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Robotics Technology and Firm-level Employment Adjustment in Japan

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Abstract: *Unlike studies that analyse the impact of robotics technology on employment at the industry or firm level, this study investigates cross-division employment adjustment within a firm in an industry with large penetration and diffusion of robotics technology. By examining the changes in the composition of employment, we measured job creation and destruction at the division level and explored whether robotics technology, as a leading example of automation, not only displaces workers but also introduces new jobs in favour of labour. We made use of unique, division-level employment data for Japan's manufacturing firms, together with industry-level data on the installation of industrial robots. We found that industry-level adoption of robots positively affects the rates of firm-level job creation and job destruction. Because the magnitude of the impact is larger for job destruction, robot adoption has an overall negative impact on firms' net employment growth. Our finding suggests that the labour displacement effect of robotics technology and the emergence of new jobs due to technological change coexist even at the firm level.*

Keywords: firm-level data; robot; job creation; job destruction.
JEL Classification: F15; F23

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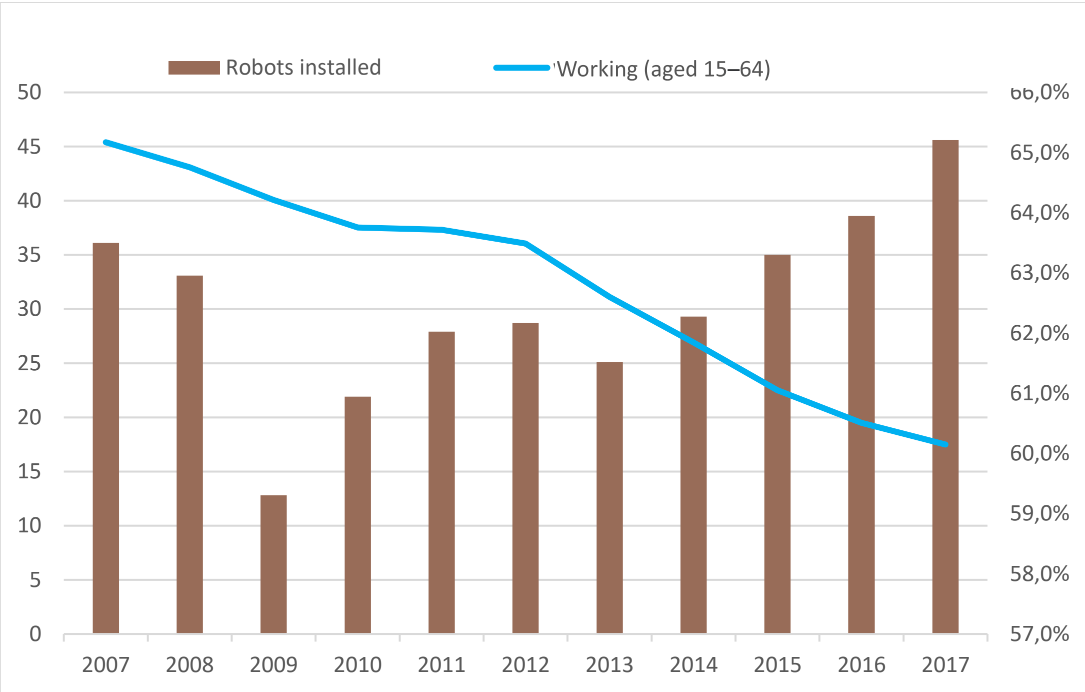
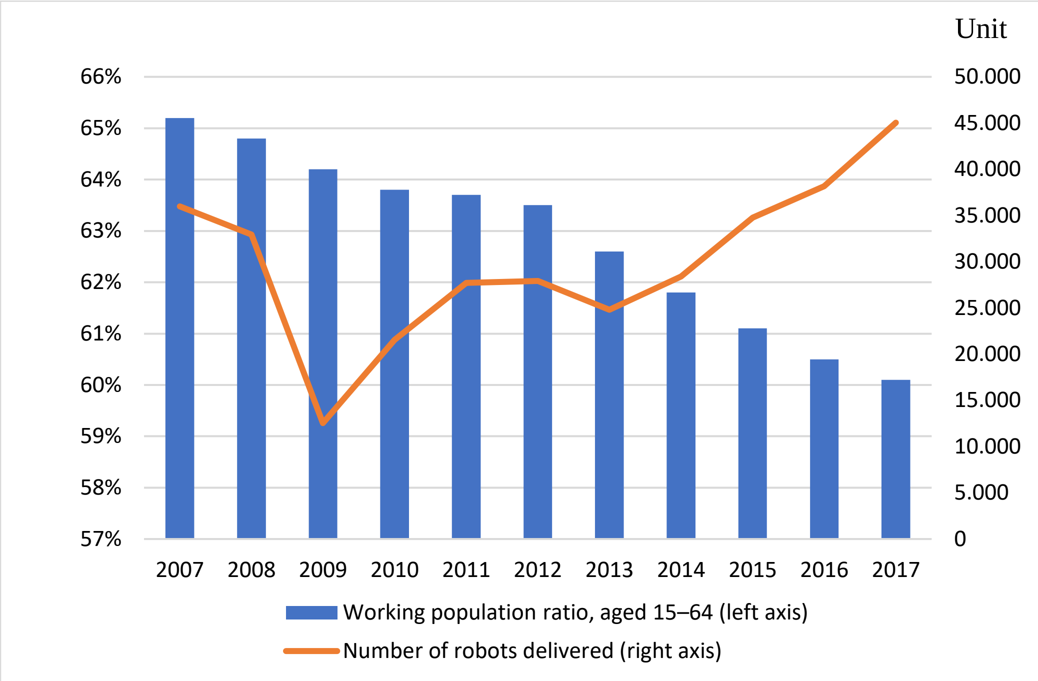
1. Introduction

Many industries are on the verge of a second digital revolution known as the fourth industrial revolution (Makridakis, 2017). With the challenges arising from an ageing society and labour shortage, especially in advanced economies, industrial digitalisation, robotics technology, and artificial intelligence will play a significant role in helping countries make the transition. Figure 1 shows a clear growing trend of installation of industrial robots together with a downward trend of the working population ratio. The utilisation of robotics technology seems inevitable in Japan and in other highly mature economies.

Figure 1. Robots Installed and Working Population in Japan





Source: Authors' calculation using data for industrial robots (World Robotics database) and working population ratio (Federal Reserve Economic Data).

The adoption of industrial robots or automation can help Japan's industries ease the burden, but the acceleration of automated tasks that used to be performed by labour raises concerns that new technologies will make labour redundant (e.g. Brynjolfsson and McAfee [2012], Akst [2014], Autor [2015]). The main cause of concern is the replacement of humans by machines and other technology to perform certain types of jobs. Technology could make the production process more capital-intensive by automating labour-intensive tasks. The loss of advantage conferred by cheap labour might result in concentrated production tasks in developed countries. Therefore, countries that specialise in the labour-intensive part of the supply chain might see jobs evaporate. Within an industry, routine workers, who are more likely to be replaced by robots, are more prone to job loss.

If we go a step further and examine the within-firm labour structure, the situation is even more complicated. Manufacturing firms usually have different divisions with various functions: sales, marketing, production, research and development (R&D), and administration, amongst others. In some divisions such as R&D, it is common practice for firms to hire the most talented workers, while in production or assembly divisions, firms tend to recruit ‘unskilled’ workers. In other divisions, workers with different skill levels are mixed. Most studies tended to look at net employment growth of firms and failed to identify within-firm labour dynamics caused by automation. Since the net employment growth is the difference between total job creation and job destruction within a firm, detecting the overall impact does not necessarily mean job creation and job destruction occurring in the same direction. Thus, the conventional argument on the substitution or complementation relationship between labour and automation for skilled or unskilled categorisations cannot be simply applied if we use overall labour changes. This study will fill this blank by separating job creation from job destruction and investigate whether automation affects them in different ways.

Unlike the literature, this study defines job creation as the aggregated number of newly added jobs for all divisions within a firm, and job destruction as the aggregated number of newly eliminated jobs for all divisions. One obvious advantage of such a measurement is that the individual impact of foreign direct investment on job creation and destruction can be captured, which helps elucidate firm’s decision-making from different perspectives.

The next section reviews related literature. Section 3 describes the data. Section 4 introduces the estimation strategy. Section 5 shows the estimation results. Section 6 provides the robustness check. The final section offers conclusions and policy recommendations.

2. The Literature and the Contribution of This Study

This study is broadly related to the literature on the implications of technological change for employment, wages, and productivity (see Acemoglu and Autor [2011] for a survey). Although how the introduction of new technology transforms the labour market is not a new question, the ongoing process of automation such as advances in robotics technology has triggered renewed concern about massive joblessness. Frey and Osborne (2017), for example, estimated that 47% of total United States (US) employment is in occupations that are potentially automatable in a decade or two. The argument about which jobs are susceptible to automation, however, does not speak to the equilibrium impact because it overlooks how other industries and occupations will respond to the changes (Acemoglu and Restrepo, 2020). The equilibrium impact on employment and wages of automation technologies, and especially the increased use of industrial robots, was recently investigated, theoretically and empirically, in a series of papers by Acemoglu and Restrepo (2018, 2019, 2020).

Acemoglu and Restrepo (2018) made the first attempt to develop a task-based framework to study the implications of automation technology for the labour market. Their conceptual innovation was to propose a theoretical model in which tasks previously performed by labour are automated ('displacement effect'), whilst new technologies introduce new tasks in which labour has comparative advantage ('reinstatement effect'). The authors presumed that automation, together with the associated introduction of new tasks, impacts the task content of production by changing the allocation of tasks to factors of production. Such presumption is consistent with what we are witnessing amidst rapid automation due to advances in robotics technology: whilst the tasks of production workers are being performed by industrial robots, tasks are emerging related to programming, design, maintenance, and other more specialised tasks (Acemoglu and Restrepo, 2019). Acemoglu and Restrepo (2018) documented the fact that about half of employment growth in the US over 1980–2015 took place in occupations with new job titles or tasks.

Based on the task-based framework, Acemoglu and Restrepo accumulated empirical evidence supporting the relative importance of the displacement effect for industrial robots – as a leading example of automation technology – unlike capital deepening or other types of factor-augmenting technologies. Acemoglu and Restrepo (2020) showed that industrial robots are associated with lower labour share and labour demand at the industry level and lower labour demand in local labour markets exposed to the technology in the US. Acemoglu and Restrepo (2019) showed that the sluggish growth of US employment over the last 3 decades is accounted for by a stronger displacement effect, especially in manufacturing, and a considerably weaker reinstatement effect than in previous decades.

Applying the empirical methodology of Acemoglu and Restrepo (2020), the local labour market effects of industrial robots were studied in Japan (Adachi et al., 2020) and Germany (Dauth et al., 2018). Unlike in the US, both studies found no significant effect of industrial robots on total employment in local markets. Looking into changes in the composition of employment, Adachi et al. (2020) detected a positive correlation between exposure to robotics technology and demand for production workers in Japan's local labour markets. In contrast, Dauth et al. showed that robots led to job losses in manufacturing, which were offset by the expansion of business service industries in Germany's local labour markets. Instead of exploring the local labour market effect, Graetz and Michaels (2018) conducted cross-country cross-industry comparisons and found that industrial robots did not reduce overall employment but significantly reduced employment of low-skilled workers.

Departing from the aggregate equilibrium impacts of industrial robots, a handful of studies recently explored the mechanisms and adjustment processes at the level of firms (e.g., Koch et al. [2019]) and workers (Dauth et al., 2018). Using a rich dataset of manufacturing firms in Spain, Koch et al. estimated the effect of robotics technology on firm-level outcomes, including employment, and showed that robot-adopting firms raised the number of workers in high- and low-skilled groups. Using employer–employee data in Germany, Dauth et al. analysed the impact of robotics technology on individual workers and found that workers in manufacturing industries with larger diffusion of robotics technology were more likely to continue working with the original employer. The authors found that many incumbent workers responded to technological change by performing more diverse occupations at their original workplace than before, which suggests the importance of within-firm employment adjustment to the change.

This study contributes to the literature by shedding light on the impact of industrial robots on the creation and destruction of jobs across different groups of activities or divisions within a manufacturing firm. We analyse whether a manufacturing firm in an industry with larger diffusion of robotics technology simultaneously expanded or shrank employment in different production and non-production divisions. Our firm-level study complements the worker-level evidence of Dauth et al. (2018) by presenting additional supporting evidence of significant within-firm employment adjustment to robotics technology. Our findings of massive job creation as well as destruction can be interpreted through the lens of

Acemoglu and Restrepo's task-based framework, and suggest that robotics technology not only displaces some workers from their original job titles or tasks but also simultaneously brings in a set of new tasks in favour of labour even at the firm level.

To examine within-firm employment adjustment in response to industry-level robotics technology diffusion, we used division-level employment data for manufacturing firms obtained from the Basic Survey of Japanese Business Structure and Activities (BSJBSA). We not only looked at overall change in employment at the firm level but also paid attention to the simultaneous expansion and shrinkage of employment in different divisions even within a single firm, in line with Liu (2018) and Liu and Bin (2018).

The standard measurement of job creation is the aggregation of net employment increases across all establishments that expand employment, and of job destruction the aggregation of net employment decreases across all establishments that downsize (see Davis et al. [1996]). Aggregations are typically done by industry or by the group of establishments (or firms) in terms of the firm size, extent of internationalisation, and so on. Gross job flows are the sum of job creation and destruction, and net job flows are their difference.

In Japan's context, for example, Ando and Kimura (2015) and Kodama and Inui (2015) applied the above measurements to analyse the effect of foreign direct investment on gross and net changes in domestic employment. These and most related studies might have underestimated actual employment adjustment because they overlooked the jobs created and destroyed within a firm. The exceptions are Ando and Kimura (2017), Liu (2018), and Liu and Bi (2018), who calculated job creation (destruction) at the firm level by aggregating net employment increases (decreases) across the expanding (downsizing) divisions. To better approximate employment adjustment by manufacturing firms in Japan, we follow the latter strand of related literature.

To be more precise, we employed the measurements of job creation and destruction originally proposed by Liu (2018), using the BSJBSA. Within a manufacturing firm, we considered the net changes in employment in divisions, including not only production but also non-production divisions such as R&D and commercial activities. Unlike Moser et al. (2010), who used establishment data from Germany, we could not identify a new hire from outside one firm or any separation of a worker from the firm at the division level by using the BSJBSA. More importantly, however, our measurements of job creation and destruction captured within-firm inflows and outflows of workers across divisions in addition to employment reallocation across firms. The cross-division employment adjustment involved incumbent workers performing different tasks under different occupations than before. This is of interest to us in examining how firms respond to the diffusion of robotics technology at the industry level.

3. Data

3.1. Data Source

We combined data from two separate sources. First, firm-level data was obtained from the BSJBSA, which is conducted annually by the Ministry of Economy, Trade, and Industry. The survey's response rate is over 80% with about 30,000 firms completing the questionnaire each year. The BSJBSA's scope covers almost all medium-sized and large firms in Japan and includes smaller firms that employ 50 or more workers and have ¥30 million or more worth of capital. We focused our analysis on manufacturing firms in operation from 1996 to 2017.

We used detailed information on the composition of employment: the respondent firm reported the total number of 'full-time workers' broken down into different divisions by function for corporate headquarters or main office (headquarter-function and operations sections) and for affiliated establishments (domestic only).[1][2] The headquarter-function section is disaggregated into five divisions: planning; information processing; R&D; international business; and other headquarter functions (e.g. accounting, human resource management). The operations section is disaggregated into six divisions: manufacturing, mining, electricity, and gas; commercial business; eating and drinking places; information and communications; service business; and other operational functions. The affiliated establishments have eight divisions: manufacturing, mining, electricity and gas; commercial business; eating and drinking places; information and communications; service business; research institutions; warehouse, transportation, and distribution; and other functions.

We presumed that workers were performing different sets of tasks or jobs in different divisions. Although tasks might be diverse even within a division, we supposed that cross-division variations of tasks were much more diverse than within-division variations. If the number of workers declined in some divisions (i.e. job destruction) whilst the number of workers increased in the others (job creation), we interpret such dual changes in the composition of employment as suggesting that job displacement was accompanied by the introduction of new jobs.

[1] The BSJBSA defines 'full-time workers' as those who have been employed for a period unspecified or at least 1 month. Full-time workers include regular employees, regular staff members, part-timers, and casual employees. For example, 'temporary workers' are employed for less than 1 month or brought in on a daily basis and are not, therefore, full-time workers.

[2] The hours worked are not reported by division.

Second, the data for industrial robots were obtained from the International Federation of Robotics (IFR, 2018) World Robotics database, which has received increasing attention in recent studies: e.g. a pioneering study of Graetz and Michaels (2018), followed by Acemoglu and Restrepo (2019, 2020) and Dauth et al. (2018). The database provided the number of industrial robots delivered ('flow') and the number in operation ('operational stock') by country and industry from 1993 onwards. The industrial robots under the IFR's definition are 'an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which might be either fixed in place or mobile for use in industrial automation applications' as defined by ISO 8373.

All the data on Japan reported in World Robotics was based on domestic shipment statistics by demand industry, which was originally provided by the Japan Robot Association (JARA). The original JARA documents (JARA, 2012–2018) showed only the number of industrial robots delivered domestically. In contrast, World Robotics reported the number of delivered robots, which included not only domestic shipments but also imports. The IFR appears to have estimated the imported figures based on its own information collected from global major manufacturers of industrial robots.[3] The original JARA documents did not report operational stock data. Upon the request from the IFR for the operational stock figures, the JARA arbitrarily calculated the stock of robots as the total number of delivered robots in the past 10 years.[4]

[3] JARA domestic shipment data are available in a consistent format only from 2001. For data on Japan before 2001 reported in World Robotics, the IFR appears to have substantially manipulated data to obtain the estimated figures, although IFR documents offered no explanation on this matter.

[4] In the World Robotics database, operational stock was simply calculated as the total number of delivered robots in the past 12 years for most of the sample countries. There is no clear explanation why the JARA chose 10 instead of 12 years to consider robot depreciation.

As our main variable of interest, we used the flow data of the number of delivered robots rather than the operational stock data. This is because, due to the arbitrary calculation, Japan's operational stock was almost unchanged from the early 1990s through the 2000s, and declined continuously after 2010. Our sample period extended to 2017, so operational stock figures beyond 2010 were significantly lower because of the global financial crisis of 2008–2009. Such a measurement issue would underestimate the dynamics of industries utilising industrial robots, especially in the 2010s. Thus, we believe that the flow data of delivered robots is a better measurement to capture the penetration of robotics technology.

We relied mainly on the flow data of the number of delivered robots obtained from the World Robotics online database. We also manually collected data on the value of domestically delivered robots from JARA publications (JARA, 2012–2018) to check for robustness.[5] Unlike World Robotics, the JARA reported not only the units but the total monetary values (in yen) of domestically delivered robots by demand industry. The value information reflected the relative magnitude of investments in robotics technology that could be compared across industries as well as over time, although it was available only for domestic shipments.[6]

Data on industrial robots were organised at the industry level according to the latest version of International Standard Industrial Classification (ISIC), Revision 4. We constructed the robot flow measure at the 2-digit level of the ISIC, Revision 4 across years, which was matched with firm-level employment data.

[5] For the robustness check, we used 'robot density', which is the number of industrial robots in operation (i.e. operational stock) per 1,000 persons employed and is often used in the related literature. To calculate robot density, we obtained data for total employment by country and industry from the Organisation for Economic Co-operation and Development Structural Analysis database, and data for stock of operational robots by country and industry from the World Robotics database.

[6] More sophisticated robots have recently entered the market, taking the place of simple ones.

4. Empirical Methodology and Identification Strategy

4.1. Job Creation and Destruction

The idea of calculating job creation and destruction is similar to that of Davis and Haltiwanger (1999); the essential difference is that our calculations are at the division level. First, the magnitude of job creation in firm *i* in year *t* is defined as the sum of all new jobs in expanding divisions of firm *i* in year *t*:

$$JC_{i,t} = \sum_{d=1}^{S} \Delta N_{i,d,t}^{C}$$

with

$$\Delta N_{i,d,t}^{C} = N_{i,d,t} - N_{i,d,t-1} \text{ ,}$$

conditioned on

$$N_{i,d,t} - N_{i,d,t-1} < 0,$$

where *d* denotes each division of firm *i* and *S* is the total number of divisions in firm *i*. $N_{i,d,t}$ is the number of workers employed in division *d* of firm *i* in year *t*.

Similarly, the magnitude of job destruction in firm *i* in year *t* is defined as the sum of all disappeared jobs in downsizing divisions of firm *i* in year *t*, represented as follows:

$$JD_{i,t} = \sum_{d=1}^{S} \Delta N_{i,d,t}^{D}$$

with

$$\Delta N_{i,d,t}^{D} = -(N_{i,d,t} - N_{i,d,t-1}),$$

conditioned on

$$N_{i,d,t} - N_{i,d,t-1} < 0.$$

In general, the average level of JD is higher than that of JC, which leads to on average negative net employment growth in most manufacturing industries.[7] This is in accordance with the trend that the total number of employees in manufacturing is shrinking. The exceptions are 'automotive' and 'electrical equipment', where continued and increased need for labour persists.

4.2. Data Overview of Job Creation, Job Destruction, and Robotics Technology

Figure 2 compares the calculated job creation (JC) and job destruction (JD), averaged across firms and years, amongst manufacturing industries. The larger the number of workers, the larger the values of JC and JD tend to be. To adjust for the size of employment varying across firms, we looked at the rates of JC (JCR) and JD (JDR) defined as follows:

$$JCR_{it} = \frac{JC_{it}}{(N_{idt}+N_{idt-1})/2};\ JDR_{it} = \frac{JD_{it}}{(N_{idt}+N_{idt-1})/2}.$$

In most manufacturing industries, JD (red bars) was, on average, greater than JC (blue bars), accompanied by a negative growth rate of net employment (green bars). This is in accordance with the trend that the total number of employees in manufacturing is shrinking. The exceptions are 'automotive' and 'pharmaceuticals', in which continuing and increasing needs for labour persist.[8]

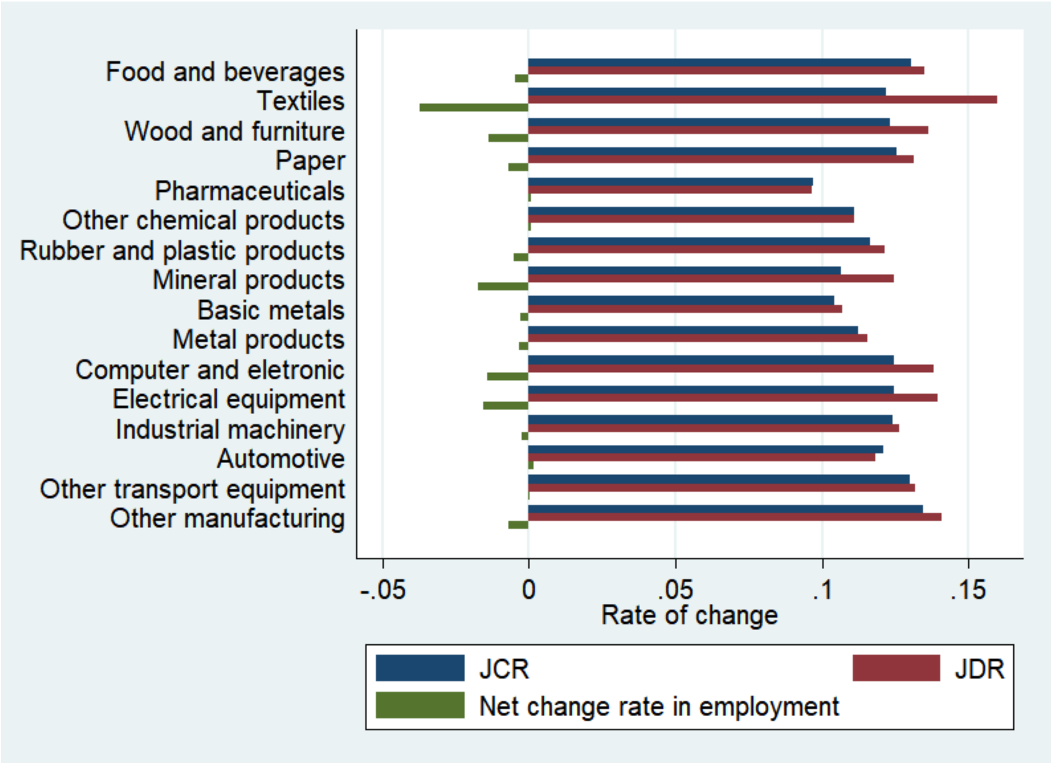
Figure 3 shows the by-industry distribution of the number of industrial robots delivered across years. Amongst manufacturing industries, 'automotive', which requires a lot of assembly work and is demanding in terms of precision, adopted the largest number of robots, indicating the need for automation. Others, such as

[7] See Table A1 for the yearly average figures for all manufacturing sectors.
[8] See Table A1 for the yearly figures of JCR, JDR, and net employment change rate averaged across firms for all manufacturing industries.

‘computer and electronic’ and ‘electrical equipment’, also had high levels of robot installation, as expected.

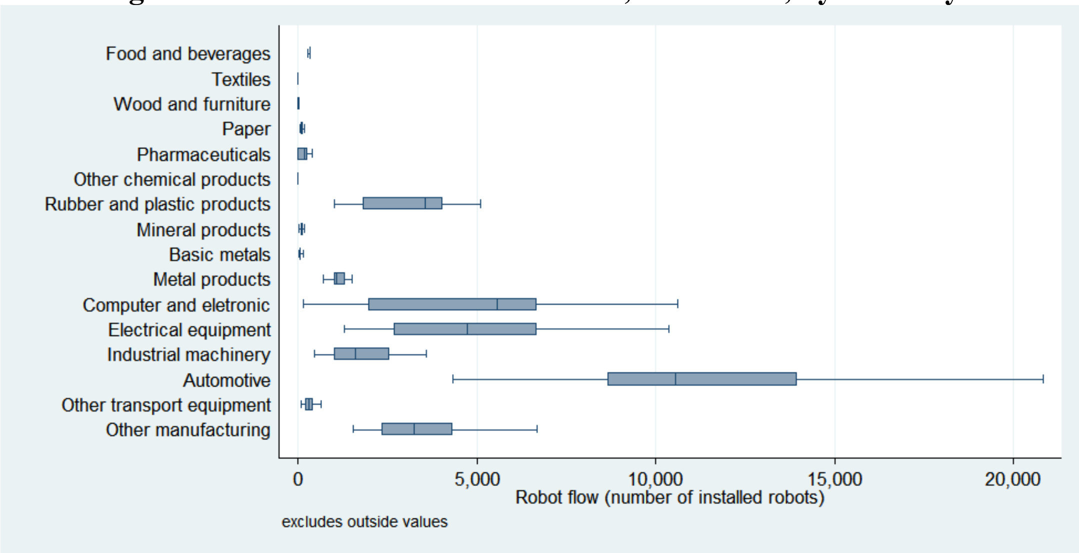
In general, the industries that adopted the most robots (Figure 3), such as ‘automotive’. ‘computer and electronic’, and ‘electrical equipment’, experienced relatively large job creation and destruction (Figure 2).

Figure 2: Job Creation and Destruction Rates, Averaged across Firms and Years 1996–2017, by Industry



JCR = job creation rate, JDR = job destruction rate.
Note: Both JCR and JDR, by definition, take non-negative values. Net employment change rate can be positive or negative.
Source: Authors, using firm-level employment composition data (Basic Survey of Japanese Business Structure and Activities).

Figure 3: Number of Robots Delivered, 1996–2017, by Industry



Source: Authors, using industrial robots data (World Robotics).

4.3. Baseline Estimation

To explore how the adoption of robots affected within-firm job creation and destruction, we consider the following baseline equation of job creation to be estimated using fixed-effects model:

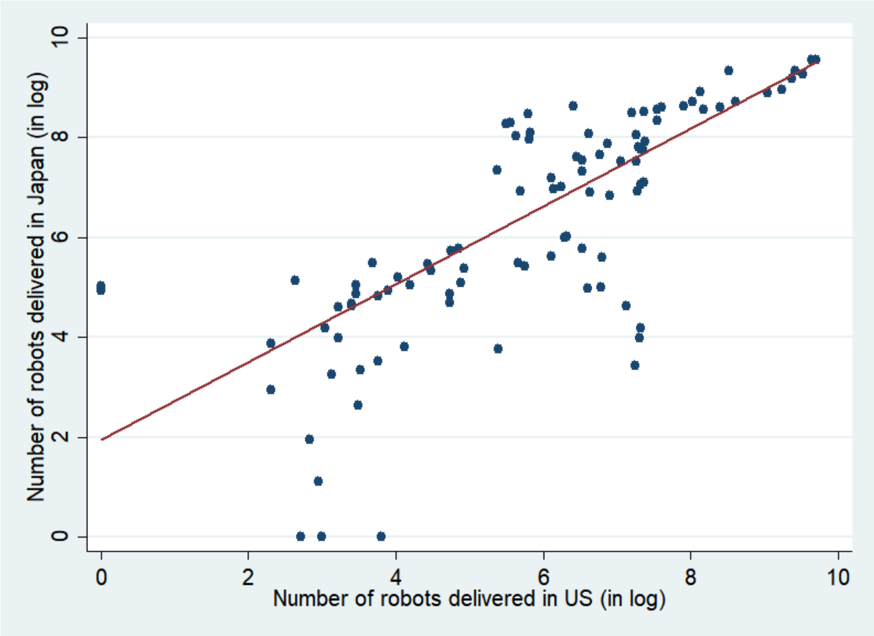
$$job\_creation_{ijt} = \alpha_1 Robot\_flow_{jt} + \alpha_2 control\_variables_{ijt} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{ijt}^{jc}, \quad (1)$$

where $job\_creation_{ijt}$ refers to jobs created in firm i of industry j at year t. $Robot\_flow_{jt}$ is the number of robots installed per 1,000 workers in industry j (2-digit level) at time t. $control\_variables_{ijt}$ is a group of control variables, which include whether the firm belongs to the manufacturing industry, capital–labour ratio, R&D ratio with respect to sales, revenue, total employment, foreign capital rate, and firm age, amongst others. We include firm, year–industry fixed effects as well. Adverse shocks that destroy (or create) jobs are not included in the estimation equation because firms are not able to predict such shocks. ε_{ijt}^{jc} is firm-specific error term. We estimate job destruction in the same manner.

4.4. Endogeneity Issues

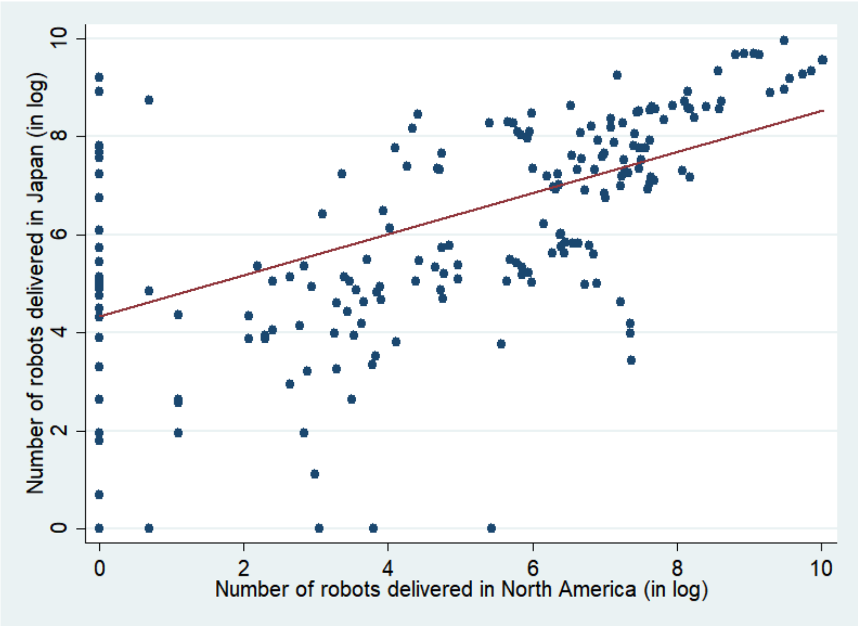
Apart from the omitted variable problem, one might argue that firms operating in industries with high robot adoption rates are more exposed to high technology, and from the point view of minimising cost, intense competition can cause firms to adjust labour more frequently than in other industries. If so, self-selection bias would occur. To further identify the causal impact of the diffusion of robotics technology on job creation and destruction, we first applied an instrument variable (IV) method. An ideal candidate is one that is closely related to robot adoption in Japan's manufacturing industries but does not affect employment adjustment within Japan's manufacturing firms. Since our variable of interest is at the industry level (robot flow), the IVs that we can naturally consider are industry-level measures. Fortunately, we have access to the data of robot flow in the US, the Republic of Korea, the whole North American region, and other regions. Taking into account that robot application trends in advanced economies are similar to one another (confounding condition), robots adopted in US industries will have a less substantial impact on labour reallocation within firms in Japan (exclusion condition). Thus, we used the robot flow by 2-digit industry in the US and the whole North American region as the instrument and conducted IV estimation. We tested the credibility of the instruments by calculating the correlation between the variable of interest and the instruments. The robot applications in Japan, the US, and the rest of North America have a highly positive correlation with each other (Figure 4, Figure 5). The weak instrument test was conducted in the analysis.

Figure 4: Correlation of Robot Flows between Japan and the United States



Source: Authors, using industrial robots data (World Robotics) for 2011–2017.

Figure 5: Correlation of Robot Flows between Japan and North America



Source: Authors, using industrial robots data (World Robotics) for 2004–2017.

5. Estimation Results

5.1. Some Simple Regression Results

Table 1. Baseline Estimation

Dependent Variable	(1) jc	(2) jd	(3) net employ.	(4) jcr	(5) jdr	(6) net employ. rate
$\ln(RobotFlow_{jt})$	6.036***	8.838***	-3.868*	0.0159***	0.0136***	-0.00176
	(1.882)	(1.952)	(2.123)	(0.00438)	(0.00428)	(0.00359)
$\ln(KL_{ijt})$	-32.15***	-2.858	-33.43***	-0.0284***	0.0394***	-0.0692***
	(3.795)	(4.196)	(4.141)	(0.00214)	(0.00279)	(0.00340)
$R\&D_{ijt}$	-19.20**	-16.88**	-8.500	-0.0496***	-0.0322**	-0.00521
	(9.294)	(8.466)	(12.43)	(0.0160)	(0.0152)	(0.0102)
$Foreign_{ijt}$	-0.00258	0.0324	-0.0461	-1.41e-05	-1.25e-05	2.55e-06
	(0.0437)	(0.0536)	(0.0292)	(1.45e-05)	(1.35e-05)	(1.10e-05)
Age_{ijt}	-0.00212	-0.00250	0.00724	-1.61e-07	2.76e-06	2.30e-06
	(0.01000)	(0.00883)	(0.00816)	(8.36e-06)	(7.37e-06)	(9.71e-06)
$\ln(Revenue_{ijt})$	16.34***	8.714***	8.163***	9.12e-05	-0.0166***	0.0183***
	(2.204)	(2.685)	(2.665)	(0.00240)	(0.00261)	(0.00233)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry_year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,439	160,439	145,334	145,334	145,334	145,334
R-squared	0.007	0.005	0.009	0.021	0.023	0.056
Number of eternal_no	21,811	21,811	20,136	20,136	20,136	20,136

Note: Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors, using data for firm-level employment composition (Basic Survey of Japanese Business Structure and Activities) and industrial robots (World Robotics).

Table 2. Instrument Variable Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Instrument	Robot flow in the United States			Robot flow in the whole North American region		
Dependent Variable	jcr	jdr	net employ. rate	jcr	jdr	net employ. rate
$\ln(RobotFlow_{jt})$	0.000938	0.0166**	-0.0113**	0.00122	0.00889**	-0.00737***
	(0.00805)	(0.00834)	(0.00522)	(0.00431)	(0.00425)	(0.00284)
$\ln(KL_{ijt})$	-0.0395***	0.0341***	-0.0787***	-0.0380***	0.0343***	-0.0736***
	(0.00375)	(0.00388)	(0.00243)	(0.00243)	(0.00239)	(0.00160)
$R\&D_{ijt}$	-0.0139	-0.0351	0.0253*	-0.0323**	-0.0285*	0.00727
	(0.0218)	(0.0226)	(0.0141)	(0.0157)	(0.0155)	(0.0103)
$Foreign_{ijt}$	3.15e-05	-0.000156	9.58e-05	2.85e-05	3.10e-05	-5.07e-06
	(0.000188)	(0.000194)	(0.000122)	(2.20e-05)	(2.17e-05)	(1.45e-05)
Age_{ijt}	-0.000522	-0.00116***	0.00133***	3.69e-06	7.52e-06	5.20e-06
	(0.000410)	(0.000425)	(0.000266)	(1.08e-05)	(1.06e-05)	(7.12e-06)
$\ln(Revenue_{ijt})$	0.0105*	-0.0391***	0.0499***	-0.00144	-0.0322***	0.0323***
	(0.00546)	(0.00566)	(0.00354)	(0.00313)	(0.00309)	(0.00207)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry_year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,806	36,806	36,806	75,274	75,274	75,274
Number of eternal_no	8,029	8,029	8,029	11,938	11,938	11,938
Cragg-Donald Wald F statistic	971.567	971.567	971.567	2075.695	2075.695	2075.695

Note: Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculation using data for firm-level employment composition (Basic Survey of Japanese Business Structure and Activities) and industrial robots (World Robotics).

The measurement of industrial robot adoption – *ln_Robot_flow* – has a positive and significant impact on within-firm JC and JD, and it does have a negative influence on the net employment of the firm (Table 1, columns [1]–[3]). When we use growth rate instead of level, we can predict that the application of robots has positive impact on JCR and JDR, and its impact on the net employment growth rate of the firm is consistently negative as well (Table 1, columns [4]–[6]). We attempted to include more firm-level characteristics that might affect JC or JD.[9] We used alternative combinations of variables and came up with robust results. The other control variables had mixed results in different specifications. *Ln_capital_labour_ratio* is negatively significant in the case of job creation and net employment, which points to the fact that the more capital-intensive a firm is, the more the number of workers decreases. *R&D_ratio* is negative in all kinds of specifications, which indicates that as a firm invests more in R&D, the more the accumulated new technology can perform routine tasks usually done by workers. To some extent, this supports our argument that high technology (such as robots) can have a substitutional effect on firms' labour.

The results of IV estimation are in Table 2. *ln_Robot_flow* has the same signs as the baseline estimation in all specifications, except that it loses significance in the case of job creation. A similar trend can be observed whether or not we use *Robot_flow* in the US or the whole North American region as the instrument. The Cragg-Donald Wald F statistic indicates the weak instrument test has been passed, which verifies the validity of the instruments.

[9] Apart from the control variables mentioned in section 4, we included total labour, total factor productivity, average cost, export intensity (export value divided by revenue), amongst others. Such practice does not change our predictions on the impact of robot application.

6. Robustness Checks and Further Issues

To verify whether industry size matters for the impact of robot application, we used the average number of workers at the industry level (about 470,000) to divide industries into large and small. We ran the IV estimation using different samples and included the same set of control variables in the analysis. The impacts of *robot_flow* on different labour measurement are similar to those described in the previous section (Table 3, columns [1]–[3]). The more robots an industry adopts, the more a firm in that industry tends to increase JCR and JDR, but the overall impact is negative, as indicated by the negative sign of net employment rate (although the coefficient is not significant). When we focused on industries with fewer workers, the impact of robot adoption on firm-level labour dynamics was not as substantial as in the industries with more workers. *robot_flow* lost significance in all specifications. The message is that firms in large industries were more likely than others to adjust their labour in response to the adoption of robots. Because large industries usually have more labour-intensive or routine jobs, which robots can easily do, *robot_flow* will negatively affect firms' net employment. Industries with less labour are not affected much by the introduction of robots.

Table 3. Instrument Variable Estimation by Industry Size (in terms of labour)

	(1)	(2)	(3)	(4)	(5)	(6)
Industry type		**Large**			**Small**	
Instrument		**Robot flow in the US**			**Robot flow in the US**	
Dependent Variable	**jcr**	**jdr**	**net employ. rate**	**jcr**	**jdr**	**net employ. rate**
$\ln(RobotFlow_{jt})$	0.147*	0.187**	-0.0382	0.00963	0.00155	0.00189
	(0.0791)	(0.0832)	(0.0496)	(0.00713)	(0.00703)	(0.00462)
$\ln(KL_{ijt})$	-0.0385***	0.0393***	-0.0862***	-0.0317***	0.0325***	-0.0648***
	(0.00541)	(0.00569)	(0.00340)	(0.00374)	(0.00369)	(0.00243)
$R\&D_{ijt}$	-0.0239	-0.0391	0.0163	-0.0574**	-0.0568**	0.000149
	(0.0251)	(0.0265)	(0.0158)	(0.0260)	(0.0256)	(0.0168)
$Foreign_{ijt}$	-5.49e-05	7.70e-05	-6.42e-05	2.39e-06	-1.78e-05	-5.01e-06
	(0.000271)	(0.000285)	(0.000170)	(3.01e-05)	(2.96e-05)	(1.95e-05)
Age_{ijt}	-0.00140**	-0.00242***	0.00195***	6.42e-06	1.88e-05	-5.97e-06
	(0.000681)	(0.000717)	(0.000428)	(1.69e-05)	(1.66e-05)	(1.09e-05)
$\ln(Revenue_{ijt})$	-0.00899	-0.0581***	0.0519***	0.00507	-0.0166***	0.0247***
	(0.0110)	(0.0116)	(0.00692)	(0.00511)	(0.00504)	(0.00331)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry_year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,183	21,183	21,183	30,922	30,922	30,922
Number of eternal_no	4,762	4,762	4,762	5,127	5,127	5,127

Note: Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors, using data for firm-level employment composition (Basic Survey of Japanese Business Structure and Activities) and industrial robots (World Robotics).

To further confirm the robustness of our findings, we manually collected robot shipment data provided by JARA Robot Jukyu Dokou. We used four categories: quantity of manipulating robots, value of manipulating robots, quantity of industrial robots in a broad sense, and value of industrial robots in a broad sense. The quantity unit is 10,000 and the value unit ¥100 million. While the IFR uses the period 1996–2017, shipment data are only for 2001–2017. In the following analysis, we used the log of quantity of manipulating robots as the representative proxy for robot flow.[10] Whether or not we used robot flow in the whole North American region or the US as the instrument, the IV estimation always showed a result similar to that obtained previously: the application of industrial robots promoted labour reallocation through job creation and destruction channels, and the overall effect was negative, which translates to the negative sign of *ln_Manipulating_robot_flow* in the case of net employment rate (Table 4). This confirms our finding that the impact of robot adoption on net employment variation is different from its individual effects on JC or JD. Further analysis is needed to make clear the mechanism of how robots can affect labour in different industries or different tasks.

[10] We also tried three other kinds of measurement and came up with similar results, which are available upon request.

Table 4. Instrument Variable Estimation using Japan Robot Association Data

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Instrument	**Robot flow in the whole North American region**			**Robot flow in the United States**		
Dependent Variable	**jcr**	**jdr**	**net employ. rate**	**Jcr**	**jdr**	**net employ. rate**
$\ln(RobotFlow_{jt})$	0.0148	0.0536*	-0.0322*	0.00963	0.0278**	-0.0147*
	(0.0292)	(0.0291)	(0.0193)	(0.0116)	(0.0121)	(0.00751)
$\ln(KL_{ijt})$	-0.0389***	0.0344***	-0.0757***	-0.0421***	0.0339***	-0.0829***
	(0.00269)	(0.00268)	(0.00178)	(0.00404)	(0.00420)	(0.00261)
$R\&D_{ijt}$	-0.0286*	-0.0271*	0.00954	-0.0167	-0.0355	0.0235
	(0.0161)	(0.0160)	(0.0107)	(0.0227)	(0.0235)	(0.0147)
$Foreign_{ijt}$	1.63e-05	1.82e-05	6.34e-06	-3.01e-05	-5.31e-05	-2.64e-05
	(2.33e-05)	(2.32e-05)	(1.54e-05)	(0.000202)	(0.000210)	(0.000130)
Age_{ijt}	5.92e-06	3.06e-06	1.12e-05	-0.00107**	-0.00162***	0.00114***
	(1.24e-05)	(1.24e-05)	(8.21e-06)	(0.000503)	(0.000523)	(0.000325)
$\ln(Revenue_{ijt})$	-0.00604	-0.0426***	0.0371***	0.00841	-0.0422***	0.0515***
	(0.00567)	(0.00565)	(0.00375)	(0.00589)	(0.00612)	(0.00381)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry_year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,944	63,944	63,944	32,812	32,812	32,812
Number of eternal_no	10,786	10,786	10,786	7,540	7,540	7,540

Note: Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculation using data for firm-level employment composition (Basic Survey of Japanese Business Structure and Activities) and industrial robots (World Robotics).

7. Conclusions and Policy Recommendation

We made use of firm-level data obtained from the BSJBSA and industry-level robot shipment data obtained from the IFR and JARA to investigate the causal effect of the industry-wide diffusion of robotics technology on within-firm labour reallocation. Deviating from the literature focusing on net employment changes, we looked at how robot adoption (flow) at the two-digit industry level affects job creation and destruction in individual firms. To mitigate the endogeneity issue, we applied robot flow data for the US and the whole North American region to conduct an IV analysis. We found that robot adoption positively affected job creation (rate) and job destruction (rate). Robot adoption's overall impact on firms' net employment was negative, consistent with studies such as Acemoglu and Restrepo (2020). We provide new evidence to show that the adoption of robots can affect firms' labour allocation through complementary and substitutional channels simultaneously. Further studies are necessary to identify the specific industries and tasks through which such mechanism works.

By rigorously assessing how automation of production affects labour dynamics within a firm, this study provides evidence suggesting the importance of government policy and interventions to increase user-friendly robot adoption to support creativity and innovation.

In the longer term, the current study will be replicable in other countries with similar or different socio-techno-economic conditions surrounding robotics technology, as well as industrial digitalization and artificial intelligence. The interdisciplinary nature of the study will contribute to debates amongst social sciences and science technology.

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Appendix

Table A1. Annual Results: Job Creation Rate, Job Destruction Rate, Net Employment Change Rate, and Within-firm Job Reallocation Rate

	Job creation rate	Job destruction rate	Net employment change rate	Within-firm job reallocation rate (average values of all firms)*
1996	21.41	21.98	−0.67	17.55
1997	17.80	17.71	−0.03	13.92
1998	23.92	24.57	−0.77	20.39
1999	20.46	22.00	−2.17	16.90
2000	13.27	14.58	−1.40	9.81
2001	15.05	15.91	−0.94	11.25
2002	12.57	14.35	−1.84	8.76
2003	11.44	12.57	−1.20	7.61
2004	12.74	12.78	−0.10	8.53
2005	13.89	13.62	0.21	9.60
2006	14.15	13.22	0.87	9.56
2007	15.54	14.09	1.40	10.77
2008	14.57	13.13	1.37	9.78
2009	13.98	14.20	−0.27	9.73
2010	12.78	13.74	−1.02	9.00
2011	12.27	12.12	0.09	8.40
2012	12.23	12.29	−0.11	8.67
2013	12.16	12.08	0.02	8.53
2014	11.70	11.02	0.62	7.83

Note: Within-firm reallocation is the lower bound of job creation and job destruction for each firm.

Source: Authors, based on the Basic Survey of Japanese Business Structure and Activities.

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