RIETI Discussion Paper Series 23-E-082

Automation and the Disappearance of Routine Work in Japan

KIKUCHI, Shinnosuke
MIT

FUJIWARA, Ippei
RIETI

SHIROTA, Toyoichiro
Aoyama Gakuin University

RIETI
Research Institute of Economy, Trade & Industry, IAA

The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 23-E-082
November 2023

Automation and the Disappearance of Routine Work in Japan[1]

Shinnosuke Kikuchi — MIT
Ippei Fujiwara — Keio/ANU/CEPR/RIETI
Toyoichiro Shirota — Aoyama Gakuin

Abstract

We examine the implications of automation technology in Japan since 1980, comparing different local labor markets with different degrees of automation exposure. First, we do not find that automation reduces the employment rate within demographic groups and that automation encourages workers to move from regular to non-regular employment. Second, we show that automation shifts employment from routine occupations in the manufacturing sector to service sectors, while *increasing* the share of establishments and sales in the manufacturing sector. Finally, we show that this shift in labor demand is attributed to younger generations and non-college-educated workers.

Keywords: Automation, Occupation, Task, Labor Market
JEL classification: J24

[1] We thank Daron Acemoglu, David Autor, and Sagiri Kitao for their helpful comments. We also thank seminar participants at RIETI for their comments. We thank Satoshi Ichikawa for his excellent research assistance. This study is a part of the Project "Macroeconomy and Automation" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). We acknowledge permission to access the micro-data of the following government statistics: the Employment Status Survey by the Ministry of Internal Affairs and Communications, the Establishment Census of Japan by the Ministry of Internal Affairs and Communications, the Establishment and Enterprise Census of Japan by the Ministry of Internal Affairs and Communications, the Economic Census for Business Frame by the Ministry of Internal Affairs and Communications, the Census of Manufacture by the Ministry of Economy, Trade, and Industry, and the Census of Commerce by the Ministry of Economy, Trade, and Industry. Kikuchi is grateful to Keio University, where he worked on the empirical analyses using micro-data, for its hospitality during his visits. We thank RIETI for providing their help with the data access. We also thank Daisuke Adachi for his help in using data in Adachi et al (2022).

1 Introduction

In the last few decades, many countries have observed polarization of labor markets. For example, Autor et al. (2003) show that the number of workers in the middle skill class has experienced slower growth than that in low and high skill levels, resulting in a U-shaped pattern across the skill distribution spectrum in the US. Ikenaga and Kambayashi (2016) conclude that the same pattern holds for Japan. A possible cause of this polarization is technological advancements in the manufacturing sector, in particular, the introduction of industrial robots. Empirical studies have indeed demonstrated that innovations in manufacturing technology have led to the displacement of routine tasks, which are traditionally performed by middle-skilled workers. As a result, there has been a decline in the demand for workers engaged in routine tasks, as documented in Autor et al. (2003) and Ikenaga and Kambayashi (2016) among others in the literature.

In this paper, we examine the impact of automation on the labor market, with particular attention to heterogenous impacts by occupation, in Japan. Studying the influence of robots on Japan's labor market holds immense importance. Japan, renowned for its cutting-edge robotics, has held the title of the world's leading robot producer for a considerable period.[1] The widespread adoption of robots in the country is noteworthy. Moreover, Japan has been at the forefront of robot integration since the 1980s. This extended period of implementation allows us to thoroughly analyze its impact on the labor market, offering a valuable perspective compared to other countries.

We first construct a measure of exposure to automation across local labor markets in Japan as examined in Acemoglu and Restrepo (2020) and Dauth et al. (2021) for the US and Germany, respectively. We then investigate how the changes in the exposure to automation affect the total employment rate, occupation share, industrial employment share, and these measures across different demographic groups.

Our main findings are as follows. First, we do not find that automation decreases overall employment rates. This null effect on employment rate is different from the finding in Acemoglu and Restrepo (2020), who study the same effect in the US, but is consistent with Dauth et al. (2021), who investigate Germany. This null effect for overall employment does not come from heterogeneous effects across demographic groups. Based on the sub-sample analysis within each of the different demographic groups, we do not find any evidence showing that automation decreases employment rates for particular demographic groups.

Second, we show that automation displaces employment in routine occupations and shifts labor demand to service sectors. Expanding service sectors offsets task displacement in routine occupation of manufacturing sectors, consistent with the finding in Dauth et al. (2021) for Germany.

Third, we show that automation increases the number of establishments in the manufacturing sector and the share of the number of establishments in the manufacturing sector relative to the one in the service sector. This suggests that automation shifts labor from the manufacturing sector while expanding the activities in the manufacturing sector.

Fourth, we show that this shift of employment from routine occupations in manufacturing sectors to service sectors is attributed to the shifts of younger workers or non-college-educated workers. This is consistent with Kikuchi and Kitao (2020) for the US and Dauth et al. (2021) for Germany.

[1] According to the International Federation of Robotics (IFR) in International Federation of Robotics (2023), Japan is still the predominant robot-producing country with its market share of 46% of world production in 2022.

Related Literature This paper contributes to the broad literature, which studies the effect of technology on labor demand, including Autor et al. (2003), Acemoglu and Autor (2011), Webb (2019), Acemoglu and Restrepo (2020), Acemoglu and Restrepo (2022) among others. This paper studies the impact of labor-replacing technology, automation, on labor markets, which have also been studied extensively by the previous literature, including Graetz and Michaels (2018), Acemoglu and Restrepo (2020), Dauth et al. (2021), Acemoglu and Restrepo (2022), and Adachi et al. (2022). The contribution of this paper is to study the effect in Japan, which is the largest robot exporting country in the world, and where robots have been used extensively over 40 years, compared to papers on other countries, except for Adachi et al. (2022).

This paper also contributes to the literature, which studies the impact of technology on the Japanese labor markets. Ikenaga and Kambayashi (2016) show an industry-level correlation between ICT capital penetration and decreases in routine task score. Hamaguchi and Kondo (2018) study the implication of artificial intelligence. Adachi et al. (2022) study the implication of robot penetration on overall employment across industries and commuting zones using the same data as ours.

Compared to Adachi et al. (2022), there are four key differences. First, our interests are on changes in occupational distribution due to task displacement, which is tightly connected to automation, while they primarily study the effect on overall employment. Null results on the employment rate or increases in the level of employment in the manufacturing sector can be an artifact of using a noisy running variable or endogeneity of robot penetration due to positive demand shock, respectively. Our result of the unaffected employment rate and the disappearing routine occupation is reassuring and confirms that the finding in Adachi et al. (2022) is robust. Second, we use a different instrumental variable, relying on the price of robots exported abroad to eliminate mechanical bias from domestic price to domestic quantity. To be more concrete, while they use domestic robot price by application to predict industry-level robot price based on the initial share of application by industry, we use exporting robot price by application. Third, we follow the literature (Acemoglu and Restrepo, 2020; Dauth et al., 2021) to use the adjusted robot penetration, taking out the effect of demand shock from industry-level growth of output, rather than un-adjusted robot penetration, which can contaminate industry-level demand shock. We show in Appendix B that the adjusted penetration of robots precisely captures the improvement of automation technology. Fourth, we drop the sample of 2017 from the analysis because some of the covariates, including capital in different types, are not available in JIP data. Adachi et al. (2022) impute these with one (zero after taking log) in 2017, but this can introduce undesirable bias across industries with different capital stock values before 2017.

2 Data

2.1 Data

2.1.1 Employment Status Survey (ESS)

We use the microdata of the Employment Status Survey (ESS) by the Ministry of Internal Affairs and Communications. ESS aims to capture the employment status and occupation of workers at both regional and national levels. Since 1982, this survey has been conducted every five years. The survey is nationally representative, and the coverage is extensive: the survey in 2017, for instance, includes approximately 1.08 million individuals from 520,000 households residing in

33,000 survey districts around the nation, and past surveys have similar levels of coverage.[2]

Sample Restriction We construct various variables at the commuting-zone-level from the ESS data, combined with industry-level data. Here, we describe how we restrict samples to construct data at the commuting-zone-level from the raw ESS data at the individual level. When we study the effect of automation on labor markets, we are interested in demographic groups with fairly strong attachment to labor markets. Thus, when we analyze commuting-zone-level outcomes conditional of employed, we restrict our samples to full-time workers in non-agricultural sectors, aged 25 to 64.[3]

Occupation Groups We divide the employed into three groups according to their occupations. To construct occupation categories, we use the most detailed occupation category in each survey round.[4] into three groups: Abstract, Routine, and Manual, following Acemoglu and Autor (2011).

Occupations are classified as follows.

- **Abstract**: Administrative and managerial workers, Professional and engineering workers, Clerical support workers, and Sales workers
- **Routine**: Craft and manufacturing process workers, Plant and machine operation workers, Extractive workers, Construction workers
- **Manual**: Service workers and Elementary occupations

For example, Table 1 summarizes the specific mapping of each occupation group in the 2017 survey. In 2017, ESS data used the Japan Standard Classification of Occupations (JSCO) revised in 2009. We classify groups A, B, and C to Abstract occupation, H, J to Routine occupation, and D, E, F, and K to Manual occupation. To be consistent with the classification in 1982 and 1997, we classify machine operator workers in I group (I64) in 2017 into Routine occupation and transport workers in I group (I61-I63) in 2017 into Manual occupation. This is feasible because ESS data has detailed occupation categories in 2012 and 2017. See Table A.2 for other years.

Table 1: Mapping of occupation groups into 3 categories

Categories	Occupation groups in 2017 survey
Abstract	A. Administrative and managerial workers, B. Professional and engineering workers, C. Clerical workers D. Sales workers,
Routine	H. Manufacturing process workers, I-64. Machine operation workers, J. Construction and mining workers
Manual	E. Service workers, F. Security workers, I-61 $\sim$ I-63. Transport workers, K. Carrying, clearing, packing, and related workers

[2]See Table A.1 for the coverage by survey year.

[3]When we define full-time workers, we use a survey answer of employment status and drop workers who respond either that they work but mainly do housework or that they work bu mainly go to school.

[4]Explain.

Local Labor Market We consolidate the municipal level data of ESS into the commuting-zone-level data using the Adachi et al. (2020)'s definition of commuting zone in 2015 and Kondo (2023)'s time-consistent municipal code. Specifically, we construct the following data by commuting-zone-level; the employment rate, 3-type occupation shares, the share of manufacturing employment in total employment, female workers share, college education share, old-to-young population ratio, and old-to-young workers ratio. Further, by combining the commuting-zone-level share of employers by industry with robot stocks and other data by industry, we construct the robot's exposures and other covariates by commuting zone as in Acemoglu and Restrepo (2020).

2.1.2 Establishment Census, Establishment and Enterprise Census, and Economic Census for Business Frame

We also use the microdata from the Establishment Census in 1981, the Establishment and Enterprise Census in 1996, and the Economic Census for Business Frame in 2014 by the Ministry of Internal Affairs and Communications. These surveys aim to describe the basic structure of establishments and prepare a list of establishments and enterprises for the implementation of various censuses. We construct the number of establishments in the manufacturing sector and the one in the service sector for each local labor market. We use data in 1981, 1996, and 2014 to proxy the size of the activities in the manufacturing and service sectors in each local labor market for 1982, 1997, and 2012, respectively.

2.1.3 JARA Data

We use the Production and Shipments of Manipulators and Robots from the Japan Robot Association (JARA), We use data complied by Adachi et al. (2022). JARA data is the primary source of Japan's robot data, which is different from the International Federation of Robots (IFR), which is well-known and widely used in previous studies (*e.g.* Graetz and Michaels (2018), Acemoglu and Restrepo (2020)). JARA data consists of robot shipments (both in units and sales value) by destination industry and robot application from 1978 to 2017.[5] Compared to the IFR's data that has been available since 1993, the JARA robots data has a more extended time series that includes the 1980s, a period of rapid robot adoption in Japan's manufacturing process.

Robots capital stock is accumulated for each industry using the perpetual inventory method and assuming that the depreciation rate is 12 % as in Adachi et al. (2022). The specific 2-digit industry categories are "iron and steel," "nonferrous metals," "metal products," "general machinery and equipment," "electrical machinery and equipment," "precision machinery," "transport machinery and equipment," "food, beverage, tobacco, and feedstuff," "pulp, paper, paper products, and printing," "chemical," "ceramic and stone products," "other manufacturing," and "non-manufacturing."

2.1.4 JIP Data

We also use the Japan Industrial Productivity Database 2015 (JIP), which is compliant with the EU-KLEMS dataset.[6] We use data complied by Adachi et al. (2022). JIP data contains labor

[5]The JARA booklet "Production and Shipments of Manipulators and Robots" consists of Table A, B, and C. Table A presents sales and the number of robots by industry and robots' structure. Table C presents the shipment of robots by country and applications.

[6]For details, see Fukao et al. (2007) and Fukao et al. (2021).

inputs, capital stocks, exports, imports, and outputs by industry from 1982 to 2012. JIP data is also consolidated into the above 13 industries.

3 Specification

We use stacked-difference specification across commuting zone c. We stack three 15-year log differences across commuting zones for periods of 1982-1997 and 1997-2012.[7] Our main specification is as follows

$$\Delta Y_{c,t,t+15} = \beta \cdot APR_{c,t,t+15} + X'_{c,t}\Gamma_1 + \Delta X'_{c,t,t+15}\Gamma_2 + \mu_t + \varepsilon_{c,t}.$$

$\Delta Y_{c,t,t+15}$ is 15-year changes in an outcome, including employment rate, occupation shares, and others, in commuting zone c from year t to $t+15$.

Running Variable Our running variable is $APR_{c,t,t+15}$, which is an adjusted penetration of robots in commuting zone c from year t to $t+15$. As in Acemoglu and Restrepo (2020), we construct commuting-zone-level robot exposure $APR_{c,t,t+15}$ from employment-weighted average of industry level robot exposure

$$APR_{c,t,t+15} = \sum_i \ell_{c,i,t} \cdot APR_{i,t,t+15}$$

Here, $\ell_{c,i,t}$ denotes a ratio of workers in commuting zone c worked in industry i relative to total workers in commuting zone c, and $APR_{i,t,t+15}$ denotes industry level adjusted penetration of robots, which we define as follows.[8]

$$APR_{i,t,t+15} = \frac{\Delta R_{i,t,t+15}}{L_{i,t}} - \frac{\Delta Y_{i,t,t+15}}{Y_{i,t}} \frac{R_{i,t}}{L_{i,t}}$$

where $\Delta R_{i,t,t+15}$ is a change in the number of robots in industry i from year t to $t+15$, $L_{i,t}$ is a number of workers in industry i in year t, $\Delta Y_{i,t,t+15}$ is a change in a real output in industry i, $Y_{i,t}$ is a real output in industry i. In Table D.3, we use the un-adjusted penetration of robots instead of our adjusted one and show that our results are robust.

Covariates We control a vector of initial period covariates $X_{c,t}$ and a vector of contemporaneous changes in demographic changes and technology exposure $\Delta X_{c,t}$ as explained below. To control different economic and demographic environments across commuting zones, we first control commuting-zone-level covariates, $X_{c,t}$. We include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 20-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-49) workers relative to old (aged 45-64) workers, and share of manufacturing employment in the initial period. We also control contemporaneous demographic changes across commuting zones, 15-year changes in the ratio of female workers, college-educated workers, and young population. Finally, to separate the effects of automation from the effects of other capital investments or international trade, we control technology exposure covariates, which

[7]We drop data in 2017 from the analysis because some of the covariates, including capital in different types, are not available in JIP data. Adachi et al. (2022) imputes these with one (zero after taking the log) in 2017, but this introduces undesirable bias across industries with different stock values before 2017.

[8]In Appendix B, we show why this measure is consistent with task framework as in Acemoglu and Restrepo (2020).

include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. To convert these industry-level variables, we compute commuting-zone-level exposures as follows:

$$\Delta x_{c,t,t+15} = \sum_i \ell_{c,i,t} \cdot \Delta x_{i,t,t+15}$$

where $\ell_{c,i,t}$ denotes a ratio of workers in commuting zone c worked in industry i relative to total workers in commuting zone c, and $\Delta x_{i,t,t+15}$ is a change in technology or trade values in real, for instance, changes in real IT capital stock in industry i from year t to $t+15$.

Instrumental Variable Our instrumental variable is a shift-share instrumental variable, predicted changes in the price of robots, $\Delta \ln \tilde{p}^R_{c,t,t+15}$, constructed as follows:

$$\Delta \ln \tilde{p}^R_{c,t,t+15} = \sum_i \ell_{c,i,1982} \cdot \Delta \ln \tilde{p}^R_{i,t,t+15}$$

where $\ell_{c,i,1982}$ is an employment share of industry i in commuting zone c in 1982, and $\Delta \ln \tilde{p}^R_{i,t,t+15}$ is a predicted value of industry-level changes in robot price. Using an actual change in industry-level robot price can lead to a severe issue. When the demand from a particular industry is high, robot-producing firms can invest in more on types of robots used in the industry so that the price decreases. Therefore, we rather use a predicted value of industry-level robot price changes by leveraging the availability of robot unit price and robot quantities by application and industry.[9] Specifically, we construct the predicted price as follows:

$$\Delta \ln \tilde{p}^R_{i,t,t+15} = \sum_a \omega_{i,a,1982} \cdot \Delta \ln p^{R,EX}_{a,t,t+15}$$

where $\omega_{i,a,1982}$ is the share of robot quantities of application a in industry i, and $\Delta \ln p^{R,EX}_{a,t,t+15}$ is the 15-year changes in price of robots of application a, which are exported abroad.

4 Summary Statistics

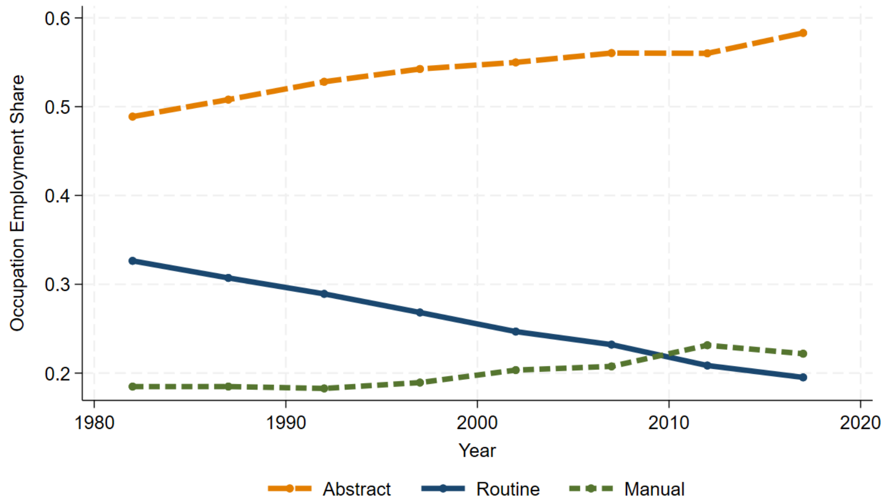
4.1 Macro Trends

To start the analysis, we first show the time trend of employment share by occupation groups in Japan. Figure 1 shows the employment share by the three occupation groups from 1982 to 2017. Over the 25 years, the share of routine occupation has decreased from 32% to 20% while the shares of abstract occupation have increased.[10]

[9] The specific application types are "Handling operations and machine tending", "Welding and soldering", "Dispensing", "Processing", "Assembling and disassembling", and "Others".

[10] As shown in Kawaguchi and Mori (2019), Kitao and Mikoshiba (2020), and others, the labor force participation rate for females has increased dramatically recently in Japan. One concern to interpret the pattern in Figure 1 is that it can be solely driven by the composition effects. Figure C.1a in the Appendix negates this concern by showing that the shift from routine to abstract occupations are common across gender.

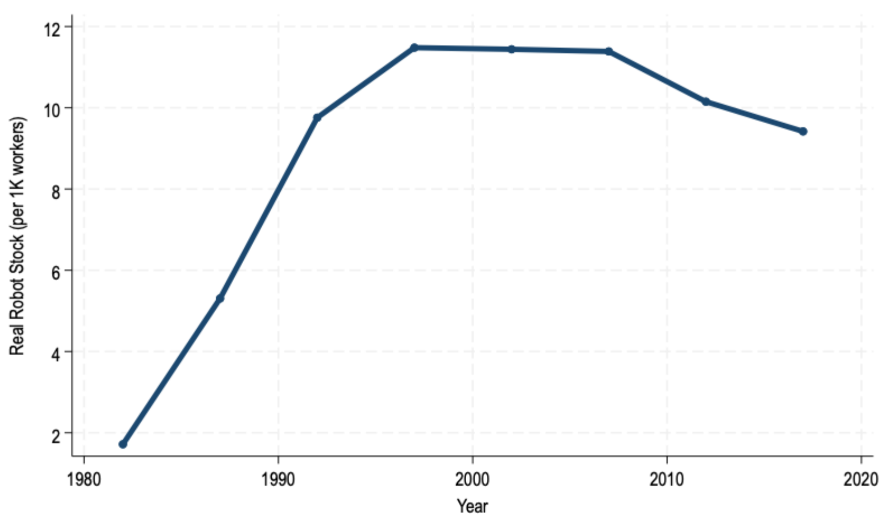
Figure 1: Employment Share by Occupation Group in Japan



Notes: The figure shows the employment share by occupation group in Japan. Data is from ESS.

Figure 2 shows the number of robot stocks per 1,000 workers in the manufacturing sectors in Japan. From 1982 to 1997, the robot stock dramatically increased from 2 per 1,000 workers to nearly 12 per 1,000 workers. After 1997, however, the stock has stopped to increase and slightly decreased. This stagnation of investment is consistent with other capital investments in Japan in the same period.

Figure 2: Number of Robots per 1,000 Workers in Manufacturing Sectors in Japan



Notes: The figure shows the number of robot stocks per 1,000 workers in the manufacturing sectors in Japan. Data is from Adachi et al. (2022), which is originally from JARA. The stock of robots is calculated using a depreciation rate of 12% per year in Adachi et al. (2022).

In the following part of the paper, we study how these two macro phenomena are related, by comparing different local labor markets in Japan with different degrees of exposure to automation technology.

4.2 Summary Statistics

Table 2 shows the summary statistics for the main variables we use for the analysis. The samples are 203 CZs for two 15-year periods (1982-1997 and 1997-2012). The table shows the mean, standard deviation, p25, median, and p75 for each variable. Adjusted penetration of robots is the running variable defined in the previous subsection, and the mean is 0.32 with a standard deviation of 2.67. The employment rate is defined as the ratio of the employed population to the total population aged between 25 and 64. The ratio of old to young population is defined as the ratio of the population aged 20 to 59 to those aged 60 to 119. The ratio of old to young workers is defined as the ratio of workers aged 25 to 44 to those aged 45 to 64.

Table 2: Summary Statistics

	Num.	Mean	Std. Dev.	p25	p50	p75
Adjusted Penetration of Robots	406	0.32	2.67	-1.57	0.09	2.53
Log Changes in Exporting Robot Price	406	0.21	0.35	-0.14	0.19	0.57
Employment Rate	406	0.76	0.05	0.73	0.76	0.80
Abstract Occupation Employment Share	406	0.47	0.07	0.42	0.46	0.51
Routine Occupation Employment Share	406	0.33	0.07	0.28	0.33	0.38
Manual Occupation Employment Share	406	0.20	0.05	0.17	0.20	0.23
Non-Routine Manufacturing Employment Share	406	0.06	0.03	0.04	0.06	0.08
Routine Manufacturing Employment Share	406	0.18	0.07	0.12	0.17	0.22
Non-Routine, Service Employment Share	406	0.61	0.08	0.55	0.60	0.66
Routine, Service Employment Share	406	0.15	0.04	0.12	0.15	0.18
Share of Manufacturing Establishments	406	0.12	0.07	0.07	0.10	0.14
Changes in Employment Rate	406	2.23	3.82	-0.01	2.09	4.13
Changes in Abstract Occupation Employment Share	406	3.95	5.38	1.59	3.97	6.35
Changes in Routine Occupation Employment Share	406	-8.18	5.41	-11.10	-8.49	-4.42
Changes in Manual Occupation Employment Share	406	4.23	5.71	0.41	4.02	7.67
Changes in Non-Routine Manufacturing Employment Share	406	0.15	1.78	-0.89	0.15	1.14
Changes in Routine Manufacturing Employment Share	406	-2.98	3.80	-4.96	-2.80	-0.68
Changes in Non-Routine, Service Employment Share	406	8.03	5.88	4.06	8.18	11.63
Changes in Share of Manufacturing Establishments	406	-1.85	2.96	-2.51	-1.19	-0.39
Ratio of Female Workers	406	0.72	0.10	0.67	0.73	0.79
Ratio of College-Educated Population	406	0.13	0.08	0.08	0.11	0.17
Ratio of Old to Young Population	406	0.38	0.14	0.28	0.36	0.47
Ratio of Old to Young Workers	406	0.45	0.07	0.39	0.46	0.50

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the summary statistics, mean, standard deviation, p25, median, and p75 for each variable. Adjusted penetration of robots and log changes in exporting robot prices are constructed from industry-level data and converted to commuting zone-level variables as explained in the main text. The employment rate is defined as the ratio of the employed population to the total population aged between 25 and 64. The ratio of old to young population is defined as the ratio of the population aged 20 to 59 to those aged 60 to 119. The ratio of old to young workers is defined as the ratio of workers aged 25 to 44 to those aged 45 to 64.

5 Effects of Automation on Labor Demand across Local Labor Markets

5.1 First Stage

Table 3 shows the first stage of our regression. It shows the relationship between exposure to changes in the log price of exporting robots and automation exposure across commuting zones in Japan. Each observation is weighted by its initial population size. The first stage is strong. If the price of exporting robots increases, robot penetration decreases, and the F-statistics is 353.75.

Table 3: First Stage using Price of Exporting Robots as IV

	(1)
Price of Exporting Robots	-46.47
	(3.67)
Observations	406
Initial CZ Covariates	✓
Tech Change Covariates	✓
Demographic Change Covariates	✓
Period FEs	✓

Notes: Samples are 205 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between exposure to changes in the log price of exporting robots and automation exposure across commuting zones in Japan. The regression includes covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 20-59) population relative to the old (aged 60 and up) population, and the share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size.

5.2 Changes in Employment Rate and Occupation Employment Share

Changes in Employment Rate and Occupation Share We first examine the effect on employment share. Table 4 shows the result on the relationship between adjusted penetration of robots and log employment rate across commuting zones between 1987 and 2012 using IV regressions.[11] Column (1) uses changes in employment rate relative to population as an outcome. Columns (2), (3), and (4) use changes in occupational employment share in abstract, routine, and manual occupation respectively. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-49) workers relative to old (aged 50 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All

[11] Table D.2 in Appendix shows the results using OLS regressions.

of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

Contrary to the findings in Acemoglu and Restrepo (2020) for the US, we do not find evidence that robots lead to decreases in total employment rate as shown in Column (1).[12] However, this null, aggregate employment effect does not mean that robots do not affect employment. Column (3) shows that robots decrease the share of routine occupation employment while Column (2) indicates that labor demand shifts to abstract occupation instead.

Table 4: Effects of Automation on Changes in Employment Rate and Occupation Share

	Dep. Var. Changes in Employment Rate			
	Total	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)
Adjusted Penetration of Robots	-0.13	1.33	-1.69	0.36
EHW	[-0.63 0.37]	[0.77 1.88]	[-2.47 -0.91]	[-0.25 0.97]
AKM	[-0.34 0.09]	[0.98 1.68]	[-2.06 -1.32]	[0.13 0.59]
Observations	406	406	406	406
Initial CZ Covariates	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. Column (1) uses changes in employment rate relative to population as an outcome. Columns (2), (3), and (4) use changes in occupational employment share in abstract, routine, and manual occupation respectively. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to the old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

Mechanism: Manufacturing to Service To study the mechanism behind the finding in Table 4, we first study changes in occupation share within manufacturing sectors and industry employment share. Here, we combine abstract and manual occupations within each industry and

[12] In fact, Table D.1 in Appendix shows that none of the subgroups of workers experiences declines in employment. Moreover, Table D.5 shows that automation did not increase the share of non-regular workers, whose jobs are typically lower-paid.

consider the following four categories: non-routine manufacturing, routine manufacturing, non-routine service, and routine service employment. We regress changes in employment share of each category on APR separately. Table 5 shows the results.

The decline in routine share within each sector is clear, and this is mostly offset by the expansion of non-routine occupation in the service sector, not the rise in non-routine occupation employment within manufacturing sectors.

Table 5: Effects of Automation on Changes in Employment Rate and Occupation Share

	Dep. Var.: Changes in Employment Rate			
	Manufacturing		Service	
	Non-Routine	Routine	Non-Routine	Routine
	(1)	(2)	(3)	(4)
Adjusted Penetration of Robots	0.28	-0.88	1.40	-0.81
EHW	[-0.15 0.72]	[-1.50 -0.26]	[0.59 2.22]	[-1.31 -0.31]
AKM	[-0.01 0.58]	[-1.43 -0.32]	[0.99 1.82]	[-1.23 -0.40]
Observations	406	406	406	406
Initial CZ Covariates	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓

Notes: Samples are 201 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. Column (1) uses the share of employment in non-routine occupations in the manufacturing sector relative to total employment. Column (2) uses the share of employment in routine occupation in the manufacturing sector relative to total employment. Column (3) uses the share of employment in non-routine occupations in the service sector relative to total employment. Column (4) uses the share of employment in routine occupation in the service sector relative to total employment. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

5.3 Expanding Manufacturing Sector

The previous section shows that automation shifted the labor demand from routine occupations in the manufacturing sector to non-routine occupations in the service sector. In this section, we examine the impact on the number of establishments in the manufacturing sector. Table 6 shows the result. Column (1) uses the log changes in the number of establishments in the manufacturing sector. Column (2) uses those in the service sector. Column (3) uses the changes in the share of the number of establishments in the manufacturing sector.

The result is clear that automation increased the number of establishments in the manufacturing sector and the share of the manufacturing sector. Together with the findings in the previous section on the shift in labor demand, this indicates that automation decreases labor demand while increasing activities in the manufacturing sector. While Table 6 shows that the manufacturing sector expands in terms of the number of establishments, Table D.4 shows that the expansion is the robust feature when we analyze the relative sales of the manufacturing sectors to a narrower definition of service sectors.

Table 6: Effects of Automation on Changes in the Number of Establishments

	Log Changes		Changes
	Manufacturing	Service	Manufacturing Share
	(1)	(2)	(3)
Adjusted Penetration of Robots	8.10	-1.78	1.15
EHW	[3.71 12.49]	[-4.32 0.76]	[0.55 1.75]
AKM	[2.81 13.39]	[-3.85 0.29]	[0.33 1.97]
Observations	406	406	406
Initial CZ Covariates	✓	✓	✓
Tech Change Covariates	✓	✓	✓
Demographic Change Covariates	✓	✓	✓
Period FEs	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and the changes in the number of establishments across commuting zones in Japan. Column (1) uses the log changes in the number of establishments in the manufacturing sector. Column (2) uses those in the service sector. Column (3) uses the changes in the share of the number of establishments in the manufacturing sector. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

5.4 Heterogeneous Effects across Demographic Groups

In this subsection, we study which demographic groups lead the results of commuting zones as a whole. We study the effect by gender, age, and education groups.

Changes in Occupation Share by Gender We start our sub-sample analysis by studying the effect of automation on occupation shares by gender. We compute occupation share in each gender in each commuting zone and repeat the same analysis as previously shown.

Table 7 shows the results. Columns (1)-(3) show the results for occupation for male workers, and Columns (4)-(6) show the ones for female workers. The shift from routine to abstract occupation is significant for both types of workers.

Table 7: Effects of Automation on Changes in Employment Share by Gender

	Dep. Var.: Changes in Employment Rate					
	Male Workers			Female Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted Penetration of Robots	1.54	-2.03	0.49	1.09	-1.16	0.07
EHW	[0.87 2.20]	[-2.85 -1.21]	[-0.19 1.18]	[0.40 1.79]	[-2.27 -0.05]	[-0.88 1.01]
AKM	[1.17 1.90]	[-2.42 -1.64]	[0.18 0.81]	[0.40 1.79]	[-2.24 -0.08]	[-0.41 0.54]
Observations	400	400	400	400	400	400
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓

Notes: Samples are 200 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. Columns (1)-(3) show the results for occupation for male workers, and Columns (4)-(6) show the ones for female workers. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

Changes in Occupation Share by Worker Age Group Next, we study the effect on occupation employment share by worker age groups. Table 8 shows the results. Columns (1)-(3) show the results for young workers (aged 25-44), and Columns (4)-(6) show the ones for middle and old workers (aged 45-64).

The estimates for middle and old-aged workers are insignificant and smaller in size compared to significant estimates for young workers' shifts from routine occupation in manufacturing sectors to service sector employment. This suggests that the adjustment of labor markets only occurs for young workers rather than old workers, which is consistent with the findings in Kikuchi and Kitao (2020) for the US and with the ones in Dauth et al. (2021) for Germany.

Changes in Occupation Share by Education Group Finally, we study the effect on occupation employment share by workers' education groups. Table 9 shows the results. Columns (1)-(3) show the results for college-educated workers, and Columns (4)-(6) show the ones for non-college-educated workers.

Table 8: Effects of Automation on Changes in Employment Share by Demographic Group

	Dep. Var.: Changes in Employment Rate					
	Young Workers (aged 25-44)			Middle-Old Workers (aged 45-64)		
	Abstract	Routine	Manual	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted Penetration of Robots	2.01	-2.19	0.18	0.37	-0.81	0.44
EHW	[1.18 2.83]	[-3.04 -1.34]	[-0.54 0.90]	[-0.47 1.22]	[-1.92 0.30]	[-0.54 1.41]
AKM	[1.39 2.62]	[-2.73 -1.64]	[-0.11 0.47]	[0.05 0.70]	[-1.32 -0.30]	[0.14 0.74]
Observations	406	406	406	406	406	406
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. Columns (1)-(3) show the results for occupation for young workers (aged 25-44), and Columns (4)-(6) shows the ones for middle and old workers (aged 45-64). All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

Again, the shift is only apparent for non-college-educated workers, moving from routine to abstract occupation, and college-educated workers experience no shift in occupation in response to automation.

6 Concluding Remarks

This paper shows that advances in automation technology since 1980 shifted labor demand from routine occupation in manufacturing sectors to service sectors, comparing local labor markets in Japan.

There are several promising avenues for future research. First, studying the impact of inequality would be important as in Acemoglu and Restrepo (2022). The ESS data does not contain data for either income or hours, and these variables are available only as rough bins. One can use data on wages from the Basic Survey on Wage Structure from the Ministry of Health, Labour and Welfare as in Kambayashi et al. (2008) or Kawaguchi and Mori (2016). Second, it would be fruitful to examine the effect on skill distribution, namely educational upgrading.[13]

[13] Arai et al. (2015) studies the educational upgrading of the youth in Japan in the same period.

Table 9: Effects of Automation on Changes in Employment Share by Education Group

	Dep. Var.: Changes in Employment Rate					
	College-Educated Workers			Non-College Educated Workers		
	Abstract	Routine	Manual	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted Penetration of Robots	0.36	-0.18	-0.18	1.68	-1.75	0.07
EHW	[-0.73 1.44]	[-1.14 0.78]	[-0.82 0.46]	[1.04 2.31]	[-2.60 -0.90]	[-0.57 0.72]
AKM	[-0.11 0.82]	[-0.52 0.16]	[-0.39 0.04]	[1.30 2.05]	[-2.15 -1.35]	[-0.20 0.35]
Observations	304	304	304	304	304	304
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓

Notes: Samples are 152 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. Columns (1)-(3) show the results for occupation for college-educated workers, and Columns (4)-(6) show the ones for non-college-educated workers. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

References

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, Volume 4, pp. 1043–1171. Elsevier.

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political economy 128*(6), 2188–2244.

Acemoglu, D. and P. Restrepo (2022). Tasks, automation, and the rise in us wage inequality. *Econometrica 90*(5), 1973–2016.

Adachi, D., T. Fukai, D. Kawaguchi, and Y. Saito (2020). Commuting zones in japan. Discussion papers 20-E-021, Research Institute of Economy, Trade and Industry (RIETI).

Adachi, D., D. Kawaguchi, and Y. Saito (2022). Robots and Employment: Evidence from Japan, 1978-2017. Discussion papers 20-E-051, Research Institute of Economy, Trade and Industry (RIETI).

Adao, R., M. Kolesár, and E. Morales (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics 134*(4), 1949–2010.

Arai, Y., H. Ichimura, and D. Kawaguchi (2015). The educational upgrading of japanese youth, 1982–2007: Are all japanese youth ready for structural reforms? *Journal of the Japanese and International Economies 37*, 100–126.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association 19*(6), 3104–3153.

Fukao, K., S. Hamagata, T. Inui, K. Ito, H.-U. Kwon, T. Makino, T. Miyagawa, Y. Nakanishi, and J. Tokui (2007). Estimation Procedures and TFP Analysis of the JIP Database 2006 Provisional Version. Discussion papers 07-E-003, Research Institute of Economy, Trade and Industry (RIETI).

Fukao, K., K. Ikeuchi, T. Inui, H.-U. Kwon, Y.-G. Kim, S. Tahara, J. Tokui, T. Makino, T. Matsura, and T. Miyagawa (2021). JIP Database 2018: Estimation Procedures and Overview (in Japanese). Technical papers 21-T-001, Research Institute of Economy, Trade and Industry (RIETI).

Graetz, G. and G. Michaels (2018). Robots at Work. *The Review of Economics and Statistics 100*(5), 753–768.

Hamaguchi, N. and K. Kondo (2018). Regional employment and artificial intelligence in japan. Discussion papers 18-E-032, Research Institute of Economy, Trade and Industry (RIETI).

Ikenaga, T. and R. Kambayashi (2016). Task polarization in the japanese labor market: Evidence of a long-term trend. *Industrial Relations: A Journal of Economy and Society 55*(2), 267–293.

International Federation of Robotics (2023). World robotics 2023 report. Technical report, International Federation of Robotics.

Kambayashi, R. (2013). Differences in definitions of non-regular employees in government statistics. *Japan Labor Review 10*(4), 55–66.

Kambayashi, R. (2017). *Standard Workers, Non-Standard Workers; Seiki no Sekai, Hiseiki no Sekai (in Japanese)*. Keio University Press.

Kambayashi, R., D. Kawaguchi, and I. Yokoyama (2008). Wage distribution in japan, 1989–2003. *Canadian Journal of Economics/Revue canadienne d'économique 41*(4), 1329–1350.

Kawaguchi, D. and H. Mori (2019). The labor market in japan, 2000-2018. *IZA World of Labor*.

Kawaguchi, D. and Y. Mori (2016). Why has wage inequality evolved so differently between japan and the us? the role of the supply of college-educated workers. *Economics of Education Review 52*, 29–50.

Kikuchi, S. and S. Kitao (2020). Welfare effects of polarization: Occupational mobility over the life-cycle. Discussion papers 20-E-043, Research Institute of Economy, Trade and Industry (RIETI).

Kitao, S. and M. Mikoshiba (2020). Females, the elderly, and also males: Demographic aging and macroeconomy in japan. *Journal of the Japanese and International Economies 56*, 101064.

Kondo, K. (2023). Municipality-level Panel Data and Municipal Mergers in Japan. Technical papers 23-T-001, Research Institute of Economy, Trade and Industry (RIETI).

Webb, M. (2019). The impact of artificial intelligence on the labor market. *Available at SSRN 3482150*.

A Data Appendix

Coverage of ESS Table A.1 shows the coverage of the ESS data across survey years. The latest survey (2017 survey) includes approximately 1.08 million individuals from 520,000 households residing in 33,000 survey districts around the nation, and past surveys have similar levels of coverage.

Table A.1: The coverage of ESS

Survey year	Individuals	Households	Survey districts
1982	0.83 million	330,000	23,000
1987	0.83 million	330,000	25,000
1992	1.05 million	430,000	29,000
1997	1.1 million	430,000	29,000
2002	1.05 million	440,000	29,000
2007	1 million	450,000	30,000
2012	1 million	470,000	32,000
2017	1.08 million	520,000	33,000

Occupation Group Table A.2 shows the mapping of occupation groups in ESS data each year into our 3 categories. We list the mapping for the three years (1982, 1997, 2012) using our main regressions. In 2012, ESS data used the Japan Standard Classification of Occupations (JSCO) revised in 2009. We classify groups A, B, and C to Abstract occupation, H, J to Routine occupation, and D, E, F, and K to Manual occupation. To be consistent with the classification in 1982 and 1997, we classify machine operator workers in I group (I64) in 2012 into Routine occupation and transport workers in I group (I61-I63) in 2012 into Manual occupation. This is feasible because ESS data has detailed occupation categories in 2012 and 2017. In 1997, ESS data used JSCO revised in 1986. In 1982, ESS data follows JSCO revised in 1979 at the category level we are using.[14] We exclude workers in agricultural and fishing industries from our analysis.

[14] To be precise, ESS data uses the classification used in the Census in 1980, but the classification is the same as JSCO revised in 1979 at the category level we are using.

Table A.2: Mapping of occupation groups into 3 categories

Panel A: Occupation groups in 2012 survey	
Abstract	A. Administrative and managerial workers, B. Professional and engineering workers, C. Clerical workers D. Sales workers,
Routine	H. Manufacturing process workers, I-64. Machine operation workers, J. Construction and mining workers
Manual	E. Service workers, F. Security workers, I-61 $\sim$ I-63. Transport workers, K. Carrying, clearing, packing, and related workers
Panel B: Occupation groups in 1997 survey	
Abstract	A. Professional and engineering workers, B. Managerial workers, C. Clerical workers D. Sales workers,
Routine	I. Manufacturing process, construction, and mining, machine operation workers
Manual	E. Service workers, F. Security workers, H. Transport and Communication workers
Panel C: Occupation groups in 1982 survey	
Abstract	A. Professional and engineering workers, B. Managerial workers, C. Clerical workers D. Sales workers,
Routine	F. Mining workers, H. Manufacturing process, machine operation workers
Manual	G. Transport and Communication workers, I. Security workers, J. Service workers,

This table shows the mapping of occupation groups reported in the ESS survey into three groups we use in the analysis for 1982, 1997, and 2012.

B Theoretical Rationale for Adjusted Penetration of Robots

In this section, we derive our measure of adjusted penetration of robots based on a simple task framework.

Our measure is

$$\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} = \frac{dM_i}{L_i} - \frac{dY_i}{Y_i}\frac{M_i}{L_i},$$

and we show that this measure is consistent with the standard task model as follows.

B.1 Set up

Consider an industry-level partial equilibrium model with the following production function.

$$Y = \alpha^{-\alpha}(1-\alpha)^{\alpha-1}\left[\min_{s\in[0,1]} x(s)\right]^{\alpha} K^{1-\alpha},$$

where Y is the output, $x(s)$ is the quantity of task s, and K is non-robot capital exogenously given at price p^K. $\alpha^{-\alpha}(1-\alpha)^{\alpha-1}$ is a convenient normalization.

Each task $x(s)$is produced by either robot $M(s)$ or labor $L(s)$ as follows:

$$x(s) = \begin{cases} \gamma_M M(s) + \gamma_L L(s) & \text{if } s < \theta \\ \gamma_L L(s) & \text{if } s \geq \theta \end{cases}$$

If $s < \theta$, both robot capital $M(s)$ and labor $L(s)$ can produce task $x(s)$ while only labor can produce $x(s)$ if $s \geq \theta$.

R and W are robot capital price and wages, respectively. We assume robot capital is freely tradable and the price R is exogenously given.

Assume that the technology constraint is always binding, that is,

$$\frac{R}{\gamma_M} < \frac{W}{\gamma_L}.$$

B.2 Characterization

Since automation is always profitable, all the tasks, that can be technologically automated, will be automated, and the factor share for robots is given by

$$RM_i = \alpha\theta_i Y_i,$$

and the equilibrium quantity of each task will be

$$\min_{s\in[0,1]} x^*(s) = \frac{\gamma_M M_i}{\theta_i} = \frac{\gamma_L L_i}{1-\theta_i}.$$

Log linearizing the factor share for robots,

$$\frac{dY_i}{Y_i} = \frac{dM_i}{M_i} - \frac{d\theta_i}{\theta_i}.$$

Using $\frac{M_i}{L_i} = \frac{\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M}$ from the equilibrium quantity of each task,

$$\frac{dY_i}{Y_i}\frac{M_i}{L_i} = \frac{dM_i}{M_i}\frac{M_i}{L_i} - \frac{d\theta_i}{\theta_i}\frac{M_i}{L_i} = \frac{dM_i}{M_i}\frac{M_i}{L_i} - \frac{d\theta_i}{\theta_i}\frac{\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M},$$

which leads to

$$\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} = \frac{dM_i}{L_i} - \frac{dY_i}{Y_i}\frac{M_i}{L_i}.$$

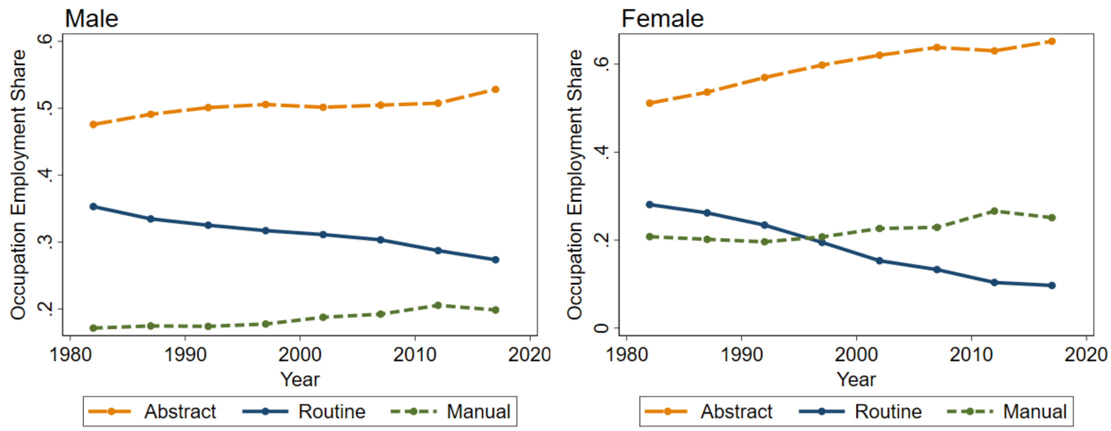
■

C More Facts

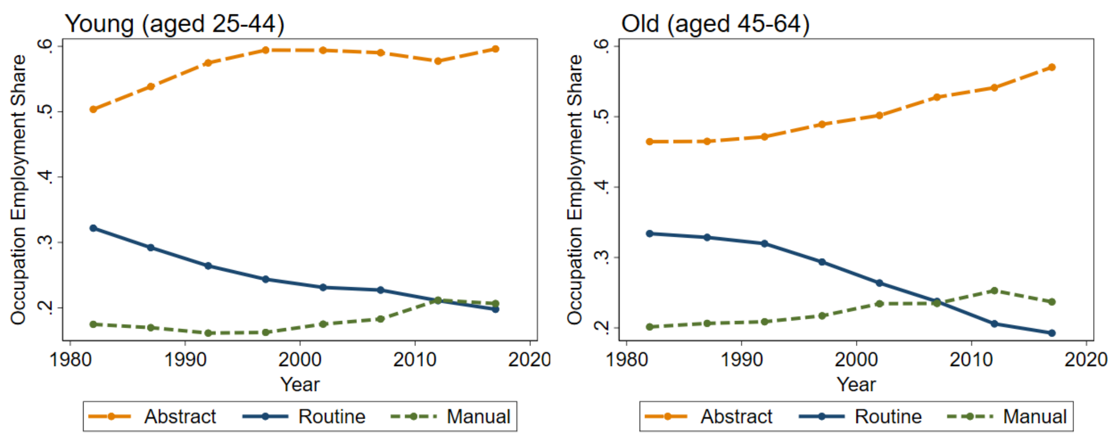
Figure C.1 shows the occupation share over time for each gender. It shows that the shift from routine to abstract occupations are common across gender and across age groups, but the shift is only appear for non-college educated workers.

Figure C.1: Employment Share by Occupation Group in Japan: By Demographic Group

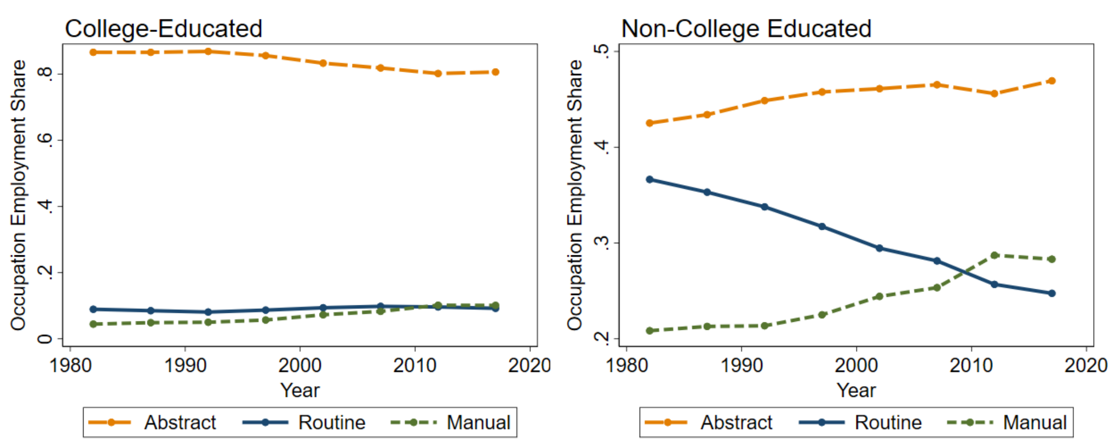
(a) Gender



(b) Age



(c) Education



Notes: The figure shows the employment share by occupation group in Japan. Data is from ESS.

D Robustness

D.1 Employment Effects across Subgroups

Table D.1 shows the relationship between automation and changes in employment rate relative to the population for different demographic groups across commuting zones in Japan. We use IV regressions. Column (1) uses males, Column (2) uses females, Column (3) uses young labor force (aged 25-44). Column (4) uses the middle or old labor force (aged 45-64), Column (5) uses the college-educated, and Column (6) uses the non-college-educated as samples.

Table D.1: Effects of Automation on Changes in Employment Rate across Demographic Groups

	Dep. Var. Changes in Employment Rate					
	Males	Females	Young	Old	College	Non-College
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted Penetration of Robots	-0.42	-0.11	-0.16	-0.14	-0.17	-0.26
EHW	[-1.02 0.17]	[-0.85 0.64]	[-0.83 0.51]	[-0.88 0.59]	[-1.00 0.67]	[-0.86 0.33]
AKM	[-0.66 -0.19]	[-0.42 0.21]	[-0.38 0.05]	[-0.48 0.20]	[-0.60 0.27]	[-0.53 0.00]
Observations	344	344	344	344	344	344
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓

Notes: Samples are 172 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and changes in employment rate relative to population for different demographic groups across commuting zones in Japan. We use IV regressions. Column (1) uses males, Column (2) uses females, Column (3) uses young labor force (aged 25-44). Column (4) uses middle or old labor force (aged 45-64), Column (5) uses the college-educated, and Column (6) uses the non-college-educated as samples. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

D.2 OLS Results

In the main text, we present results based on IV regressions. In this subsection, we present the OLS regressions versions for tables.

Table D.2 shows the OLS version of Table 4 in the main text. The estimate (-0.91) for the decline in routine occupation share shown in Column (3) of Table D.2 is smaller than the one of Table 4 (-1.69). The OLS estimate is smaller in magnitude because robot adoption at the industry level correlates with the expansion of the manufacturing sectors, which extensively use robots. This makes the OLS estimates biased towards zero for the decline in routine occupation share.

Table D.2: Effects of Automation on Changes in Employment Rate and Occupation Share: OLS

	Dep. Var. Changes in Employment Rate			
	Total	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)
Adjusted Penetration of Robots	-0.13	0.63	-0.91	0.28
EHW	[-0.46,0.20]	[0.21,1.06]	[-1.42,-0.41]	[-0.19,0.75]
AKM	[-0.25 -0.01]	[0.52 0.75]	[-1.06 -0.77]	[0.14 0.41]
Observations	406	406	406	406
Initial CZ Covariates	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. We use OLS regressions. Column (1) uses changes in employment rate relative to population as an outcome. Column (2), (3), and (4) use changes in occupational employment share in abstract, routine, and manual occupation respectively. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

D.3 Different Measure of Robot Penetration

In the main text, we use adjusted penetration of robots to remove the mechanical positive effects of robot adoption on manufacturing employment as in Acemoglu and Restrepo (2020) and Dauth et al. (2021). When manufacturing sectors expand, demand for robots increases. Thus, directly using the increases in the number of robots would capture mechanical effects on employment. However, some papers, including Adachi et al. (2022), use the raw numbers of robots normalized by employment, $PR_{c,t,t+15}$, which is an un-adjusted penetration of robots in commuting zone c from year t to $t + 15$. They construct commuting-zone-level robot exposure $PR_{c,t,t+15}$ from employment-weighted average of industry level robot exposure

$$PR_{c,t,t+15} = \sum_i \ell_{c,i,t} \cdot PR_{i,t,t+15}$$

Here, $\ell_{c,i,t}$ denotes a ratio of workers in commuting zone c worked in industry i relative to total workers in commuting zone c, and $PR_{i,t,t+15}$ denotes industry level un-adjusted penetration of robots, which we define as follows.

$$PR_{i,t,t+15} = \frac{\Delta R_{i,t,t+15}}{L_{i,t}}$$

where $\Delta R_{i,t,t+15}$ is a change in the number of robots in industry i from year t to $t + 15$, $L_{i,t}$ is a number of workers in industry i in year t.

We confirm that our results are robust even if we use the un-adjusted measure in Table D.3. Here, we run the same regressions, but using $PR_{c,t,t+15}$ instead of $APR_{c,t,t+15}$ as the running variable.

Table D.3: Effects of Automation on Changes in Employment Rate and Occupation Share

	Dep. Var. Changes in Employment Rate			
	Total	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)
Penetration of Robots	-0.19	1.96	-2.49	0.53
EHW	[-0.93 0.55]	[1.09 2.83]	[-3.74 -1.25]	[-0.38 1.45]
AKM	[-0.52 0.14]	[1.72 2.20]	[-2.89 -2.10]	[0.15 0.91]
Observations	406	406	406	406
Initial CZ Covariates	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓
Demographic Change Covariates	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and employment outcomes across commuting zones in Japan. Column (1) uses changes in employment rate relative to population as an outcome. Columns (2), (3), and (4) use changes in occupational employment share in abstract, routine, and manual occupation respectively. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to the old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

D.4 Different Measures of Sectoral Activities across Local Labor Market

Additional Data Source Our first additional data source is the Census of Manufactures (CoM) for the manufacturing sector. The Ministry of Economy, Trade, and Industry (METI) conducts the Japanese Census of Manufactures annually to gather information on the current status of establishments in the manufacturing sector. We use data in 1982, 1997, and 2012. We also use the Census of Commerce for the retail and wholesale sectors. The Ministry of Economy, Trade, and Industry (METI) surveys to gather information on the current status of establishments in the retail and wholesale sectors. We use data from 1985, 1997, and 2014 as these are the closest years for our years of interest, 1982, 1997, and 2012, respectively.

Results Table D.4 shows the relationship between automation and sectoral activities across commuting zones in Japan. Column (1) uses log changes in the total shipment of the manufacturing sector, Column (2) uses log changes in the total sales of the retail and wholesale sector, and Column (3) uses log changes in the ratio of the shipment in the manufacturing sector to retail and wholesales sectors' sales. While the effect on log shipment in the manufacturing sector is not significant, the estimate for the ratio of the manufacturing sector to the retail and wholesale sectors is positive, which means that automation expands the manufacturing sector relatively.

Table D.4: Effects of Automation on Changes in Sectoral Activities

	Dep. Var. Log Changes in		
	Manufacturing	Sales	Manufacturing/Sales
	(1)	(2)	(3)
Adjusted Penetration of Robots	8.72	-6.13	14.85
EHW	[-0.42 17.87]	[-14.42 2.17]	[4.11 25.60]
AKM	[-0.36 17.81]	[-13.96 1.71]	[3.63 26.08]
Observations	406	406	406
Initial CZ Covariates	✓	✓	✓
Tech Change Covariates	✓	✓	✓
Demographic Change Covariates	✓	✓	✓
Period FEs	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and sectoral activities across commuting zones in Japan. Column (1) uses log changes in the total shipment of the manufacturing sector, Column (2) uses log changes in the total sales of the retail and wholesale sector, and Column (3) uses log changes in the ratio of the shipment in the manufacturing sector to retail and wholesales sectors' sales, respectively. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to the old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

D.5 Effects on Regular Workers' Share and Level of Employment

Table D.5 shows the relationship between automation and the share of regular workers and the levels of employment and population. Column (1) uses log changes in the share of regular workers, Column (2) uses log changes in employment, and Column (3) uses log changes in population. None of the estimates is significant, in particular the first column, the share of regular workers. This implies that automation did not increase the share of non-regular workers.[15]

Table D.5: Effects of Automation on Regular Workers' Share and Levels

	Dep. Var. Log Changes in		
	Regular Share	Employment	Population
	(1)	(2)	(3)
Adjusted Penetration of Robots	0.14	1.03	1.40
EHW	[-0.67 0.96]	[-3.16 5.22]	[-2.85 5.64]
AKM	[-0.61 0.89]	[-0.99 3.05]	[-0.55 3.34]
Observations	406	406	406
Initial CZ Covariates	✓	✓	✓
Tech Change Covariates	✓	✓	✓
Demographic Change Covariates	✓	✓	✓
Period FEs	✓	✓	✓

Notes: Samples are 203 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the relationship between automation and sectoral activities across commuting zones in Japan. Column (1) uses log changes in the share of regular workers, Column (2) uses log changes in employment, and Column (3) uses log changes in population. All columns include covariates that control initial commuting zone characteristics, exposure to technological change, and demographic change. The initial commuting zone characteristics include the ratio of female workers, the ratio of college-educated workers, the ratio of young (aged 25-59) population relative to the old (aged 60 and up) population, the ratio of young (aged 25-44) workers relative to old (aged 45 and up) workers, and share of manufacturing employment in the initial period. The technology exposure covariates include changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports. All of these industry-level changes are converted to commuting-zone-level exposure as in the running variable. The demographic change covariates include changes in the ratio of female workers, college-educated workers, and young population. Each observation is weighted by its initial population size. EHW is the 95% confidence interval based on the Eicker-Huber-White standard error clustered at commuting-zone-level, and AKM is the 95% confidence interval based on the shift-share standard errors from Adao et al. (2019).

[15] We use the questionnaire of workplace titles in the ESS data to define regular and non-regular workers because several papers suggest that a title/description in the workplace is more closely connected to working conditions than the length of the labor contract. See Kambayashi (2013) or Kambayashi (2017) for the discussion.