	3.40	334	16.99	0.98	204	13.76	4.74	WDI
INTH20	income share held by the fourth 20%	538	21.43	4.15	334	22.54	0.62	204	19.62	6.29	WDI
INH20	income share held by the highest 20%	538	40.77	9.75	334	39.87	3.73	204	42.26	15.00	WDI

Figure 1a. Robot stocks 2004-2016: full sample

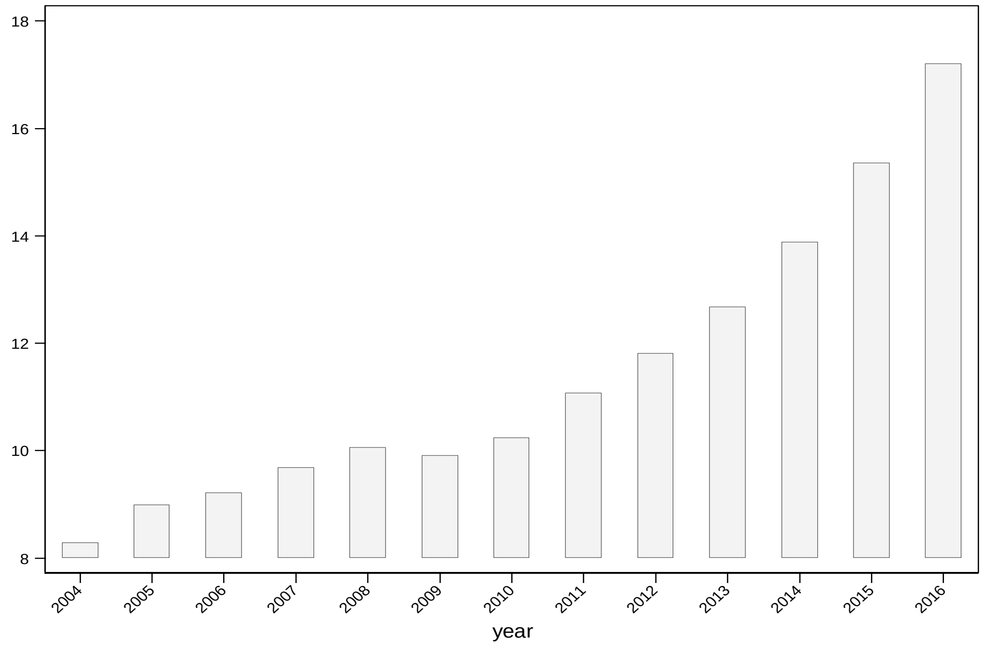
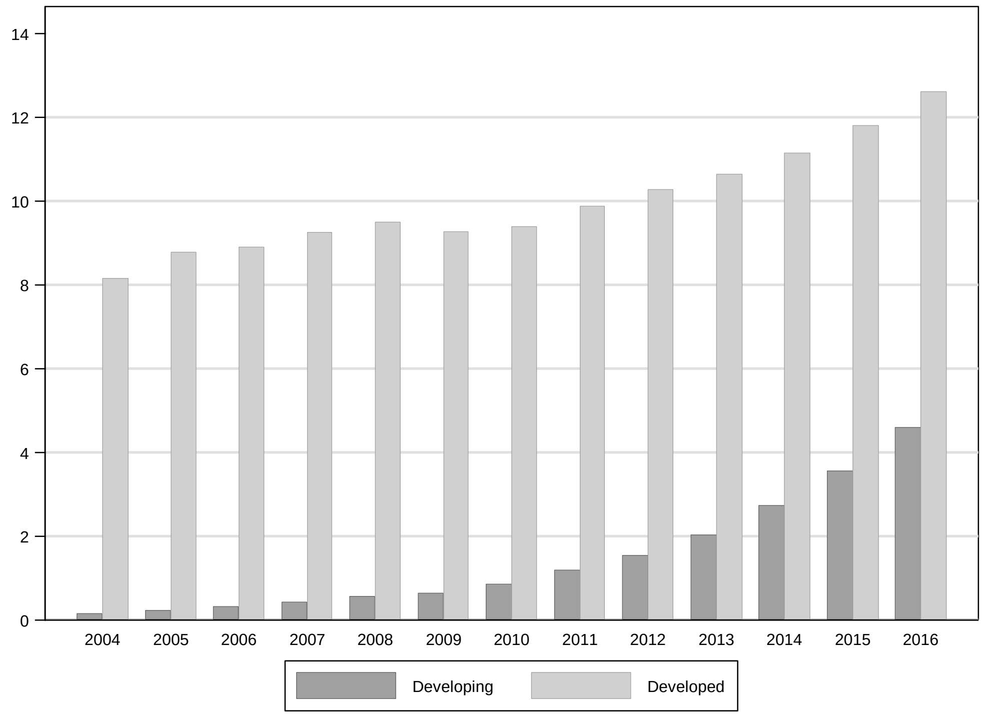


Figure 1b. Robot stocks 2004-2016: developed vs. developing economies



Source: Official website of International Federation of Robotics

Table 2. Robot stock and labour productivity

Dep. Var.: *LNLFP*	(1)	(2)	(3)	(4)	(5)	(6)
	All	Developed	Developing	All	Developed	Developing
LNROBOT	0.037***	0.019***	0.003			
	(0.01)	(0.01)	(0.01)			
L.LNROBOT				0.032***	0.012*	-0.006
				(0.01)	(0.01)	(0.01)
LNSIZE	-0.422***	-0.530***	0.258	-0.412***	-0.515***	0.299
	(0.13)	(0.11)	(0.21)	(0.15)	(0.12)	(0.25)
HCL	0.002***	0.000	0.003***	0.002***	0.000	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EXPORT	-0.002***	0.001	-0.002	-0.002***	0.001	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
constant	17.112***	19.324***	4.471	17.000***	19.130***	3.797
	(2.22)	(1.72)	(3.76)	(2.48)	(1.96)	(4.55)
R^2	1.00	0.99	0.99	1.00	0.99	0.99
No. of Obs.	739	486	253	677	446	231

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 3. Robot stock and labour income of GDP

Dep. Var.: *LIS*	(1)	(2)	(3)	(4)	(5)	(6)
	All	Developed	Developing	All	Developed	Developing
LNROBOT	0.546	0.701*	-1.882			
	(0.42)	(0.42)	(13.70)			
LLNROBOT				-0.022	0.042	-36.300**
				(0.46)	(0.46)	(10.45)
IMPORT	-0.088	-0.063	-0.120	-0.086	-0.057	0.221
	(0.06)	(0.07)	(0.46)	(0.06)	(0.08)	(0.30)
EXPORT	-0.266***	-0.288***	-0.134	-0.299***	-0.314***	0.192
	(0.06)	(0.06)	(0.76)	(0.06)	(0.06)	(0.46)
PWT	-12.360***	-13.826***	-3.812	-16.710***	-17.516***	7.907
	(4.42)	(5.03)	(36.84)	(4.55)	(5.10)	(9.20)
HCL	0.097	0.075	0.131	0.150**	0.145**	-0.988
	(0.06)	(0.06)	(0.76)	(0.07)	(0.07)	(0.51)
LNPATN	-1.051	-0.666	-0.816	-0.710	-0.452	19.652
	(0.81)	(0.83)	(20.33)	(0.94)	(0.96)	(12.20)
_cons	72.004***	72.221***	58.786	73.282***	72.406***	115.838
	(7.91)	(8.57)	(138.23)	(9.99)	(11.29)	(83.08)
R^2	0.96	0.96	0.96	0.97	0.96	0.99
N	220	196	23	191	169	19

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 4. Robot stock and total employment

Dep. Var.: *EMP_TOTAL*	(1) All	(2) Developed	(3) Developing	(4) All	(5) Developed	(6) Developing
LNROBOT	1.186***	1.452***	0.614			
	(0.21)	(0.26)	(0.39)			
L.LNROBOT				0.965***	1.260***	0.231
				(0.23)	(0.29)	(0.46)
GDPGR	0.102***	0.116***	0.129**	0.097***	0.105***	0.132**
	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.06)
LNSIZE	12.806**	15.260***	5.063	11.762*	14.508**	2.413
	(5.52)	(5.69)	(7.83)	(6.49)	(6.63)	(8.85)
EXPORT	-0.060***	-0.080***	0.020	-0.078***	-0.099***	-0.012
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)
IMPORT	0.049**	0.061**	0.026	0.058**	0.074**	0.035
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
POP15	0.221*	0.354*	0.112	0.244*	0.349*	0.094
	(0.13)	(0.19)	(0.27)	(0.15)	(0.21)	(0.30)
constant	-178.509*	-222.221**	-48.384	-160.338	-207.500*	2.742
	(91.71)	(95.30)	(124.88)	(108.48)	(110.93)	(141.57)
R^2	0.96	0.95	0.98	0.96	0.95	0.98
No. of Obs.	707	496	211	654	461	193

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 5. Robot stock and employment by academic background *(EMP_EDU_BAS & EMP_EDU_INT)*

Dep. Var:	*EMP_EDU_BAS*				*EMP_EDU_INT*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Developed	Developing	Developed	Developing	Developed	Developing	Developed	Developing
LNROBOT	1.120**	1.234**			0.759**	1.647**		
	(0.49)	(0.53)			(0.32)	(0.66)		
L.LNROBOT			0.663	1.134**			0.471	1.297**
			(0.53)	(0.55)			(0.36)	(0.57)
GDPGR	0.249***	0.228***	0.236***	0.235***	0.196***	0.248***	0.185***	0.249***
	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	(0.08)	(0.05)	(0.08)
LNSIZE	34.195***	-26.955***	31.813***	-27.850***	13.547**	-15.464	13.814*	-23.087
	(9.49)	(8.60)	(10.71)	(10.63)	(6.65)	(12.95)	(7.57)	(15.28)
EXPORT	-0.168***	-0.129**	-0.189***	-0.146***	-0.127***	-0.105**	-0.141***	-0.142***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)
IMPORT	0.162***	0.139**	0.171***	0.155**	0.122***	0.012	0.135***	0.053
	(0.04)	(0.06)	(0.04)	(0.07)	(0.03)	(0.06)	(0.03)	(0.06)
POP15	0.904**	1.310***	0.914**	1.245***	0.730***	0.421	0.623**	0.471
	(0.36)	(0.39)	(0.39)	(0.41)	(0.24)	(0.43)	(0.26)	(0.40)
constant	-527.769***	468.362***	-486.009***	489.342***	-178.237*	325.793	-172.781	458.930*
	(141.91)	(136.91)	(161.69)	(171.39)	(101.06)	(205.12)	(115.99)	(250.00)
R^2	0.84	0.96	0.84	0.96	0.75	0.93	0.77	0.92
No. of Obs.	445	203	413	187	452	192	419	177

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 6. Robot stock and employment by gender

Dep. Var.:	*EMP_MALE*				*EMP_FEMALE*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Developed	Developing	Developed	Developing	Developed	Developing	Developed	Developing
LNROBOT	1.478***	0.897**			1.547***	0.403		
	(0.29)	(0.39)			(0.35)	(0.42)		
L.LNROBOT			1.291***	0.447			1.386***	0.082
			(0.32)	(0.48)			(0.41)	(0.49)
GDPGR	0.147***	0.119**	0.135***	0.128**	0.080**	0.136**	0.072**	0.135**
	(0.05)	(0.06)	(0.04)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)
LNSIZE	3.349	-14.797*	1.590	-16.045*	42.230**	24.073***	46.249**	20.213**
	(4.52)	(7.88)	(5.12)	(8.84)	(17.26)	(8.42)	(20.18)	(9.76)
EXPORT	-0.132***	-0.011	-0.154***	-0.045	-0.015	0.041	-0.026	0.010
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)
IMPORT	0.111***	0.073	0.124***	0.090*	0.046	-0.017	0.062	-0.015
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
POP15	0.316*	0.339	0.294	0.255	0.528	-0.131	0.559	-0.099
	(0.18)	(0.29)	(0.19)	(0.34)	(0.39)	(0.27)	(0.42)	(0.30)
constant	-19.351	296.086**	12.784	326.966**	-680.554**	-376.494***	-746.001**	-307.481*
	(66.71)	(125.14)	(75.88)	(140.77)	(302.84)	(135.16)	(351.16)	(157.44)
R^2	0.92	0.99	0.92	0.99	0.94	0.99	0.94	0.99
No. of Obs.	494	211	459	193	495	211	460	193

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 7. Robot stock and income inequality

Dep. Var.: *GINI*	(1) All	(2) Developed	(3) Developing	(4) All	(5) Developed	(6) Developing
LNROBOT	-0.154	0.120	0.716***			
	(0.16)	(0.22)	(0.23)			
L.LNROBOT				-0.209	0.171	0.674***
				(0.15)	(0.23)	(0.22)
EXPORT	0.016	-0.031*	0.043**	0.011	-0.037**	0.055**
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
EMP_AGR	-0.011	0.170	-0.187**	0.011	0.144	-0.160**
	(0.06)	(0.10)	(0.07)	(0.06)	(0.12)	(0.07)
EMP_IND	-0.333***	-0.291***	-0.452***	-0.329***	-0.269***	-0.384***
	(0.06)	(0.07)	(0.11)	(0.07)	(0.08)	(0.11)
LNGOV	-0.008	-1.993	-0.884	0.133	-1.821	-0.340
	(1.07)	(1.54)	(1.24)	(1.19)	(1.78)	(1.25)
GDPGR	0.049*	0.020	0.154***	0.048*	0.024	0.156***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Constant	43.152*	88.330**	70.315**	39.889	83.606*	54.608*
	(25.62)	(37.67)	(29.07)	(28.70)	(43.10)	(29.81)
R^2	0.98	0.95	0.99	0.98	0.96	0.99
No. of Obs.	481	327	154	444	302	142

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix A. List of sample economies

Developed economies(45)			Developing economies(29)	
Argentina	Iceland	Portugal	Belarus	Peru
Australia	Ireland	Puerto Rico	Bosnia and Herzegovina	Philippines
Austria	Israel	Qatar	Brazil	Romania
Belgium	Italy	Saudi Arabia	Bulgaria	Russian
Canada	Japan	Singapore	China	Serbia
Chile	Korea, Rep.	Slovak	Colombia	South Africa
Croatia	Kuwait	Slovenia	Egypt	Thailand
Czech Republic	Latvia	Spain	India	Tunisia
Denmark	Lithuania	Sweden	Indonesia	Turkey
Estonia	Macao SAR, China	Switzerland	Iran	Ukraine
Finland	Malta	United Arab Emirates	Korea, Dem.	Uzbekistan
France	Netherlands	United Kingdom	Malaysia	Venezuela
Germany	New Zealand	United States	Mexico	Vietnam
Greece	Norway		Moldova	
Hong Kong SAR, China	Oman		Morocco	
Hungary	Poland		Pakistan	

Appendix B. Correlation matrix

Panel A:	LNLFP	LNROBOT	LNSIZE	HCL	EXPORT
LNLFP	1.00				
LNROBOT	0.37	1.00			
LNSIZE	-0.41	0.45	1.00		
HCL	0.64	0.34	-0.34	1.00	
EXPORT	0.27	-0.11	-0.54	0.18	1.00

Panel B:	LIS	LNROBOT	IMPORT	EXPORT	PWT	HCL	LNPATN
LIS	1.00						
LNROBOT	0.45	1.00					
IMPORT	0.03	-0.33	1.00				
EXPORT	0.08	-0.14	0.75	1.00			
PWT	-0.34	-0.07	-0.02	-0.05	1.00		
HCL	0.31	0.23	0.08	0.33	-0.18	1.00	
LNPATN	0.35	0.75	-0.57	-0.43	-0.10	-0.04	1.00

Panel C:	GINI	LNROBOT	EXPORT	EMP_AGR	EMP_IND	LNGOV	GDPGR
GINI	1						
LNROBOT	-0.13	1.00					
EXPORT	-0.44	-0.06	1.00				
EMP_AGR	0.30	-0.38	-0.20	1.00			
EMP_IND	-0.25	0.04	0.22	-0.18	1.00		
LNGOV	0.15	0.78	-0.42	-0.33	-0.19	1.00	
GDPGR	0.20	-0.24	0.06	0.24	0.05	-0.19	1.00

Panel D:	EMP_TO~L	EMP_ED~B	EMP_ED~V	EMP_ED~S	EMP_ED~T	EMP_MALE	EMP_FE~L	LNROBOT	GDPGR	LNSIZE	EXPORT	IMPORT	POP15
EMP_TOTAL	1.00												
EMP_EDU_LTB	0.26	1.00											
EMP_EDU_ADV	0.55	0.00	1.00										
EMP_EDU_BAS	0.55	0.77	0.24	1.00									
EMP_EDU_INT	0.69	0.30	0.67	0.73	1.00								
EMP_MALE	0.81	0.47	0.28	0.73	0.64	1.00							
EMP_FEMAL	0.87	0.00	0.62	0.24	0.53	0.42	1.00						
LNROBOT	0.13	-0.06	0.22	-0.03	0.11	-0.04	0.24	1.00					
GDPGR	0.17	0.10	0.12	0.18	0.17	0.27	0.04	-0.18	1.00				
LNSIZE	0.12	0.40	-0.03	0.30	0.07	0.40	-0.15	0.36	0.01	1.00			
EXPORT	0.18	-0.15	0.22	-0.02	0.22	-0.01	0.29	0.02	0.10	-0.49	1.00		
IMPORT	-0.01	-0.19	0.14	-0.08	0.15	-0.16	0.12	-0.06	0.04	-0.42	0.88	1.00	
POP15	0.12	-0.13	0.14	-0.07	0.12	-0.12	0.29	-0.01	0.10	-0.43	0.49	0.51	1.00

Appendix C. Robot stock and labour productivity (excluding China, Japan, and Korea)

Dep. Var.: *LNLFP*	(1)	(2)	(3)	(4)	(5)	(6)
	All	Developed	Developing	All	Developed	Developing
LNROBOT	0.036***	0.020***	0.003			
	(0.01)	(0.01)	(0.01)			
LLNROBOT				0.031***	0.013*	-0.007
				(0.01)	(0.01)	(0.01)
LNSIZE	-0.411***	-0.531***	0.410**	-0.392***	-0.516***	0.519**
	(0.13)	(0.11)	(0.20)	(0.15)	(0.12)	(0.24)
HCL	0.002***	0.000	0.002***	0.002***	0.000	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EXPORT	-0.002***	0.001	-0.001	-0.002**	0.001	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
_cons	16.930***	19.272***	1.895	16.667***	19.076***	0.012
	(2.23)	(1.72)	(3.55)	(2.52)	(1.96)	(4.21)
R^2	1.00	0.99	0.99	1.00	0.99	0.99
N	707	462	245	647	424	223

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix D. Robot stock and labour income of GDP (excluding China, Japan, and Korea)

Dep. Var.: *LIS*	(1)	(2)	(3)	(4)	(5)	(6)
	All	Developed	Developing	All	Developed	Developing
LNROBOT	0.527	0.699	-1.882			
	(0.43)	(0.44)	(13.70)			
LLNROBOT				-0.094	-0.017	-36.300**
				(0.48)	(0.47)	(10.45)
IMPORT	-0.085	-0.064	-0.120	-0.092	-0.071	0.221
	(0.06)	(0.07)	(0.46)	(0.06)	(0.08)	(0.30)
EXPORT	-0.267***	-0.290***	-0.134	-0.303***	-0.317***	0.192
	(0.07)	(0.07)	(0.76)	(0.07)	(0.07)	(0.46)
PWT	-11.842**	-13.246**	-3.812	-16.487***	-17.091***	7.907
	(4.63)	(5.28)	(36.84)	(4.78)	(5.32)	(9.20)
HCL	0.100*	0.079	0.131	0.158**	0.154**	-0.988
	(0.06)	(0.06)	(0.76)	(0.07)	(0.07)	(0.51)
LNPATN	-1.105	-0.735	-0.816	-0.847	-0.641	19.652
	(0.85)	(0.87)	(20.33)	(0.97)	(0.99)	(12.20)
_cons	71.347***	71.903***	58.786	73.838***	73.316***	115.838
	(8.15)	(8.86)	(138.23)	(10.21)	(11.55)	(83.08)
R^2	0.96	0.95	0.96	0.96	0.96	0.99
N	206	182	23	179	157	19

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix E. Robot stock and total employment (excluding China, Japan, and Korea)

Dep. Var.: *EMP_TOTAL*	(1) All	(2) Developed	(3) Developing	(4) All	(5) Developed	(6) Developing
LNROBOT	1.213***	1.491***	0.614			
	(0.22)	(0.27)	(0.39)			
LLNROBOT				1.004***	1.307***	0.231
				(0.24)	(0.30)	(0.46)
GDPGR	0.102***	0.114***	0.129**	0.097***	0.103***	0.132**
	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.06)
LNSIZE	13.119**	15.482***	5.063	12.140*	14.826**	2.413
	(5.51)	(5.56)	(7.83)	(6.51)	(6.54)	(8.85)
EXPORT	-0.054**	-0.069***	0.020	-0.073***	-0.089***	-0.012
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
IMPORT	0.044**	0.051**	0.026	0.054**	0.065**	0.035
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
POP15	0.280*	0.508**	0.112	0.290*	0.465*	0.094
	(0.14)	(0.23)	(0.27)	(0.16)	(0.25)	(0.30)
_cons	-186.970**	-234.632**	-48.384	-169.207	-218.970**	2.742
	(91.97)	(93.99)	(124.88)	(109.20)	(110.47)	(141.57)
R^2	0.96	0.95	0.98	0.96	0.95	0.98
N	681	470	211	630	437	193

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix F. Robot stock and employment by academic background *(EMP_EDU_BAS & EMP_EDU_INT)* (excluding China, Japan & Korea)

	EMP_EDU_BAS				*EMP_EDU_INT*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Developing	Developed	Developed	Developing	Developing	Developed	Developed	Developing
LNROBOT	1.120**	1.234**			0.785**	1.647**		
	(0.49)	(0.53)			(0.32)	(0.66)		
LLNROBOT			0.663	1.134**			0.497	1.297**
			(0.53)	(0.55)			(0.37)	(0.57)
GDPGR	0.249***	0.228***	0.236***	0.235***	0.197***	0.248***	0.185***	0.249***
	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	(0.08)	(0.05)	(0.08)
LNSIZE	34.195***	-26.955***	31.813***	-27.850***	13.886**	-15.464	14.226*	-23.087
	(9.49)	(8.60)	(10.71)	(10.63)	(6.67)	(12.95)	(7.62)	(15.28)
EXPORT	-0.168***	-0.129**	-0.189***	-0.146***	-0.125***	-0.105**	-0.139***	-0.142***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)
IMPORT	0.162***	0.139**	0.171***	0.155**	0.121***	0.012	0.133***	0.053
	(0.04)	(0.06)	(0.04)	(0.07)	(0.03)	(0.06)	(0.03)	(0.06)
POP15	0.904**	1.310***	0.914**	1.245***	0.769***	0.421	0.668**	0.471
	(0.36)	(0.39)	(0.39)	(0.41)	(0.24)	(0.43)	(0.27)	(0.40)
_cons	-527.769***	468.362***	-486.009***	489.342***	-186.151*	325.793	-182.288	458.930*
	(141.91)	(136.91)	(161.69)	(171.39)	(101.38)	(205.12)	(116.82)	(250.00)
R^2	0.84	0.96	0.84	0.96	0.75	0.93	0.77	0.92
N	445	203	413	187	447	192	414	177

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix G. Robot stock and employment by gender (excluding China, Japan, and Korea)

	EMP_MALE				*EMP_FEMAL*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Developed	Developing	Developed	Developing	Developed	Developing	Developed	Developing
LNROBOT	1.520***	0.897**			1.588***	0.403		
	(0.30)	(0.39)			(0.36)	(0.42)		
LLNROBOT			1.350***	0.447			1.430***	0.082
			(0.33)	(0.48)			(0.42)	(0.49)
GDPGR	0.146***	0.119**	0.134***	0.128**	0.076**	0.136**	0.067*	0.135**
	(0.05)	(0.06)	(0.05)	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)
LNSIZE	3.725	-14.797*	2.081	-16.045*	42.778**	24.073***	46.911**	20.213**
	(4.63)	(7.88)	(5.26)	(8.84)	(16.68)	(8.42)	(19.56)	(9.76)
EXPORT	-0.126***	-0.011	-0.151***	-0.045	0.008	0.041	-0.001	0.010
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)
IMPORT	0.104***	0.073	0.118***	0.090*	0.031	-0.017	0.045	-0.015
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
POP15	0.379*	0.339	0.309	0.255	0.873*	-0.131	0.882	-0.099
	(0.21)	(0.29)	(0.22)	(0.34)	(0.53)	(0.27)	(0.56)	(0.30)
_cons	-29.458	296.086**	3.918	326.966**	-708.424**	-376.494***	-773.844**	-307.481*
	(67.57)	(125.14)	(77.26)	(140.77)	(300.39)	(135.16)	(347.86)	(157.44)
R^2	0.92	0.99	0.92	0.99	0.94	0.99	0.94	0.99
N	468	211	435	193	469	211	436	193

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix H. Robot stock and income inequality (excluding China, Japan, and Korea)

Dep. Var.: *GINI*	(1)	(2)	(3)	(4)	(5)	(6)
	All	Developed	Developing	All	Developed	Developing
LNROBOT	0.021	0.543**	0.694***			
	(0.17)	(0.23)	(0.23)			
LLNROBOT				-0.095	0.516**	0.666***
				(0.15)	(0.24)	(0.21)
EXPORT	-0.001	-0.064***	0.040**	-0.002	-0.069***	0.053**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
EMP_AGR	-0.025	0.147	-0.187***	-0.002	0.124	-0.161**
	(0.06)	(0.11)	(0.07)	(0.06)	(0.12)	(0.07)
EMP_IND	-0.281***	-0.206***	-0.456***	-0.285***	-0.197**	-0.384***
	(0.06)	(0.08)	(0.11)	(0.07)	(0.09)	(0.11)
LNGOV	-1.480***	-3.273***	-0.549	-1.151*	-3.002***	-0.214
	(0.57)	(0.84)	(0.75)	(0.61)	(0.94)	(0.74)
GDPGR	0.056**	0.026	0.152***	0.054**	0.029	0.156***
	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
_cons	77.724***	116.498***	62.525***	70.339***	110.223***	51.648***
	(13.52)	(19.84)	(17.83)	(14.55)	(22.18)	(17.76)
R^2	0.98	0.96	0.99	0.98	0.96	0.99
N	477	323	154	440	298	142

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Appendix I. Robot stock and income decile

Dep. Var.: *INL20*	decile (0, 20%]						(80%, 100%]					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	All	Developed	Developing	All	Developed	Developing	All	Developed	Developing	All	Developed	Developing
LNROBOT	0.066	-0.137**	-0.145				0.262	0.395**	0.645			
	(0.05)	(0.06)	(0.09)				(0.27)	(0.19)	(0.68)			
LLNROBOT				0.088*	-0.146**	-0.096				0.258	0.346*	1.194*
				(0.05)	(0.06)	(0.08)				(0.24)	(0.19)	(0.65)
EXPORT	-0.002	0.018***	-0.016**	-0.002	0.019***	-0.018**	-0.014	-0.044***	0.005	-0.014	-0.047***	0.027
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.05)	(0.02)	(0.02)	(0.05)
EMP_AGR	0.044	-0.058**	0.091**	0.040	-0.044*	0.084*	-0.009	0.116	-0.003	0.009	0.099	0.023
	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.05)	(0.26)	(0.09)	(0.41)	(0.30)	(0.10)	(0.43)
EMP_IND	0.112***	0.073***	0.184***	0.123***	0.073***	0.184**	-0.032	-0.136**	0.288	0.008	-0.124*	0.467
	(0.03)	(0.02)	(0.06)	(0.03)	(0.02)	(0.07)	(0.21)	(0.06)	(0.58)	(0.24)	(0.07)	(0.63)
LNGOV	0.307	1.110***	-0.091	0.216	1.112***	-0.243	-1.650	-2.169***	-1.503	-1.635	-1.877**	-1.918
	(0.21)	(0.18)	(0.28)	(0.24)	(0.21)	(0.31)	(1.55)	(0.72)	(2.39)	(1.79)	(0.79)	(2.71)
GDPGR	-0.005	0.012	-0.059***	-0.004	0.010	-0.059***	0.091***	0.039*	0.020	0.089***	0.042**	0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.09)	(0.03)	(0.02)	(0.10)
_cons	-4.185	-21.191***	2.787	-2.377	-21.327***	6.460	80.544***	95.615***	66.947	79.035**	88.738***	68.163
	(4.68)	(4.14)	(5.90)	(5.31)	(4.77)	(6.64)	(30.28)	(17.32)	(42.74)	(35.72)	(18.73)	(49.49)
R^2	0.95	0.97	0.93	0.95	0.97	0.93	0.88	0.95	0.88	0.87	0.95	0.87
N	502	327	175	464	302	162	502	327	175	464	302	162

*Notes: Figures in parentheses are country-level clustered standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Due to space limitations, the estimated results of the impact of robot adoption on income in other ranges of income deciles are available upon request.*